

Literature Review Report

AI-Based Estimation of Carbon Emissions Using Satellite Imagery:

A Case Study on Urban and Agricultural Areas in Saudi Arabia

Prepared By:

Mohammad Wajeih Bader

ID: 251000462

Program:

Master of Science in Artificial Intelligence

Institution:

College of Informatics

Midocean University, UAE

Supervisor:

Dr. Amjad Qataish

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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.

References

- Alcibahy, M., Abdul Gafoor, F., Mustafa, F., El Fadel, M., Al Hashemi, H., Al Hammadi, A., & Al Shehhi, M. R. (2025). Improved estimation of carbon dioxide and methane using machine learning with satellite observations over the Arabian Peninsula. *Scientific Reports*, 15, 766. <https://doi.org/10.1038/s41598-024-84593-9>
- Buchwitz, M., Reuter, M., Schneising, O., Boesch, H., Guerlet, S., Dils, B., ... & Crevoisier, C. (2018). The Greenhouse Gas Climate Change Initiative (GHG-CCI): Comparison and quality assessment of near-surface-sensitive satellite-derived CO₂ and CH₄ global data sets. *Remote Sensing of Environment*, 162, 344-362.
- Crisp, D., Pollock, H. R., Rosenberg, R., Chapsky, L., Lee, R. A., Oyafuso, F. A., ... & Wunch, D. (2012). The on-orbit performance of the Orbiting Carbon Observatory-2 (OCO-2) instrument and its radiometrically calibrated products. *Atmospheric Measurement Techniques*, 10(2), 549-594.
- Deb, D., & Das, K. (2025). Improving power plant CO₂ emission estimation with deep learning and satellite/simulated data. *arXiv preprint arXiv:2502.02083*.
- 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>
- Harsányi, E., Mirzaei, M., Arshad, S., Alsilibe, F., Vad, A., Nagy, A., ... Mohammed, S. (2024). Assessment of advanced machine and deep learning approaches for predicting CO₂ emissions from agricultural lands: Insights across diverse agroclimatic zones. *Earth Systems and Environment*, 8, Article 135941. <https://doi.org/10.1007/s41748-024-00424-x>
- He, W., Song, Y., Ma, M., Tian, J., & Zhao, H. (2024). Spatio-temporal modeling of satellite-observed CO₂ columns in China using deep learning. *Science of The Total Environment*, 904, 166226. <https://doi.org/10.1016/j.scitotenv.2023.166226>
- IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.
- Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., ... & Olivier, J. G. (2019). EDGAR v4.3.2 Global Atlas of the three major greenhouse gas emissions for the period 1970–2012. *Earth System Science Data*, 11(3), 959-1002.

Le Brazidec, J. D., Vanderbecken, P., Farchi, A., Broquet, G., Kuhlmann, G., & Bocquet, M. (2025). Quantification of CO₂ hotspot emissions from OCO-3 SAM CO₂ satellite images using deep learning methods. *Geoscientific Model Development*, 18, 3607–3622.

<https://doi.org/10.5194/gmd-18-3607-2025>

Li, H., Qiu, J., & Zheng, B. (2025). Air-pollution-satellite-based CO₂ emission inversion: system evaluation, sensitivity analysis, and future research direction. *Atmospheric Chemistry & Physics*, 25, 1949–1963. <https://acp.copernicus.org/articles/25/1949/2025/>

Lu, J., Song, Y., Zhang, Y., Fang, S., & Liu, H. (2024). Full-coverage mapping of daily high-resolution XCO₂ across China from 2015 to 2020 by fusing OCO-2 and CarbonTracker data using deep learning techniques. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4700002>

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2021). Deep learning in remote sensing applications: A meta-analysis and review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 152, 166–177.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), 195–204.

Saudi Vision 2030. (2016). *Saudi Arabia's Vision for 2030*. Council of Economic and Development Affairs. <https://www.vision2030.gov.sa/>

Sun, Z., Guan, X., Chu, D., Xie, G., Wang, Y., & Shen, H. (2023). A remote sensing-based method for generating a global continuous carbon dioxide concentration dataset. *ESS Open Archive*. <https://doi.org/10.22541/essoar.170516094.40471815>

Wu, S., Chen, Y., Liu, Q., & Zhao, J. (2023). Developing unbiased estimation of atmospheric methane via machine learning and multiobjective programming based on TROPOMI and GOSAT data. *Remote Sensing of Environment*, 298, 113754.

<https://doi.org/10.1016/j.rse.2023.113754>

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