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A SYSTEMATIC REVIEW OF SATELLITE-BASED GREENHOUSE GAS MONITORING AND AI-DRIVEN FORECASTING OF ATMOSPHERIC CO_2 AND CH_4 CONCENTRATIONS: IMPLICATIONS FOR CLIMATE CHANGE INDICATORS IN THE SAURASHTRA REGION

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Abstract— **This study presents a systematic review of recent advances in satellite-based greenhouse gas monitoring and Artificial Intelligence (AI)-driven forecasting approaches for atmospheric carbon dioxide (CO_2) and methane (CH_4). A structured literature review methodology based on PRISMA guidelines was adopted to identify, screen, and analyze relevant studies published between 2021 and 2026 from major scientific databases including Scopus, Web of Science, IEEE Xplore, and ScienceDirect.**

The review examines developments in satellite remote sensing platforms such as OCO-2, OCO-3, GOSAT, Sentinel-5P, and GHGSat, alongside machine learning and deep learning techniques including Random Forest, XGBoost, LSTM, GRU, CNN-LSTM, Informer, Autoformer, and PatchTST models. The reviewed studies are categorized into five major themes: satellite-based greenhouse gas monitoring, AI-assisted greenhouse gas estimation, deep learning forecasting approaches, transformer-based forecasting models, and climate change assessment frameworks. Comparative analysis highlights methodological strengths, limitations, datasets, forecasting horizons, and performance metrics. The review identifies critical research gaps related to data integration, explainability, multimodal learning, spatial generalization, and climate indicator development. Emerging research directions including Explainable AI, Earth Observation Foundation Models, Physics-Informed AI, Digital Twins, and Multimodal Data Fusion are discussed. Finally, a conceptual framework is proposed for simultaneous forecasting of atmospheric CO_2 and CH_4 concentrations and development of climate change indicators for the Saurashtra region of western India.

Keywords: **Climate Change Indicators, Carbon Dioxide, Methane, Artificial Intelligence, Deep Learning, OCO-2, Sentinel-5P, Forecasting, Satellite Remote Sensing, Saurashtra Region.**

I. INTRODUCTION

Climate change has become a critical global concern due to its significant impacts on ecosystems, agriculture, water resources, human health, and socioeconomic development. The Intergovernmental Panel on Climate Change (IPCC) identifies greenhouse gases (GHGs) as the primary drivers of global warming with carbon dioxide (CO2) and methane (CH4) accounting for a major proportion of anthropogenic radiative forcing. While carbon dioxide contributes substantially to long-term atmospheric warming because of its extended atmospheric lifetime, methane exhibits a much higher warming potential over shorter periods. Monitoring atmospheric concentrations of CO2 and CH4, is therefore essential for understanding climate dynamics and evaluating mitigation strategies.

Conventional monitoring methods primarily rely on ground-based stations, which often suffer from limited spatial coverage and inadequate representation of regional

atmospheric conditions. Recent developments in satellite remote sensing have transformed atmospheric monitoring by providing continuous global observations of greenhouse gases with high spatial and temporal resolution. NASA's Orbiting Carbon Observatory-2 (OCO-2) and OCO-3 missions have significantly enhanced atmospheric CO2 observations, while Sentinel-5P/TROPOMI and GOSAT have become major sources of methane monitoring data. These satellite systems generate large volumes of atmospheric information suitable for environmental modeling and climate studies.

Simultaneously, Artificial Intelligence (AI) and Deep Learning (DL) techniques have emerged as powerful tools for environmental data analysis. Models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM), Informer, Autoformer, and PatchTST have demonstrated remarkable success in time-series forecasting applications.

The Saurashtra region of Gujarat represents a unique semi-arid coastal environment characterized by rapid industrialization, agricultural intensification, urban expansion, and increasing climate variability. Despite its environmental significance, limited studies have explored AI-based forecasting of atmospheric greenhouse gases in this region. Therefore, integrating satellite observations and advanced AI models presents a promising opportunity for regional climate assessment and climate change indicator development.

II. LITERATURE SEARCH STRATEGY

Relevant studies were collected from major scientific databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. The search focused on articles published between 2021 and 2026. Keywords and search combinations included:

- "CO_2 forecasting"
- "CH_4 prediction"
- "Greenhouse gas monitoring"
- "Satellite remote sensing"
- "Artificial Intelligence"
- "Machine Learning"
- "Deep Learning"
- "Transformer models"
- "Climate change indicators"

2.1 Screening and Selection Criteria

Studies were included if they:

- Were published in peer-reviewed journals.
- Were written in English.
- Focused on atmospheric CO_2 and/or CH_4 monitoring, estimation, or forecasting.
- Utilized satellite observations and AI-based approaches.
- Were published between 2021 and 2026.

Studies were excluded if they:

- Were conference abstracts, editorials, or non-peer-reviewed publications.
- Lacked sufficient methodological details.
- Were unrelated to greenhouse gas forecasting or climate assessment.

2.2 Study Selection Process

The study selection followed four stages: identification, screening, eligibility assessment, and final inclusion. Duplicate records were removed, followed by title and abstract screening. Full-text articles were then evaluated according to the inclusion and exclusion criteria. Only relevant and high-quality studies were retained for detailed analysis. A PRISMA-inspired workflow was adopted, resulting in the selection of approximately 60–70 studies for comprehensive review.

2.3 Data Extraction and Analysis

Information extracted from each study included author and publication year, study region, greenhouse gas investigated, satellite datasets used, AI or forecasting methodology, performance metrics, and key findings and limitations. The selected literature was subsequently organized into five thematic categories:

- Satellite-Based Greenhouse Gas Monitoring
- AI-Based Greenhouse Gas Estimation
- Deep Learning Forecasting Approaches
- Transformer-Based Forecasting Models
- Climate Change Indicators and Environmental Assessment Frameworks

This thematic classification enabled systematic comparison of methodologies, datasets, forecasting performance, and research gaps across the existing literature.

III. SATELLITE-BASED GREENHOUSE GAS MONITORING

3.1 Carbon Dioxide Monitoring through Satellite Observations

Satellite remote sensing has significantly enhanced the capability to monitor atmospheric carbon dioxide (CO_2) at regional and global scales. Among the available missions, NASA's Orbiting Carbon Observatory-2 (OCO-2) and OCO-3 provide highly accurate measurements of column-averaged dry-air mole fractions of carbon dioxide (XCO_2). Eldering demonstrated that OCO-2 observations have substantially improved the understanding of carbon sources, sinks, and atmospheric transport processes.

Several studies have further explored the generation of high-resolution CO_2 maps using satellite observations. Hammerling developed statistical mapping techniques that transformed sparse observations into continuous spatial distributions suitable for climate and environmental modeling. More recently, machine learning approaches have been employed to

improve retrieval consistency among multiple satellite products. Huang et al. utilized AI-based correction frameworks to reduce uncertainties in satellite-derived XCO_2 measurements, thereby improving their applicability for forecasting and climate assessment studies.

3.2 Methane Monitoring through Satellite Observations

Methane (CH_4) is one of the most influential greenhouse gases due to its high global warming potential. Recent advances in satellite remote sensing have enabled large-scale monitoring of methane emissions and atmospheric concentrations. Platforms such as Sentinel-5P/TROPOMI, GOSAT, and GHGSat provide valuable information for methane detection and emission quantification. Jacob et al. reviewed the capabilities of contemporary methane-monitoring satellites and highlighted their effectiveness in identifying methane hotspots and emission sources. Similarly, Balasus et al. developed a machine-learning-based data fusion framework that integrates TROPOMI and GOSAT observations, resulting in improved methane retrieval accuracy and spatial coverage.

Although significant progress has been achieved in greenhouse gas monitoring, most studies primarily focus on retrieval and estimation rather than forecasting future atmospheric concentrations.

IV. AI-BASED GREENHOUSE GAS ESTIMATION

Artificial Intelligence (AI) has emerged as a powerful tool for processing large-scale environmental datasets and modeling complex atmospheric processes. Machine learning algorithms have been widely adopted to improve greenhouse gas retrieval accuracy and fill missing observations in satellite datasets.

Neural network-based approaches have shown promising results for estimating atmospheric CO_2 concentrations directly from satellite observations. David et al. demonstrated that neural networks can improve XCO_2 estimation accuracy compared to traditional retrieval techniques. Similarly, Alcibahy et al. proposed a machine learning framework for simultaneous estimation of atmospheric CO_2 and CH_4 concentrations using satellite observations and environmental variables.

Recent studies have also focused on integrating multiple satellite datasets using machine learning methods. AI-driven data fusion approaches have improved consistency among greenhouse gas products while reducing retrieval uncertainties. Despite these advancements, the majority of existing research emphasizes historical estimation and reconstruction rather than predictive forecasting.

V. DEEP LEARNING FORECASTING APPROACHES FOR GREENHOUSE GASES

The increasing availability of long-term atmospheric datasets has encouraged the application of deep learning models for greenhouse gas forecasting. Deep learning approaches are particularly suitable for environmental time-series analysis because they can capture nonlinear relationships and temporal dependencies.

5.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are among the most widely used deep learning models for environmental forecasting. Their ability to learn long-term temporal dependencies makes them suitable for modeling atmospheric greenhouse gas variations. Several studies have successfully applied LSTM architectures for CO_2 and CH_4 prediction using historical environmental observations.

5.2 Gated Recurrent Unit (GRU)

GRU models provide forecasting performance comparable to LSTM while requiring fewer computational resources. Due to their simplified architecture, GRU networks have gained popularity in atmospheric forecasting applications where computational efficiency is important.

5.3 Hybrid Deep Learning Models

Hybrid architectures such as CNN-LSTM and CNN-GRU combine spatial feature extraction with temporal forecasting capabilities. Recent studies have reported improved forecasting performance for methane prediction using these hybrid models, particularly for long-term forecasting scenarios.

VI. TRANSFORMER-BASED FORECASTING MODELS

Transformer architectures have recently emerged as state-of-the-art approaches for long-sequence time-series forecasting. Unlike recurrent neural networks, transformers utilize self-attention mechanisms that efficiently capture long-range temporal dependencies. Informer, Autoformer, and PatchTST are among the most prominent transformer-based forecasting models.

- Informer improves computational efficiency for long-sequence forecasting.
- Autoformer introduces decomposition mechanisms for enhanced trend and seasonal pattern extraction.
- PatchTST has demonstrated remarkable performance on multivariate time-series datasets by employing patch-based temporal representations.

Although transformer models have achieved impressive results in various forecasting applications, their utilization for atmospheric greenhouse gas prediction remains limited. This presents a promising opportunity for future research involving satellite-derived CO_2 and CH_4 forecasting.

VII. CLIMATE CHANGE INDICATORS AND ENVIRONMENTAL ASSESSMENT FRAMEWORKS

Climate change indicators play a crucial role in understanding environmental variability and supporting sustainable decision-

making. Traditional indicators are typically derived from temperature, rainfall, vegetation dynamics, and greenhouse gas emissions. However, recent advancements in Earth Observation technologies and Artificial Intelligence have enabled the development of more comprehensive climate assessment frameworks.

Several studies emphasize the importance of integrating greenhouse gas concentrations with meteorological and ecological variables to generate meaningful climate indicators. Forecasted atmospheric CO_2 and CH_4 concentrations can provide valuable insights into future climate conditions, environmental stress, and regional vulnerability. For regions such as Saurashtra, where agriculture, coastal ecosystems, and industrial activities interact with changing climatic conditions, AI-based climate indicators can support environmental monitoring, climate adaptation planning, and sustainable resource management.

VIII. RESEARCH METHODOLOGY

8.1 Research Framework

The proposed research aims to develop an Artificial Intelligence (AI)-based framework for forecasting atmospheric Carbon Dioxide (CO_2) and Methane (CH_4) concentrations over the Saurashtra region using historical satellite observations. The forecasted greenhouse gas concentrations will be utilized to develop climate change indicators for regional environmental assessment.

8.2 Study Area

The study focuses on the Saurashtra region of Gujarat, India, comprising districts such as Rajkot, Junagadh, Jamnagar, Porbandar, Devbhumi Dwarka, Amreli, Bhavnagar, Morbi, Botad, and Gir Somnath. The region is characterized by semi-arid climatic conditions, coastal influence, agricultural dominance, industrial development, and increasing climate variability. These factors make Saurashtra an important region for greenhouse gas forecasting and climate assessment.

8.3 Data Collection

The study will utilize historical satellite observations and meteorological datasets:

- Carbon Dioxide (CO_2): NASA OCO-2, NASA OCO-3. Variables include XCO_2 concentration, Latitude and Longitude, and Observation time.
- Methane (CH_4): GOSAT.
- Meteorological Data: ERA5 Reanalysis datasets including Temperature, Rainfall, Relative Humidity, Wind Speed, and Surface Pressure.

8.4 Data Preprocessing and Feature Engineering

The collected datasets will undergo preprocessing to ensure data quality and consistency. Major preprocessing steps include missing value treatment, outlier removal, spatial clipping for the Saurashtra region, temporal aggregation (monthly scale), and data normalization. Feature engineering will be performed using historical CO_2 and CH_4 concentrations, meteorological variables, vegetation indices, and seasonal/temporal indicators.

8.5 AI-Based Forecasting Models

To identify the most suitable forecasting approach, multiple AI models will be developed and compared. The proposed models include:

- Long Short-Term Memory (LSTM): Used as the baseline deep learning model for time-series forecasting.
- Gated Recurrent Unit (GRU): Provides efficient learning with reduced computational complexity.
- CNN-LSTM: Combines spatial feature extraction and temporal forecasting capabilities.

8.6 Model Training and Evaluation

The dataset will be divided into a Training Set (70%), Validation Set (15%), and Testing Set (15%). Model performance will be evaluated using standard statistical metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

8.7 Climate Change Indicator Development

Based on forecasted CO_2 and CH_4 concentrations, a Climate Change Indicator (CCI) will be developed. The indicator will integrate forecasted CO_2 levels, forecasted CH_4 levels, temperature, rainfall, and vegetation conditions (NDVI). The CCI will classify regional climate conditions into different levels of climate stress and support climate risk assessment.

8.8 Expected Outcomes and Novelty

The proposed research is expected to deliver AI-based forecasting models, a comparative assessment of modern deep learning models, future greenhouse gas trends over Saurashtra, and a decision-support framework for regional climate adaptation.

Novelty elements include: Simultaneous forecasting of CO_2 and CH_4; Integration of OCO-2/OCO-3, Sentinel-5P, ERA5, and MODIS datasets; Comparison of conventional and advanced AI models; Development of a composite Climate Change Indicator (CCI); First comprehensive AI-based greenhouse gas forecasting study focused on the Saurashtra region.

IX. COMPARATIVE ANALYSIS OF EXISTING LITERATURE

This Paragraph presents an enhanced comparative analysis of the reviewed literature. In addition to the original columns (study focus, data source, methodology, key findings, limitations, research gap), the enhanced table adds study region, forecasting horizon, and quantitative performance metrics (RMSE, MAE, R^2, MAPE). This multi-parameter

comparison enables side-by-side assessment across model families and application contexts, and makes visible the white space where the proposed research operates.

1. Luo et al. developed a multivariate LSTM model for methane forecasting using atmospheric CH_4 and meteorological variables. Their study found that meteorological factors improved prediction accuracy. However, the research was limited to methane forecasting in Alberta and did not integrate CO_2 prediction.
2. Psomouli et al. (2023) investigated methane forecasting using Sentinel-5P TROPOMI satellite data and recurrent neural networks (RNNs). The model achieved an R^2 of 0.91 and a MAPE of approximately 4.2%. However, the study focused only on methane and had limited geographical coverage.
3. Uluocak compared LSTM, GRU, CNN-GRU, and CNN-LSTM models using NOAA methane records. CNN-LSTM achieved the best reported performance, with an R^2 of 0.98. However, the study lacked a detailed investigation of regional influencing factors.
4. Linardatos et al. studied urban CO_2 forecasting using IoT sensor data and a hybrid ARIMA–Temporal Fusion Transformer model. Their hybrid approach outperformed conventional methods. However, the research relied on urban sensor data rather than satellite observations.
5. Ajala et al. compared ARIMA, Random Forest, XGBoost, ANN, LSTM, GRU, and BiLSTM for CO_2 emission forecasting. BiLSTM achieved the highest reported accuracy, with an R^2 of 0.97. However, the study focused on emissions rather than atmospheric CO_2 concentrations.
6. Huang et al. applied Random Forest and XGBoost to improve the consistency of satellite-derived XCO_2 products from OCO-2 and GOSAT. Their approach improved consistency by approximately 0.6 ppm. However, the study focused on retrieval enhancement rather than forecasting.
7. Balasus et al. applied machine learning-based bias correction to methane retrievals from TROPOMI and GOSAT. Their approach reduced retrieval uncertainty by approximately 20%. However, the research focused on retrieval quality rather than predicting future methane concentrations.
8. Alcibahy et al. used Support Vector Regression (SVR) and Random Forest with multi-satellite observations to estimate CO_2 and CH_4 concentrations. The study reported R^2 values of 0.94 for CO_2 and 0.91 for CH_4. However, it focused on estimation and spatial mapping without temporal forecasting.
9. Schuit et al. developed an automated machine learning framework to detect methane super-emitters using TROPOMI satellite imagery. The approach achieved a precision of 0.82 and a recall of 0.76. However, the study focused on identifying emission hotspots rather than forecasting future methane concentrations.
10. Zhou et al. proposed FEDformer, a frequency-enhanced Transformer architecture for long-term time-series forecasting. The model demonstrated strong performance on benchmark datasets such as ETT, ECL, and exchange-rate data. However, it was not evaluated on atmospheric greenhouse gas datasets.
11. Wu et al. introduced Autoformer, a Transformer architecture that uses series decomposition and autocorrelation mechanisms for long-term forecasting. The model improved forecasting performance on benchmark datasets. However, it was not specifically evaluated for atmospheric CO_2 or CH_4 prediction.
12. Nie et al. proposed PatchTST, a Transformer-based model that divides time series into patches to improve long-sequence forecasting. Their experiments demonstrated strong performance on benchmark datasets. However, its effectiveness for environmental indicators and greenhouse gas forecasting remains to be investigated.
13. Eldering et al. investigated early scientific applications of the OCO-2 satellite and established a framework for retrieving and validating atmospheric CO_2 observations. Their work demonstrated the value of OCO-2 for obtaining high-quality global XCO_2 measurements. However, it did not include predictive modelling.
14. Hammerling et al. developed methods for high-resolution atmospheric CO_2 mapping using OCO satellite observations and spatial interpolation. Their work produced detailed maps of CO_2 distribution. However, the research focused on spatial mapping rather than future concentration forecasting.
15. Jacob et al. investigated methane emission quantification using satellite observations from TROPOMI, GOSAT, and GHGSat, combining remote sensing with atmospheric inversion techniques. Their work demonstrated the capability to quantify methane emissions from global scales to individual facilities. However, the focus was emission estimation rather than future methane forecasting.
16. David et al. applied neural networks to estimate atmospheric CO_2 using OCO-2 satellite observations. Their approach demonstrated the potential of neural networks for satellite-derived CO_2 estimation. However, the study did not establish a framework for predicting future CO_2 levels.
17. Lim and Zohren reviewed deep learning approaches for time-series forecasting, covering RNNs, LSTMs, and Transformers across multiple application domains. Their work provides a useful overview of forecasting architectures. However, it is a general review rather than a specific greenhouse gas forecasting application.
18. Zhao et al. investigated optimized artificial neural networks for engineering forecasting using thermal engineering datasets. Their study demonstrated the potential of ANN optimization to improve forecasting performance. However, the research was not directly related to climate science or greenhouse gas prediction.
19. Li et al. applied artificial neural networks to spatial environmental modelling using digital elevation models and other spatial datasets. Their work demonstrated improvements in spatial prediction accuracy. However, the study provides

methodological support rather than a direct greenhouse gas forecasting application.

20. Spatial Information Research Study examined the spatial and temporal variability of methane over the Saurashtra region using satellite observations and geospatial variables. The study identified methane hotspots and seasonal variations. However, it focused on monitoring and geospatial analysis without implementing AI-based forecasting.

21. Cong et al. introduced SatMAE, a self-supervised learning approach using Vision Transformers and masked autoencoders for temporal and multispectral satellite imagery. Their approach demonstrated effective feature learning while reducing dependence on labelled data. However, the study focused on satellite image representation learning rather than greenhouse gas forecasting.

22. Jakubik et al. investigated foundation models for general-purpose geospatial artificial intelligence using diverse Earth observation and geospatial datasets. Their work demonstrated the potential of foundation models to transfer knowledge across geospatial tasks. However, the listed study did not implement a forecasting framework for atmospheric CO_2 and CH_4.

23. Benson et al. investigated neural network-based atmospheric transport modelling of carbon dioxide. Their approach demonstrated that neural networks can approximate atmospheric transport processes with lower computational costs. However, the study focused on CO_2 transport modelling rather than directly forecasting future greenhouse gas concentrations.

X. RESEARCH GAP IDENTIFICATION

The systematic review of 30-40 studies reveals that existing research, despite remarkable advances in satellite remote sensing and AI-based atmospheric modelling, leaves five clearly-defined categories of gaps that collectively justify the proposed Saurashtra-focused framework.

10.1 Data-Related Gaps: No published study integrates OCO-2/OCO-3, GOSAT, Sentinel-5P, ERA5 reanalysis and MODIS land-surface indices within a single AI forecasting pipeline. Ground-truthing and inter-satellite bias-correction datasets are rarely made available at the regional scale.

10.2 Methodological Gaps: Transformer-based models (Informer, Autoformer, FEDformer, and PatchTST) remain unapplied to satellite-derived CO_2 and CH_4 forecasting. Simultaneous multi-output forecasting of both CO_2 and CH_4 is absent.

10.3 Explainability Gaps: Virtually all deep learning models applied to greenhouse gas forecasting are black-box systems without SHAP, LIME, or attention-weight visualisations.

10.4 Spatial Generalisation Gaps: The Saurashtra region of western India has not been studied in any existing AI-based GHG forecasting work.

10.5 Climate-Assessment Gaps: No study derives a composite Climate Change Indicator (CCI) that combines forecasted CO_2 and CH_4 levels with meteorological and ecological variables.

XI. CONCLUSION

Satellite remote sensing and artificial intelligence have significantly advanced greenhouse gas monitoring and prediction capabilities. However, major research gaps remain in the simultaneous forecasting of atmospheric CO2 and CH4 concentrations using integrated satellite datasets, particularly for the environmentally unique Saurashtra region. The proposed framework aims to address these technical and geographical white spaces, delivering robust predictive and decision-support capabilities to improve regional climate resilience.

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