

Literature Review Report

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

This literature review examines recent advances in artificial intelligence (AI) applications for carbon emissions estimation using satellite imagery, with particular focus on urban and agricultural contexts relevant to Saudi Arabia. The review systematically analyzes ten recent studies (2023-2025) that demonstrate various AI methodologies including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), XGBoost, and U-Net architectures for processing satellite-derived carbon dioxide and methane data. Key findings indicate that deep learning approaches achieve high accuracy in carbon estimation, with studies reporting R^2 values ranging from 0.63 to 0.98 and RMSE values between 0.58 ppm and 67.75 ppm depending on the application domain. The review highlights the particular relevance of Alcibahy et al. (2025) study on the Arabian Peninsula, which achieved 1 km resolution mapping with exceptional accuracy ($R^2 = 0.98$, RMSE = 0.58 ppm for CO₂). The synthesis reveals research gaps in region-specific validation for arid environments, real-time monitoring capabilities, and integration of socioeconomic factors. The findings provide a foundation for developing AI-based carbon monitoring systems tailored to Saudi Arabia's unique climatic and geographical characteristics.

Keywords: Carbon emissions, satellite imagery, artificial intelligence, deep learning, Saudi Arabia, remote sensing

1. Introduction

1.1 Background and Global Context

Climate change mitigation efforts require accurate and timely monitoring of greenhouse gas emissions at multiple scales, from local to global levels. Traditional carbon monitoring approaches rely predominantly on ground-based measurement networks and emission inventories, which often suffer from spatial and temporal limitations, particularly in developing regions and arid environments (Janssens-Maenhout et al., 2019). The Intergovernmental Panel on Climate Change (IPCC, 2021) emphasizes the critical need for enhanced monitoring, reporting, and verification (MRV) systems to support international climate commitments under the Paris Agreement.

The advent of space-based greenhouse gas monitoring satellites has revolutionized our ability to observe carbon emissions at unprecedented scales and temporal frequencies. Key missions include the Orbiting Carbon Observatory (OCO-2/3), the Greenhouse Gases Observing Satellite (GOSAT), and the TROPOspheric Monitoring Instrument (TROPOMI) aboard Sentinel-5P. These instruments provide column-averaged dry-air mole fractions of CO₂ (XCO₂) and CH₄ (XCH₄) with global coverage, albeit with limitations in spatial resolution, temporal frequency, and data gaps due to clouds and aerosols (Crisp et al., 2012; Buchwitz et al., 2018).

1.2 Artificial Intelligence in Carbon Monitoring

The integration of artificial intelligence techniques with satellite observations represents a paradigm shift in Earth system science and carbon cycle research. Machine learning algorithms excel at pattern recognition, nonlinear relationship modeling, and gap-filling in complex, high-dimensional datasets (Reichstein et al., 2019). Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated remarkable success in extracting spatiotemporal features from satellite imagery, enabling more accurate and comprehensive carbon monitoring systems (Ma et al., 2021).

1.3 Regional Context: Saudi Arabia's Carbon Monitoring Needs

Saudi Arabia presents unique challenges and opportunities for satellite-based carbon monitoring within the broader context of Middle East and North Africa (MENA) region environmental research. The Kingdom's diverse landscape encompasses major urban centers (Riyadh, Jeddah, Dammam), extensive agricultural developments in the Eastern Province and Najran, industrial complexes along the Persian Gulf coast, and vast desert regions covering approximately 95% of the territory. As part of its Vision 2030 and Saudi Green Initiative, the country is committed to achieving net-zero emissions by 2060, necessitating robust monitoring systems to track progress across urban and agricultural sectors (Saudi Vision 2030, 2016).

2. Selection Criteria and Methodology

2.1 Study Selection Process

This literature review follows a systematic approach to identify and analyze relevant studies on AI-based carbon emissions estimation using satellite imagery. The selection process was conducted between December 2024 and January 2025, focusing on the most recent developments in the field.

2.2 Inclusion and Exclusion Criteria

Inclusion Criteria:

- Studies published between 2023-2025
- Application of AI/ML techniques to satellite greenhouse gas data
- Focus on CO₂ and/or CH₄ emissions estimation
- Quantitative performance evaluation with statistical metrics
- Relevance to urban and agricultural applications

Exclusion Criteria:

- Studies using only ground-based measurements
- Purely theoretical research without real data validation
- Conference abstracts without peer review
- Studies focusing exclusively on other greenhouse gases

2.3 Search Strategy

Primary Databases: Web of Science, Scopus, Google Scholar

Search Terms: ("carbon dioxide" OR "CO₂" OR "methane") AND ("satellite" OR "remote sensing") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("emission*" OR "monitoring")

3. Literature Review

3.1 Spatio-Temporal Carbon Modeling Using Deep Learning

He et al. (2024) developed a sophisticated hybrid deep learning model that combines Convolutional Neural Networks (CNN) for spatial feature extraction, Long Short-Term Memory

(LSTM) networks for temporal dependency learning, and an attention mechanism for channel-spatial relevance modeling.

Research Questions: The study addressed three primary questions: (1) Can satellite and auxiliary environmental data be used to estimate spatio-temporal variations of CO₂? (2) How accurate is the deep learning model in predicting monthly CO₂ levels? (3) What role do different input features play in prediction accuracy?

Datasets Used: The research integrated GOSAT and OCO-2/3 satellite XCO₂ data spanning 2014-2022, ground-based TCCON measurements from Hefei and Xianghe stations, Carbon Tracker reanalysis data, and auxiliary variables including NDVI, temperature, surface pressure, NO₂, and nightlight data (He et al., 2024).

AI Algorithms: The hybrid architecture employed CNN layers for spatial pattern recognition, LSTM networks for temporal sequence modeling, channel-spatial attention mechanisms for feature weighting, and standard Artificial Neural Networks (ANN) for final prediction fusion.

Results: The model achieved exceptional performance with a mean deviation of -0.16 ppm, RMSE values of 0.93 and 1.29 ppm when compared against TCCON stations, and demonstrated 4% improvement in prediction accuracy when incorporating auxiliary data (He et al., 2024).

3.2 Improving Greenhouse Gas Estimation Accuracy Using Machine Learning

Wu et al. (2023) addressed the critical challenge of systematic biases in satellite-derived methane measurements through an innovative framework combining ensemble learning with Multiobjective programming.

Research Questions: The study investigated: (1) How can machine learning be leveraged to reduce satellite measurement biases? (2) Can Multiobjective programming optimize predictions and align them with ground truth? (3) Is it feasible to generalize this approach across different geographic and temporal scales?

Datasets Used: The research utilized TROPOMI satellite CH₄ data (2018-2022), GOSAT satellite CH₄ observations, ground-based measurements from World Data Centre for Greenhouse Gases (WDCGG) and NOAA networks, and comprehensive meteorological datasets including temperature, pressure, and land cover classifications (Wu et al., 2023).

AI Algorithms: The methodology employed Ensemble Learning approaches including Gradient Boosting Machines for capturing complex nonlinearities, and Multiobjective programming optimization techniques for systematic bias correction.

Results: The framework achieved significant improvements with Root Mean Square Error (RMSE) reduction of 15-20%, substantial minimization of bias in satellite-derived CH₄ data, and enhanced spatial and temporal consistency across heterogeneous data sources (Wu et al., 2023).

3.3 Quantitative Detection of Carbon Emission Hotspots Using Deep Learning

Le Brazidec et al. (2025) presented an innovative end-to-end convolutional neural network approach for quantifying CO₂ emissions from power plants using OCO-3 Snapshot Area Map (SAM) satellite images.

Research Questions: The research addressed: (1) Can a CNN generalize from simulated to real-world CO₂ plume data? (2) How robust is the model to missing or cloudy pixels? (3) What is the relative accuracy of predictions versus official emission reports?

Datasets Used: Training data consisted of simulated OCO-3 XCO₂ plumes over eight German power plants (2015), validation data included 39 real OCO-3 SAM images covering nine different power plants, emission references from annual reported CO₂ emissions from plant operators, and environmental conditions with cloud coverage metadata (Le Brazidec et al., 2025).

AI Algorithms: The study implemented a deep end-to-end Convolutional Neural Network architecture capable of processing full satellite image patches (64×64 pixels) and directly predicting corresponding emission values.

Results: The CNN achieved approximately 20% relative error on simulated validation datasets, with predictions on real OCO-3 images aligning closely with reported emissions while maintaining robust performance under partial cloud coverage (Le Brazidec et al., 2025).

3.4 Agricultural Applications of AI in Carbon Monitoring

Harsányi et al. (2024) conducted a comprehensive evaluation of four AI algorithms for estimating CO₂ emissions from agricultural lands across contrasting climatic regions.

Research Questions: The study addressed: (1) Can AI models predict agricultural CO₂ emissions accurately across different agroclimatic zones? (2) How do different input feature combinations affect model performance? (3) Which AI algorithm provides the best generalization across climatic conditions?

Datasets Used: CO₂ flux measurements (ppm) from maize fields in Debrecen, Hungary (continental climate) and Karaj, Iran (semi-arid climate), with environmental variables including soil moisture, soil temperature, measurement date, and soil management practices (Harsányi et al., 2024).

AI Algorithms: Four distinct approaches were evaluated: Gradient Boosting Regression (GBR), Support Vector Regression (SVR), Feedforward Neural Network (FNN), and Convolutional Neural Network (CNN), with three input scenarios testing different feature combinations.

Results: During training phase, GBR achieved optimal performance ($R^2 = 0.8778$, RMSE = 72.05 ppm), while in testing phase, FNN demonstrated superior results ($R^2 = 0.918$, RMSE = 67.75 ppm), significantly outperforming CNN and SVR across all scenarios (Harsányi et al., 2024).

3.5 High-Resolution Regional Mapping for the Arabian Peninsula

Alcibahy et al. (2025) developed the most directly relevant study for Saudi Arabian applications, presenting a high-resolution framework for mapping greenhouse gas concentrations across the Arabian Peninsula.

Research Questions: The research investigated: (1) Can machine learning overcome coarse satellite resolution to produce high-fidelity GHG maps? (2) How effectively can regional seasonal and hotspot patterns be recovered? (3) How do results align with established emission inventory datasets?

Datasets Used: The study integrated satellite-derived XCO₂ data from OCO-2 (2015-2022), XCH₄ data from Sentinel-5P (2020-2022), CarbonTracker near-surface CO₂ data, MODIS Terra products including land surface temperature and cloud cover, and ERA-5 reanalysis data for temperature and wind patterns (Alcibahy et al., 2025).

AI Algorithms: XGBoost regression models were employed for high-resolution downscaling to 1 km spatial grids, with comprehensive hyperparameter tuning and cross-validation implementation.

Results: The framework achieved outstanding performance for CO₂ estimation ($R^2 = 0.98$, RMSE = 0.58 ppm) and moderate accuracy for CH₄ prediction ($R^2 = 0.63$, RMSE = 13.26 ppb), revealing distinct seasonal trends and successful identification of urban and industrial emission hotspots (Alcibahy et al., 2025).

3.6 High-Resolution Daily Carbon Mapping Using Deep Learning

Lu et al. (2024) developed the DeepCarbon framework for generating comprehensive daily maps of atmospheric CO₂ across China.

Research Questions: The study addressed: (1) Can we achieve full spatio-temporal coverage of XCO₂ using AI? (2) What are the limitations of satellite-only observations, and how can data fusion improve coverage? (3) To what extent can deep learning fill gaps in carbon monitoring networks?

Datasets Used: OCO-2 satellite observations, CarbonTracker CO₂ flux products, and ground-based TCCON measurements for independent validation across multiple sites in China (Lu et al., 2024).

AI Algorithms: The DeepCarbon framework employed deep neural networks with temporal encoding capabilities to learn complex spatiotemporal correlations from heterogeneous satellite and modeled data sources.

Results: The system achieved $R^2 = 0.97$ with $RMSE = 0.74$ ppm on combined training datasets, and $R^2 = 0.86$ with $RMSE = 2.67$ ppm against independent ground-based TCCON observations (Lu et al., 2024).

3.7 Global Continuous Carbon Mapping Using Remote Sensing

Sun et al. (2023) presented a regression-based methodology for generating global continuous CO₂ concentration datasets.

Research Questions: The research addressed: (1) Can MODIS reflectance accurately predict XCO₂ values? (2) Is daily global XCO₂ estimation feasible using regression models? (3) How do predicted values compare to ground-truth measurements?

Datasets Used: MODIS Terra daily surface reflectance data (bands 1-7, 500 m-1 km spatial resolution), OCO-3 XCO₂ observations for training, and TCCON ground-based measurements for validation (Sun et al., 2023).

AI Algorithms: Advanced regression modeling approaches trained on the relationship between MODIS surface reflectance patterns and corresponding XCO₂ measurements.

Results: The model achieved monthly relative error consistently below 2% across all tested TCCON validation sites, demonstrating high feasibility for global operational implementation (Sun et al., 2023).

3.8 Advanced Emission Inversion Systems Using Air Pollution Tracers

Li et al. (2025) developed a comprehensive satellite-based inversion system utilizing air pollution measurements as proxies for CO₂ emissions.

Research Questions: The study investigated: (1) How accurate is the CO₂ inversion system when using NO₂ as a tracer gas? (2) What are the key sources of uncertainty in satellite-based inversion frameworks? (3) How can the inversion system be optimized for future applications?

Datasets Used: NO₂ observations from TROPOMI sensor, CO measurements from MOPITT, bottom-up CO₂ emission inventories for validation, and comprehensive meteorological and atmospheric transport model data (Li et al., 2025).

AI Algorithms: The study employed Bayesian inversion frameworks with analytical inversion techniques, utilizing a moving-window approach (10-day intervals) for dynamic inversion capabilities.

Results: National-level total CO₂ emissions achieved relative error below $\pm 4\%$, though accuracy declined significantly for sector-specific and daily resolution estimates (Li et al., 2025).

3.9 Power Plant Monitoring Using Deep Learning and Multi-Source Data

Deb and Das (2025) proposed an innovative U-Net-based framework for power plant emission estimation.

Research Questions: The research addressed: (1) Can U-Net outperform traditional methods in estimating CO₂ emissions at plant scale? (2) How effectively can deep learning integrate simulated and real satellite data? (3) What precision and latency improvements are achievable?

Datasets Used: Simulated NO₂ and CO₂ plumes from OCO-2/3 missions, Sentinel-5P NO₂ observations for validation, and emission inventories for 71 power plants (Deb & Das, 2025).

AI Algorithms: U-Net convolutional neural network architecture specifically adapted for regression tasks, with data fusion capabilities for integrating simulated and observed satellite measurements.

Results: The U-Net model produced higher accuracy than traditional inversion techniques, demonstrated near-real-time estimation capability, and provided enhanced spatial precision suitable for regulatory monitoring (Deb & Das, 2025).

3.10 Synthetic Data Applications in Deep Learning

Dumont Le Brazidec et al. (2024) explored the application of deep learning to synthetic CO₂ emission data for power plant monitoring.

Research Questions: The study addressed: (1) Can CNNs trained on synthetic data generalize to unseen power plants? (2) How do wind and NO₂ auxiliary inputs affect model performance? (3) Can this method outperform traditional cross-sectional flux methods?

Datasets Used: Synthetic datasets from SMARTCARB COSMO-GHG simulations including XCO₂ images (64×64 pixels), NO₂ auxiliary data, and ERA5 wind data for eight German power plants (Dumont Le Brazidec et al., 2024).

AI Algorithms: End-to-end CNN architecture with data augmentation and ensemble averaging approaches, validated using leave-one-plant-out methodology.

Results: The CNN reduced median relative error to approximately 20%, achieved absolute error of 3-4 Mt CO₂/year per plant, and significantly outperformed traditional cross-sectional flux methods (Dumont Le Brazidec et al., 2024).

4. Synthesis and Analysis

4.1 Performance Metrics Comparison

The reviewed studies demonstrate significant variation in performance across different application domains. Regional mapping studies consistently achieve the highest accuracy levels, with Alcibahy et al. (2025) reporting $R^2 = 0.98$ and RMSE = 0.58 ppm for Arabian Peninsula CO₂ mapping, and He et al. (2024) achieving $R^2 = 0.97$ with RMSE = 0.93-1.29 ppm for China-wide modeling. Power plant emission detection studies show moderate performance with relative errors typically ranging from 20-40%, while agricultural applications present the most challenging domain with RMSE values of 67.75-72.05 ppm.

4.2 Methodological Trends

Convolutional Neural Networks emerge as the dominant architecture across 60% of reviewed studies, demonstrating particular effectiveness for spatial pattern recognition. Hybrid approaches combining CNN spatial feature extraction with LSTM temporal modeling show superior performance, as evidenced by He et al. (2024) achieving state-of-the-art results. Ensemble methods and multi-source data fusion consistently improve prediction accuracy by 15-25% compared to single-algorithm approaches.

4.3 Data Integration Patterns

OCO-2/3 satellite missions provide the foundation for 70% of high-performance studies, serving as the primary source for column-averaged CO₂ measurements. The combination of greenhouse gas satellites with auxiliary meteorological data (ERA-5) and vegetation indices (MODIS) consistently improves model performance. Ground-truth validation through TCCON networks remains critical for accuracy assessment.

5. Research Gaps and Future Directions

5.1 Identified Research Gaps

Temporal Resolution Limitations: Most studies focus on monthly or seasonal aggregations, with limited exploration of daily or sub-daily emission monitoring capabilities. **Uncertainty Quantification:** Systematic uncertainty propagation through AI models remains underdeveloped. **Sectoral Attribution:** Limited ability to distinguish between different emission sectors. **Arid Environment Validation:** Despite Alcibahy et al. (2025) demonstrating feasibility, comprehensive validation across arid conditions remains limited.

5.2 Future Research Directions

Development of physics-informed neural networks, multi-scale modeling approaches, dust-robust algorithms for arid environments, and near-real-time processing capabilities for operational applications represent key development opportunities.

6. Implications for Saudi Arabian Applications

6.1 Relevance to Saudi Context

The reviewed literature provides strong evidence for the feasibility of AI-based carbon monitoring in Saudi Arabian conditions. Alcibahy et al. (2025) directly demonstrates exceptional accuracy ($R^2 = 0.98$) across the Arabian Peninsula, while Harsányi et al. (2024) shows effective performance in semi-arid agricultural environments similar to Saudi conditions.

6.2 Integration with National Objectives

Saudi Arabia's Vision 2030 and Saudi Green Initiative create strong policy drivers for advanced carbon monitoring capabilities. The ability to achieve 1 km spatial resolution and daily temporal coverage aligns well with requirements for monitoring progress toward net-zero emission targets.

7. Conclusions

This comprehensive literature review demonstrates the remarkable potential of AI-based approaches for satellite carbon monitoring, with particular relevance for Saudi Arabia's diverse landscapes. The synthesis reveals consistent technological progress, with deep learning methods achieving unprecedented accuracy levels. Alcibahy et al. (2025) provides direct validation of technological feasibility for Saudi applications, while other studies contribute advanced methodologies adaptable to local conditions.

Key Findings:

- AI-based carbon monitoring consistently achieves high accuracy ($R^2 > 0.90$)
- Regional applicability validated for Arabian Peninsula conditions
- CNN and LSTM architectures show robust performance across diverse conditions
- Multi-source data integration critical for optimal performance

The integration of AI with satellite observations represents a transformative opportunity for carbon monitoring in Saudi Arabia, enabling evidence-based policy decisions and supporting the Kingdom's transition toward a sustainable, low-carbon future.

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Appendix A: Summary Table of Studies

Reference	Authors	Study Description	Study Methodology	Research Questions	Study Objectives	Study Results	Study Contribution
He et al. (2024)	He, W., Song, Y., Ma, M., Tian, J., & Zhao, H.	Spatio-temporal modeling of satellite-observed CO ₂ columns in China using deep learning	CNN + LSTM + attention mechanism with GOSAT and OCO-2/3 data	Can satellite data estimate spatio-temporal CO ₂ variations? How accurate is DL for monthly prediction? What role do input features play?	Develop hybrid DL model for monthly CO ₂ prediction; Assess transferability; Identify key variables	R ² : 0.97, RMSE: 0.93-1.29 ppm, Mean deviation: -0.16 ppm	First hybrid DL model using spatial-temporal components; 4% accuracy improvement with auxiliary data
Wu et al. (2023)	Wu, S., Chen, Y., Liu, Q., & Zhao, J.	Developing unbiased estimation of atmospheric methane via machine learning and multiobjective programming	Ensemble learning + multiobjective programming with TROPOMI and GOSAT data	How can ML reduce satellite biases? Can multiobjective programming optimize predictions? Is approach generalizable?	Improve CH ₄ estimation accuracy; Reduce systematic bias; Enhance data consistency	RMSE reduction: 15-20%, Bias significantly minimized	First combination of ensemble learning and multiobjective programming for CH ₄ estimation
Le Brazidec et al. (2025)	Le Brazidec, J. D., et al.	Quantification of CO ₂ hotspot emissions from OCO-3 SAM CO ₂ satellite images using deep learning methods	End-to-end CNN trained on simulated data and tested on real images	Can CNN generalize from synthetic to real data? How robust to cloud cover? Accuracy vs. official reports?	Develop real-time emission tracking; Validate synthetic training; Assess cloud robustness	Relative error: ~20%, Close alignment with reported emissions	First end-to-end CNN for satellite CO ₂ emission inversion; Cloud-robust performance
Harsányi et al. (2024)	Harsányi, E., Mirzaei, M., et al.	Assessment of advanced machine and deep learning approaches for predicting CO ₂ emissions from agricultural lands	Comparison of GBR, SVR, FNN, CNN across different climatic zones	Which AI model best predicts agricultural CO ₂ ? How do features affect performance? Can models generalize across climates?	Evaluate ML/DL performance; Compare across climates; Identify optimal features	Training: GBR R ² =0.878, Testing: FNN R ² =0.918, RMSE=67.75 ppm	Cross-climate validation of AI models; FNN superior for agricultural applications
Alcibahy et al. (2025)	Alcibahy, M., Abdul Gafoor, F., et al.	Improved estimation of carbon dioxide and methane using machine learning with satellite observations over the Arabian Peninsula	XGBoost for high-resolution (1 km) downscaling with multi-source data integration	Can ML overcome coarse resolution? How effective for regional patterns? Alignment with EDGAR inventory?	Produce 1km GHG maps for Arabian Peninsula; Reveal seasonal patterns; Identify hotspots	CO ₂ : R ² =0.98, RMSE=0.58 ppm; CH ₄ : R ² =0.63, RMSE=13.26 ppb	First 1km resolution GHG mapping for Arabian Peninsula; Strong EDGAR agreement
Lu et al. (2024)	Lu, J., Song, Y., Zhang, Y., Fang,	Full-coverage mapping of daily high-resolution XCO ₂ across China	DeepCarbon framework fusing OCO-2 and	Can AI achieve full spatio-temporal XCO ₂ coverage? How	Generate daily high-resolution CO ₂ maps; Improve spatial	Combined: R ² =0.97, RMSE=0.74 ppm; TCCON:	Demonstrates feasible data fusion; Daily mapping

	S., & Liu, H.	using deep learning techniques	CarbonTracker data	can fusion improve limitations? Can DL fill monitoring gaps?	coverage; Support climate monitoring	$R^2=0.86$, RMSE=2.67 ppm	capability; Near-real-time estimates
Sun et al. (2023)	Sun, Z., Guan, X., Chu, D., et al.	A remote sensing-based method for generating a global continuous carbon dioxide concentration dataset	Regression model with MODIS daily reflectance and OCO-3 observations	Can MODIS reflectance predict XCO ₂ ? Is daily global estimation feasible? How do predictions compare to ground truth?	Develop continuous global CO ₂ maps; Validate reflectance-based approach; Assess scalability	Monthly relative error <2% across TCCON sites	Scalable global monitoring; Novel MODIS-OCO-3 fusion; High global applicability
Li et al. (2025)	Li, H., Qiu, J., & Zheng, B.	Air-pollution-satellite-based CO ₂ emission inversion: system evaluation, sensitivity analysis, and future research direction	Bayesian inversion framework with NO ₂ from TROPOMI and CO from MOPITT	How accurate using NO ₂ as tracer? What are uncertainty sources? How to optimize for future use?	Evaluate satellite inversion accuracy; Identify uncertainty sources; Provide optimization roadmap	National level: <±4% error; Reduced accuracy for sectoral/daily resolution	First comprehensive sensitivity analysis; Identifies key uncertainty sources; Future optimization guidance
Deb & Das (2025)	Deb, D. & Das, K.	Improving power plant CO ₂ emission estimation with deep learning and satellite/simulated data	U-Net framework with fusion of OCO-2/3 observations and Sentinel-5P NO ₂ data	Can U-Net outperform traditional methods? How effective is simulated+real data integration? What precision improvements?	Develop enhanced power plant monitoring; Integrate multi-source data; Achieve near-real-time capability	Higher accuracy than inversion methods; Near-real-time capability demonstrated	First U-Net application for space-based CO ₂ estimation; Enhanced spatial precision; Real-time monitoring
Dumont Le Brazidec et al. (2024)	Dumont Le Brazidec, J., et al.	Deep learning applied to CO ₂ power plant emissions quantification using simulated satellite images	End-to-end CNN with data augmentation and ensemble using synthetic data	Can CNN generalize to unseen plants? How do auxiliary inputs affect performance? Can it outperform CSF methods?	Develop synthetic-trained models; Evaluate generalization; Compare with traditional methods	CNN: ~20% relative error, 3-4 Mt CO ₂ /year absolute error; CSF: ~40% error	First synthetic data CNN training; Significant CSF method improvement; Ensemble enhancement

AI-Based Estimation of Carbon Emissions Using Satellite Imagery:

A Case Study on Urban and Agricultural Areas in Saudi Arabia

Literature Review Report

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Abstract

The global imperative to combat climate change necessitates accurate estimation of carbon dioxide (CO₂) emissions, particularly in rapidly developing nations like Saudi Arabia. The proposed research, "AI-Based Estimation of Carbon Emissions Using Satellite Imagery: A Case Study on Urban and Agricultural Areas in Saudi Arabia," seeks to integrate machine learning (ML) and satellite imagery (e.g., Sentinel-2, Sentinel-5P) to estimate CO₂ emissions in urban and agricultural contexts. This report reviews twenty peer-reviewed studies published between 2016 and 2025, focusing on their use of AI, satellite imagery, and relevance to carbon emissions estimation in Saudi Arabia or similar regions. These studies provide methodological insights, regional context, and performance benchmarks, while highlighting a research gap in combining satellite imagery with CO₂ emissions estimation in Saudi Arabia. The findings are summarized in a comprehensive table, with a critical analysis of each study's strengths and weaknesses, reinforcing the proposed research's novelty and feasibility.

Introduction

Rising CO₂ emissions contribute significantly to global warming, making accurate monitoring critical for sustainable development. Saudi Arabia, with its urban expansion and agricultural initiatives, presents a unique case for studying emissions in arid environments. The proposed research aims to develop an AI-based model using satellite imagery (e.g., Sentinel-2, Sentinel-5P) to estimate CO₂ emissions in urban and agricultural areas. This report reviews twenty relevant studies from 2016 to 2025, assessing their methodologies, datasets, and contributions. Each study is presented with a critical analysis of its strengths and weaknesses, followed by a summary table, a discussion of their support for the proposed project, a dedicated research gap section, and a references section.

Literature Review

Paper1: Application of Artificial Intelligence to Predict CO₂ Emissions (2023)

(Nassef et al., 2023) investigated AI-driven prediction of CO₂ emissions in Saudi Arabia, aligning closely with the proposed research's objectives. Using historical emissions data from "Our World in Data" (1954–2020), the study applied Feed-Forward Neural Networks (FFNN), Adaptive Network-Based Fuzzy Inference System (ANFIS), and Long Short-Term Memory (LSTM) models. An ensemble approach achieved an R² of 93.13%, with low RMSE, indicating high predictive accuracy. The study's focus on Saudi Arabia and use of AI models provide a robust benchmark for the proposed research's ML framework, though it lacks satellite imagery

integration. Its performance metrics (R^2 , RMSE) and regional context support the proposed evaluation criteria and highlight the potential for AI in emissions forecasting.

Critical Analysis: A strength of this study is its high predictive accuracy and focus on Saudi Arabia, offering a regional benchmark for AI-based emissions forecasting. However, its reliance on historical data without spatial analysis or satellite imagery limits its applicability to the proposed research's goal of integrating geospatial data for urban and agricultural emissions estimation.

Paper2: Decision Tree-Based Ensemble Model for Predicting GHG Emissions in Saudi Arabia (2023)

Rahman et al. (2023) developed a decision tree-based ensemble model to predict greenhouse gas (GHG) emissions in Saudi Arabia, using socioeconomic and historical data from PRIMAP-hist (1750–2019) and the World Bank (1970–2021). The study compared bagged, boosted, and gradient-boosted decision trees, with the bagged model achieving an R^2 of 0.90 and low MAPE. Shapley analysis identified key predictors, enhancing model interpretability. Although satellite imagery was not used, the study's focus on Saudi Arabia and ML methodologies aligns with the proposed research's objectives. The performance metrics and regional insights provide a foundation for developing robust AI models in the proposed study.

Critical Analysis: The study's strength lies in its robust ensemble models and regional focus, providing a reliable framework for emissions prediction. Its weakness is the absence of satellite imagery, which restricts its relevance to the proposed research's geospatial approach, though its performance metrics are valuable for model evaluation.

Paper 3: AI-Based Modelling for CO₂ Emission Prediction in Saudi Arabia (2023)

Alamri and Khan (2023) employed advanced AI models, including Exponential Smoothing, Transformers, Temporal Convolutional Networks (TCN), and N-BEATS, to predict CO₂ emissions in Saudi Arabia. Using synthesized data from the World Bank, BP, and Our World in Data, the study achieved an R^2 of 0.7 for N-BEATS, with low MAE and RMSE. The focus on time-series forecasting and Saudi Arabia makes it highly relevant, though it does not incorporate satellite imagery. The study's advanced AI models and performance metrics offer valuable insights for the proposed research's ML framework and evaluation approach.

Critical Analysis: The use of cutting-edge AI models like Transformers is a key strength, providing a modern approach to emissions forecasting. However, the lack of satellite imagery and moderate R^2 (0.7) suggest limitations in spatial analysis and predictive accuracy compared to the proposed research's integrated approach.

Paper 4: Greenhouse Gas Emission Dynamics of Saudi Arabia: Potential of Hydrogen Fuel for Emission Footprint Reduction (2023)

Akinpelu et al. (2023) conducted a comprehensive review of greenhouse gas emission dynamics in Saudi Arabia, exploring the role of hydrogen fuel in reducing the country's emission footprint. The study analyzed current emission patterns, identified key sectors contributing to GHG emissions, and discussed the prospects of green hydrogen as part of Saudi Arabia's strategy to achieve net zero emissions by 2060. Using data from multiple sources including the International Energy Agency and Saudi government reports, the study provides a thorough assessment of emission reduction strategies. The research directly supports the proposed study by providing a comprehensive understanding of Saudi Arabia's emission landscape and highlighting the importance of accurate monitoring systems for policy implementation.

Critical Analysis: The study's strength lies in its comprehensive analysis of national emission dynamics and direct relevance to Saudi Arabia's Vision 2060 goals. It provides crucial context for understanding the policy landscape and emission reduction targets. However, its focus on policy and hydrogen solutions rather than monitoring technologies limits its methodological contribution to the proposed research, though it strongly supports the research's relevance and urgency.

Paper 5: Estimating CO₂ Emissions from Power Plants Using Satellite Imagery and ML (2024)

Couture et al. (2024) developed a methodology to estimate CO₂ emissions from power plants using satellite imagery (Landsat-8, Sentinel-2, PlanetScope) and ML models, including XGBoost and Convolutional Neural Networks (CNNs). The study used datasets like US EPA CAMPD and Global Energy Monitor, achieving an RMSE of 2.18 Mt CO₂ for emissions estimation. This study is directly relevant due to its integration of Sentinel-2 imagery and ML, mirroring the proposed research's methodology. Its global scope, including arid regions, and robust performance metrics provide a strong foundation for the proposed study's approach to emissions estimation.

Critical Analysis: The study's strength is its direct use of Sentinel-2 imagery for CO₂ emissions estimation, closely aligning with the proposed research's methodology. Its focus on power plants, however, limits its applicability to the proposed research's broader scope of urban and agricultural areas, necessitating adaptations for diverse land-use contexts.

Paper 6: Air Pollution Trends and Predictive Modeling Using Sentinel-5P and Deep Learning in Saudi Cities (2025)

Alkayal et al. (2025) developed an advanced forecasting model using Sentinel-5P satellite data and deep learning techniques to predict air pollution concentrations in three Saudi Arabian cities

with different characteristics. The study focused on NO₂ monitoring and demonstrated superior accuracy compared to traditional models, achieving significant improvements in prediction reliability. Using convolutional neural networks and LSTM models, the research processed atmospheric data to identify pollution patterns and trends. This study directly supports the proposed research by showcasing the effectiveness of Sentinel-5P data integration with advanced AI models in the Saudi context, providing a methodological framework for atmospheric monitoring that complements traditional land surface analysis.

Critical Analysis: The study's strength lies in its use of cutting-edge Sentinel-5P atmospheric data combined with deep learning, representing the latest technological advancement in satellite-based environmental monitoring in Saudi Arabia. Its application to three different Saudi cities provides valuable regional context and scalability insights. However, its focus on NO₂ rather than CO₂ emissions limits direct applicability, though the methodological framework for integrating atmospheric satellite data with AI models is highly relevant for the proposed research's comprehensive monitoring approach.

Paper 7: PlanetScope Nanosatellites Image Classification Using ML (2022)

Haq (2022) utilized PlanetScope satellite imagery to classify vegetation in Saudi Arabia's Al-Qassim region, a key agricultural area, using Random Forest and Multinomial Logistic Regression. The study achieved a classification accuracy of 98%, leveraging datasets like GRACE/GRACE-FO and MERRA-2 for NDVI analysis. While it does not directly address CO₂ emissions, its focus on satellite imagery and ML in a Saudi agricultural context supports the proposed research's agricultural component. The study's methodology provides insights into processing high-resolution imagery for environmental analysis.

Critical Analysis: The high classification accuracy and use of PlanetScope imagery are strengths, supporting the proposed research's agricultural focus. Its weakness is the lack of direct CO₂ emissions analysis, limiting its thematic alignment, though its methodology is relevant for satellite-based agricultural studies.

Paper 8: Estimating Carbon Stocks and Sequestration in Abha City, Saudi Arabia (2022)

Mallick et al. (2022) estimated carbon storage and sequestration capabilities in Abha, Saudi Arabia, using the InVEST model to evaluate four carbon pools (aboveground biomass, belowground biomass, soil organic carbon, and dead organic matter). The study employed multi-temporal satellite data and land use change analysis to forecast future carbon dynamics under different management scenarios. Using Landsat imagery and field measurements, the research quantified carbon stocks and their monetary valuation, providing actionable insights for developing Abha as a low-carbon city. The study achieved accurate carbon stock estimates with

validation against field data, demonstrating the effectiveness of combining satellite imagery with ecosystem service modeling for carbon assessment in Saudi urban environments.

Critical Analysis: The study's strength lies in its comprehensive carbon cycle analysis using proven InVEST methodology specifically applied to a Saudi city, providing a direct template for urban carbon assessment. Its integration of satellite imagery with ground-truth data offers robust validation approaches. However, its focus on carbon stocks and sequestration rather than active CO₂ emissions limits direct methodological applicability, though it provides valuable insights for validating emissions estimates against carbon pool changes.

Paper 9: Urban Health-Related Air Quality Indicators in MENA Countries (2019)

Elnadry et al. (2019) analyzed air quality indicators in the MENA region, including Saudi Arabia, using multiple satellite sources and ML techniques. The study focused on aerosol optical depth, providing a framework for satellite-based environmental monitoring. Although it does not directly target CO₂ emissions, its use of satellite imagery in a regional context offers methodological insights for the proposed research. The study's ML-based approach to processing satellite data supports the proposed methodology for urban areas.

Critical Analysis: The study's strength lies in its regional focus on MENA countries, including Saudi Arabia, and satellite-based methodology for environmental monitoring. Its use of multiple satellite sources and ML techniques provides valuable insights for urban environmental analysis. However, its focus on air quality indicators rather than CO₂ emissions limits its direct relevance to the proposed research, though its satellite-based ML methodology is applicable to atmospheric monitoring applications.

Paper 10: Estimation of Soil Organic Carbon in Agricultural Fields (2022)

Madugundu et al. (2022) estimated soil organic carbon in Saudi Arabian agricultural fields using Landsat-8 and Sentinel-2 imagery. The study's focus on carbon-related metrics in agricultural settings aligns with the proposed research's agricultural component. By leveraging Sentinel-2, it provides a methodological framework for processing satellite imagery, though it does not directly estimate CO₂ emissions. The study's results support the proposed research's aim to analyze carbon dynamics in arid agricultural environments.

Critical Analysis: The study's strength is its focus on soil organic carbon in Saudi agricultural contexts, directly supporting the proposed research's agricultural component. Its limitation is the lack of direct CO₂ emissions estimation, though its satellite-based methodology is highly relevant.

Paper 11: Improving Spatial Prediction of Soil Organic Carbon in Arid Regions (2020)

Taghizadeh-Mehrjardi et al. (2020) used stacking ML models to predict soil organic carbon in arid regions, including Iran, using satellite-derived covariates. The study's focus on arid environments and advanced ML techniques provides methodological insights for the proposed research's agricultural component. Although it does not address CO₂ emissions directly, its approach to satellite data and ML supports the proposed methodology for carbon analysis in similar climates.

Critical Analysis: The study's strength lies in its advanced ML methodology and relevance to arid regions, offering a framework for agricultural carbon analysis. Its lack of focus on CO₂ emissions and Saudi-specific data limits its direct applicability, though its techniques are transferable.

Paper 12: Deep Learning and Earth Observation for Sustainable Development Goals (2022)

Persello et al. (2022) reviewed the application of deep learning and Earth observation data for sustainable development goals, including climate action. The study highlights the potential of deep learning with satellite imagery, offering methodological guidance for the proposed research. While not specific to Saudi Arabia or CO₂ emissions, its insights into advanced AI techniques support the proposed research's aim to leverage cutting-edge ML models.

Critical Analysis: The study's comprehensive review of deep learning is a strength, providing methodological inspiration for the proposed research. Its broad scope and lack of regional or CO₂-specific focus are weaknesses, limiting its direct relevance but supporting advanced AI applications.

Paper 13: Predicting CO₂ Emission Footprint Using AI through Machine Learning (2022)

Meng and Noman (2022) developed and compared four SARIMA models to predict global CO₂ emissions, with particular focus on the impact of the COVID-19 pandemic on emission patterns. Using global annual CO₂ emission data from 1751 to 2018, the study implemented ARIMA-based models for different pandemic periods (pre-COVID-19, start-COVID-19, trans-COVID-19, post-COVID-19). The post-COVID-19 model achieved the highest accuracy with low MAPE, MSE, and RMSE values, providing predictions from 2022 to 2027 and beyond. While the study's global scope differs from the proposed research's Saudi focus, its advanced time-series modeling approach and consideration of external factors (pandemic impacts) offer valuable methodological insights for developing robust emissions prediction models that can account for external disruptions.

Critical Analysis: The study's strength lies in its sophisticated SARIMA modeling approach and consideration of external factors affecting emission patterns, providing a robust framework for time-series emissions prediction. Its global scope and focus on historical data rather than real-time satellite monitoring limits direct applicability to the proposed research's spatially explicit approach, though its methodological rigor is valuable for temporal modeling components.

Paper 14: Employment of GIS Techniques for Soil Organic Carbon Assessment in Hyper-Arid Conditions (2019)

Tola et al. (2019) employed GIS techniques to assess the long-term impact of tillage practices on soil organic carbon in agricultural fields under hyper-arid conditions, similar to Saudi Arabia's climate. The study utilized spatial analysis and remote sensing data to quantify carbon changes over time, demonstrating the effectiveness of GIS-based approaches for carbon monitoring in arid agricultural systems. The research provides methodological insights for integrating spatial technologies with carbon assessment, particularly relevant for understanding baseline carbon conditions in agricultural areas. The study's focus on hyper-arid environments directly supports the proposed research's agricultural component by providing proven methodologies for carbon analysis in similar climatic conditions.

Critical Analysis: The study's strength is its specific focus on hyper-arid agricultural conditions, providing directly applicable methodologies for the proposed research's agricultural component. Its emphasis on soil organic carbon rather than atmospheric CO₂ emissions is a limitation, though the GIS-based spatial analysis techniques are transferable to atmospheric emissions monitoring applications.

Paper 15: Detection of Land Use/Land Cover Changes and Urban Sprawl in Al-Khobar, Saudi Arabia (2016)

Rahman (2016) analyzed land use/land cover changes and urban sprawl in Al-Khobar, Saudi Arabia, using multi-temporal remote sensing data. The study employed satellite imagery to quantify urban expansion patterns and land cover transitions over time, achieving high accuracy in change detection. Using Landsat imagery and advanced classification techniques, the research documented rapid urban growth and its environmental implications. This study directly supports the proposed research by demonstrating the effectiveness of satellite-based monitoring in Saudi urban environments and providing a proven framework for analyzing land use changes that drive emission patterns. The Al-Khobar case study offers valuable insights for understanding urban development impacts on emissions in Saudi cities.

Critical Analysis: The study's strength lies in its direct application to a Saudi urban environment (Al-Khobar) and proven methodology for satellite-based land use change detection, providing a solid foundation for urban emission monitoring. Its focus on land cover changes rather than emissions is a limitation, though the methodological framework is highly applicable to the proposed research's urban monitoring component.

Paper 16: ML Techniques to Map Urban Heat Islands in Jeddah (2023)

Addas (2023) used ML and satellite data to map urban heat islands in Jeddah, Saudi Arabia. The study's focus on urban environmental analysis using satellite imagery aligns with the proposed research's urban component. Although it does not target CO₂ emissions, its ML-based approach to satellite data processing provides methodological insights for urban emissions estimation in the proposed study.

Critical Analysis: The study's strength is its urban focus in Saudi Arabia and use of satellite imagery, supporting the proposed research's urban component. Its focus on heat islands rather than CO₂ emissions is a weakness, though its ML methodology is relevant for urban analysis.

Paper 17: Alcibahy et al. (2025) Regional/Gulf multi-sensor modeling

Alcibahy et al. (2025) employed a gradient-boosting pipeline (XGBoost) that fuses OCO-2 (XCO₂), Sentinel-5P, MODIS, and ERA5 to estimate CO₂ and CH₄ across the Arabian Peninsula. The study produced high-fidelity spatio-temporal maps and reported very strong predictive performance ($R^2 \approx 0.98$ for CO₂). Its multi-sensor design demonstrates how optical, trace-gas, vegetation, and meteorological layers can be combined for regional-scale emission assessment. This is directly applicable to the Saudi context and supports the current project's reliance on recent satellite products and ML for area-wide estimation.

(Alcibahy et al., 2025)

Critical Analysis: The strength of this study lies in its comprehensive multi-sensor fusion framework that integrates optical and atmospheric products. Its regional scope covering the Arabian Peninsula makes it directly relevant for modeling Saudi Arabia's emissions. However, it focuses primarily on short-term predictive mapping and does not explicitly incorporate socioeconomic or industrial activity data, which limits its interpretability regarding emission sources. Nonetheless, it provides a powerful methodological foundation for regional-scale carbon estimation.

Paper 18: Mustafa et al. (2021) — Machine Learning for CO₂ Emissions (Asia)

Mustafa et al. (2021) developed a Generalized Regression Neural Network (GRNN) to estimate anthropogenic CO₂ emissions over East and West Asia using OCO-2, MODIS covariates, and the ODIAC inventory for supervision. The model captured regional emission patterns consistent with inventories and demonstrated the feasibility of linking satellite-observed XCO₂ anomalies to bottom-up emissions. The approach validates a core premise of this project: satellite-guided learning can recover spatially explicit CO₂ signals when fused with activity proxies and inventories. (Mustafa et al., 2021)

Critical Analysis: A major strength is the model's ability to reconcile top-down satellite data with bottom-up emission inventories, achieving high spatial consistency. Its use of GRNN provides flexibility in handling nonlinear dependencies across atmospheric drivers. However, its temporal generalization capability is limited since the model was evaluated mainly on annual composites. Despite that, the study directly informs this project's machine-learning design, especially the integration of multiple Earth observation layers.

Paper 19: Guo & Zhang (2024) — Clustering + Boosted Trees for Stable CO₂ Prediction

Guo & Zhang (2024) introduced a preprocessing step that clusters CO₂ concentration fields prior to training a boosted-trees model (CatBoost). Clustering reduces error variability across heterogeneous regions and stabilizes metrics (e.g., MAE/RMSE) across biomes. This directly informs our methodology: pre-segmentation (regionalization) before supervised learning is expected to improve robustness in Saudi Arabia where emission regimes vary (industrial hubs, dense urban corridors, irrigated croplands, and desert).

(Guo & Zhang, 2024)

Critical Analysis: The study's key contribution is demonstrating how spatial clustering can improve regression stability in large-scale CO₂ prediction. This methodological innovation is valuable for Saudi Arabia's heterogeneous environments. A potential weakness is the limited discussion on physical interpretation of clusters, which may complicate policy translation. Nevertheless, it offers a practical preprocessing step that enhances ML model performance and generalization.

Paper 20: Rowley & Karakuş (2023) — Multimodal CNN Fusion for Air-Quality Prediction

Rowley & Karakuş (2023) proposed AQNet, a multimodal deep architecture that fuses Sentinel-5P, Sentinel-2, meteorology, and population layers to predict NO₂/PM₁₀ at city scale. The model outperformed single-source baselines and showed good out-of-region generalization. This supports our plan to enrich CO₂-focused modeling with ancillary drivers (land cover, morphology, population mobility, and weather), improving both accuracy and transferability across Saudi urban and agricultural settings.

(Rowley & Karakuş, 2023)

Critical Analysis: The multimodal design of AQNet represents a significant methodological advancement, emphasizing the integration of both spectral and socio-environmental variables. Its strong generalization indicates potential adaptability to Saudi urban environments. However, its focus on NO₂ and PM₁₀ rather than CO₂ limits its direct thematic alignment. Still, the fusion strategy offers a transferable architecture for multimodal CO₂ estimation in future extensions of this project.

Connections between the Papers

The reviewed studies collectively form a robust foundation for the proposed research by addressing various aspects of CO₂ emissions and environmental monitoring in Saudi Arabia and similar arid environments. Several key connections emerge:

1. Regional Focus on Saudi Arabia:

Studies by (Nassef et al., 2023), (Rahman et al., 2023), (Alamri and Khan, 2023), (Akinpelu et al., 2023), (Alkayal et al., 2025), (Haq, 2022), (Mallick et al., 2022), (Madugundu et al., 2022), (Rahman, 2016), and (Addas, 2023) all focus on Saudi Arabia, providing a strong regional context. The addition of (Alcibahy et al., 2025) expands this context to the entire Arabian Peninsula, offering multi-country spatial validation that strengthens the regional perspective of the proposed project. Similarly, (Mustafa et al., 2021) links Saudi Arabia to broader Asian emission dynamics, showing how regional-scale satellite datasets can inform localized modeling efforts.

2. Use of Machine Learning and AI:

A common thread across most studies is the application of advanced ML and AI techniques. For instance, (Nassef et al., 2023) and Rahman et al. (2023) use ensemble models, Alamri and Khan (2023) employ Transformers and N-BEATS, Couture et al. (2024) and Alkayal et al. (2025) leverage CNNs and LSTMs, and Haq (2022) applies Random Forest. The new works reinforce this trend: Mustafa et al. (2021) used GRNN for satellite–inventory fusion, Guo and Zhang (2024) applied CatBoost with spatial

clustering, Alcibahy et al. (2025) combined XGBoost with multi-sensor fusion, and Rowley and Karakuş (2023) introduced a multimodal CNN (AQNet).

Collectively, these demonstrate that hybrid and ensemble-based architectures dominate recent research and justify the ML-driven approach of the proposed study.

3. Satellite Imagery Integration:

Studies such as (Couture et al., 2024), (Alkayal et al., 2025), (Haq, 2022), (Mallick et al., 2022), (Madugundu et al., 2022), (Rahman, 2016), and (Addas, 2023) already integrate satellite imagery. The newly included (Alcibahy et al., 2025), (Mustafa et al., 2021), and (Rowley and Karakuş, 2023) extend this integration by using multi-sensor data fusion (OCO-2, Sentinel-5P, MODIS, and ERA5) and multimodal deep learning, proving that satellite-driven ML is a mature and reliable paradigm. These studies reinforce the use of geospatial and atmospheric data in the proposed model design.

4. Focus on Carbon Dynamics:

Several studies examine carbon-related metrics, including CO₂ emissions (Nassef et al., 2023; Rahman et al., 2023; Alamri and Khan, 2023; Couture et al., 2024), soil organic carbon (Madugundu et al., 2022; Taghizadeh-Mehrjardi et al., 2020; Tola et al., 2019), and carbon sequestration (Mallick et al., 2022). (Mustafa et al., 2021) and (Alcibahy et al., 2025) extend this by quantifying regional-scale CO₂ and CH₄ dynamics, while (Guo and Zhang, 2024) address error stabilization in heterogeneous carbon datasets. These additions collectively enhance understanding of both spatial and temporal variability in carbon emissions.

5. Urban and Agricultural Contexts:

Existing studies already bridge both urban (Mallick et al., 2022; Rahman, 2016; Addas, 2023; Alkayal et al., 2025) and agricultural (Haq, 2022; Madugundu et al., 2022; Tola, 2019; Taghizadeh-Mehrjardi et al., 2020) settings. The new studies add greater scalability: (Rowley and Karakuş, 2023) introduce transferable multimodal fusion for urban environments, while (Mustafa et al., 2021) demonstrate generalization over wide agricultural and industrial landscapes. Together, they support the dual focus of the proposed project on urban and agricultural emission monitoring.

6. Policy Relevance and Methodological Advancement:

(Akinpelu et al., 2023) and (Mallick et al., 2022) highlight policy implications tied to Vision 2060. Complementing them, (Alcibahy et al., 2025) and (Guo and Zhang, 2024) provide actionable technical advances—regionalization and clustering—that could directly support national emission inventory refinement. This synthesis shows how recent methodological work underpins both scientific rigor and applied policy objectives in the Saudi context.

Together, these interconnections affirm the need for an integrated AI–satellite framework, forming the conceptual backbone of the proposed study.

Conflicts between Findings

While the studies share common themes, several conflicts or discrepancies arise, reflecting methodological differences, data sources, or focus areas:

1. Predictive Accuracy Variations:

- (Nassef et al., 2023) report a high R^2 of 93.13% for CO₂ prediction, while (Alamri and Khan, 2023) achieve 0.7 using N-BEATS. Newer studies such as (Alcibahy et al., 2025) and (Guo and Zhang, 2024) reach R^2 values above 0.95 due to multi-sensor fusion and spatial clustering, indicating that model architecture and feature diversity strongly affect accuracy benchmarks.

3. Satellite Imagery vs. Historical Data:

Satellite-based studies (Couture et al., 2024; Alkayal et al., 2025; Alcibahy et al., 2025; Mustafa et al., 2021) achieve high spatial precision but require extensive preprocessing. Conversely, historical-data models (Nassef et al., 2023; Rahman et al., 2023) offer simplicity but lack spatial granularity. The methodological gap between these groups highlights the need for integrated frameworks combining temporal and spatial modeling in the proposed research.

4. Focus on CO₂ vs. Other Pollutants:

While (Alkayal et al., 2025) target NO₂ and (Rowley and Karakuş, 2023) focus on NO₂/PM₁₀, the others center on CO₂ or CH₄. These differences limit direct comparability but collectively demonstrate the flexibility of AI architectures to handle diverse atmospheric constituents, supporting a multimodal extension in future work.

5. Scope of Application:

(Couture et al., 2024) focus narrowly on power plants, while (Mallick et al., 2022) and (Rahman, 2016) explore urban growth. (Mustafa et al., 2021) and (Alcibahy et al., 2025) extend to regional-scale analyses across mixed land uses. This disparity shows that scaling up model frameworks requires careful domain adaptation—precisely the challenge the proposed study intends to address.

6. Data Sources and Temporal Coverage:

Studies differ widely in temporal scope—from long historical datasets (e.g., Our World in Data 1954–2020 in (Nassef et al., 2023)) to real-time satellite data (Sentinel-5P 2021–2025 in (Alkayal et al., 2025) and (Alcibahy et al., 2025)). Such variability creates baseline inconsistencies but also reveals the opportunity to benchmark temporal generalization through unified preprocessing pipelines.

7. Methodological Rigor and Spatial Generalization:

(Guo and Zhang, 2024) demonstrate that ignoring regional heterogeneity inflates model error, while (Rowley and Karakuş, 2023) achieve cross-regional generalization using multimodal CNNs. These findings contrast temporal-only models (Meng and Noman, 2022) and highlight a trade-off between interpretability and spatial precision. The proposed research resolves this tension by integrating spatial regionalization with temporal forecasting, bridging both lines of evidence.

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Appendix A: Summary Table of Studies

Authors (Year)	Description	Dataset	Algorithms Used	Methodology	Study Questions	Objectives	Results	Contribution
(Nassef et al., 2023)	AI-based prediction of CO ₂ emissions in Saudi Arabia using historical data.	Our World in Data (1954–2020)	FFNN, ANFIS, LSTM	Ensemble modeling; 70:30 train-test split	How can AI predict CO ₂ emissions accurately?	Develop accurate AI models for CO ₂ forecasting	R ² = 93.13%, low RMSE	Demonstrates AI's potential for emissions forecasting in Saudi Arabia
Rahman et al. (2023)	Prediction of GHG emissions in Saudi Arabia using decision tree-based models.	PRIMAP-hist (1750–2019), World Bank (1970–2021)	Bagged Decision Tree, Boosted Decision Tree, Gradient Boosted Decision Tree	Bagged, boosted, gradient-boosted decision trees; Shapley analysis	Can ensemble models improve GHG prediction accuracy?	Predict GHG emissions using socioeconomic data	R ² = 0.90, low MAPE	Provides robust ML models for GHG prediction in Saudi Arabia
Alamri & Khan (2023)	AI-based CO ₂ emission prediction in Saudi Arabia using time-series models.	World Bank, BP, Our World in Data	Exponential Smoothing, Transformers, TCN, N-BEATS	Time-series forecasting	How effective are advanced AI models for CO ₂ prediction?	Forecast CO ₂ emissions using public datasets	R ² = 0.7 for N-BEATS, low MAE	Introduces advanced AI models for emissions prediction
Akinpelu et al. (2023)	Comprehensive analysis of GHG emission dynamics and hydrogen potential in Saudi Arabia.	IEA, Saudi government reports, multiple energy databases	Literature review and data analysis	Systematic review of emission sources and reduction strategies	What are Saudi Arabia's emission dynamics and hydrogen potential?	Analyze current emissions and assess hydrogen solutions for Vision 2060	Comprehensive emission assessment, hydrogen roadmap	Provides policy context and national emission landscape for Saudi Arabia
Couture et al. (2024)	CO ₂ emissions estimation from power plants using satellite imagery and ML.	US EPA CAMPD, ENTSO-E, Global Energy Monitor	XGBoost, CNNs	Cross-validation; hyperparameter tuning	Can satellite imagery estimate power plant emissions?	Develop ML models for emissions estimation using satellite data	RMSE = 2.18 Mt CO ₂	Validates satellite imagery for CO ₂ emissions estimation
Alkayal et al. (2025)	Air pollution prediction using Sentinel-5P and deep learning in Saudi cities.	Sentinel-5P, meteorological data	CNN, LSTM, Deep Neural Networks	Deep learning with atmospheric satellite data	How effective is Sentinel-5P for air quality prediction in Saudi cities?	Develop advanced models for atmospheric pollution monitoring	Superior accuracy vs traditional models, reliable NO ₂ predictions	Demonstrates latest atmospheric monitoring technology in Saudi context
Haq (2022)	Vegetation classification in Al-Qassim using PlanetScope imagery and ML.	PlanetScope, GRACE/GRACE-FO, MERRA-2	Random Forest, Multinomial Logistic Regression	Random Forest classification; NDVI analysis	How can satellite imagery classify vegetation in arid regions?	Analyze agricultural land use in Saudi Arabia	Classification accuracy = 98%	Supports satellite-based agricultural analysis in Saudi Arabia
Mallick et al. (2022)	Carbon stocks and sequestration estimation in	Landsat imagery, field measurements,	InVEST model, spatial analysis	Multi-temporal analysis, ecosystem service	How can carbon stocks be quantified in	Estimate carbon storage and	Accurate carbon stock estimates with	Provides urban carbon assessment

	Abha city using InVEST model.	land use data		modeling	Saudi urban environments?	sequestration capabilities for low-carbon city development	monetary valuation	methodology for Saudi cities
Elnadry et al. (2019)	Air quality analysis in MENA using satellite data and ML.	Multiple satellite sources, AERONET	ML-based classifiers	ML-based analysis of air quality indicators	How can satellite data monitor air quality in MENA?	Assess air quality using satellite imagery	Accurate air quality mapping	Provides methodological insights for satellite-based environmental analysis
Madugundu et al. (2022)	Estimation of soil organic carbon in Saudi agricultural fields using satellite imagery.	Landsat-8, Sentinel-2	Remote sensing algorithms	Remote sensing with Landsat-8, Sentinel-2	Can satellite imagery estimate soil organic carbon?	Quantify soil carbon in agricultural areas	Accurate soil carbon estimates	Supports carbon cycle analysis in agricultural settings
Taghizadeh-Mehrjardi et al. (2020)	Prediction of soil organic carbon in arid regions using ML and satellite data.	Satellite-derived covariates	Stacking ML models	Stacking ML models; covariate rescanning	How can ML improve soil carbon prediction in arid regions?	Enhance spatial prediction of soil carbon	Improved prediction accuracy	Offers ML methodologies for arid region carbon analysis
Persello et al. (2022)	Review of deep learning and Earth observation for sustainable development.	Earth observation data	Deep learning models	Literature review of deep learning applications	How can deep learning support sustainable development?	Explore deep learning with Earth observation data	Insights into deep learning applications	Provides methodological guidance for deep learning in environmental studies
Meng & Noman (2022)	Global CO ₂ emissions prediction using SARIMA models with pandemic impact analysis.	Global CO ₂ emissions (1751-2018)	SARIMA, ARIMA	Time-series forecasting with pandemic period analysis	How can we predict global CO ₂ emissions considering COVID-19 impacts?	Develop robust time-series models for emissions prediction	Post-COVID model: lowest MAPE, MSE, RMSE	Provides sophisticated time-series modeling for emissions with external factor consideration
Tola et al. (2019)	GIS-based assessment of tillage impact on soil organic carbon in hyper-arid conditions.	Spatial agricultural data, soil samples	GIS spatial analysis	Long-term spatial analysis of agricultural practices	How does tillage affect soil carbon in hyper-arid environments?	Assess long-term carbon impacts of agricultural practices	Quantified carbon changes over time	Provides GIS methodology for agricultural carbon monitoring in arid regions
Rahman (2016)	Land use change and urban sprawl analysis in Al-Khobar using remote sensing.	Multi-temporal Landsat imagery	Classification algorithms, change detection	Multi-temporal satellite image analysis	How can remote sensing detect urban sprawl in Saudi cities?	Monitor urban expansion and land cover changes	High accuracy change detection, urban growth quantification	Demonstrates satellite-based urban monitoring methodology in Saudi context
Addas (2023)	Mapping urban heat islands in Jeddah using ML and satellite data.	Satellite data for land use/cover	ML-based classifiers	ML-based mapping of urban heat islands	How can satellite data map urban heat islands?	Analyze urban heat in Jeddah	Accurate heat island mapping	Supports satellite-based urban environmental analysis

Alcibahy et al. (2025)	Regional estimation of CO ₂ and CH ₄ emissions over the Arabian Peninsula using multi-sensor satellite data.	OCO-2, Sentinel-5P, MODIS, ERA5	XGBoost	Multi-sensor data fusion; gradient-boosting regression; spatial mapping and cross-validation.	How can multiple satellite products be combined to estimate CO ₂ and CH ₄ over arid regions?	Integrate optical, trace-gas, and meteorological datasets to generate high-resolution emission maps.	R ² ≈ 0.98 for CO ₂ ; high spatial accuracy and strong temporal consistency.	Establishes a benchmark for multi-sensor carbon modeling applicable to Saudi Arabia.
Mustafa et al. (2021)	Estimation of anthropogenic CO ₂ emissions over East and West Asia using satellite-based ML models.	OCO-2, MODIS, ODIAC inventory	GRNN	Neural-network regression; feature fusion of satellite and inventory data.	Can satellite XCO ₂ data predict anthropogenic CO ₂ emissions accurately across Asia?	Validate the relationship between satellite-derived CO ₂ and bottom-up inventories.	High spatial agreement with ODIAC maps; robust nonlinear fitting.	Demonstrates integration of top-down and bottom-up data for regional emission modeling.
Guo & Zhang (2024)	Predicting global anthropogenic CO ₂ emissions using ML enhanced by spatial clustering.	OCO-2 derived CO ₂ concentration grids	CatBoost with clustering	Pre-clustering of spatial grids followed by boosted-tree regression.	Does spatial clustering improve stability and accuracy of CO ₂ prediction models?	Reduce regional variance and improve global CO ₂ estimation accuracy.	Lower RMSE and MAE across clustered regions; smoother error distribution.	Introduces spatial clustering as a preprocessing technique for heterogeneous environments such as Saudi Arabia.
Rowley & Karakuş (2023)	Multimodal AI framework for air-quality prediction using satellite imagery and ancillary data.	Sentinel-5P, Sentinel-2, meteorological and population data	CNN (AQNet)	Deep multimodal convolutional fusion of optical, trace-gas, and socioeconomic layers.	How does multimodal data fusion improve prediction of atmospheric pollutants?	Develop a generalizable deep-learning model integrating multiple environmental datasets.	R ² ≈ 0.92 for NO ₂ /PM ₁₀ ; outperforms single-source models.	Provides transferable multimodal fusion architecture for CO ₂ emission studies in Saudi Arabia.