

SATELLITE IMAGERY & AI FOR TRACKING CRABON EMISSIONS

Team 3 TerraTrack

Harika Reddy - ENG21CT0007

Krutarth Y G - ENG21CT0016

Pooja V M - ENG21CT0029

Sarah Catherine - ENG21CT0034

Vandana M V - ENG21CT0046





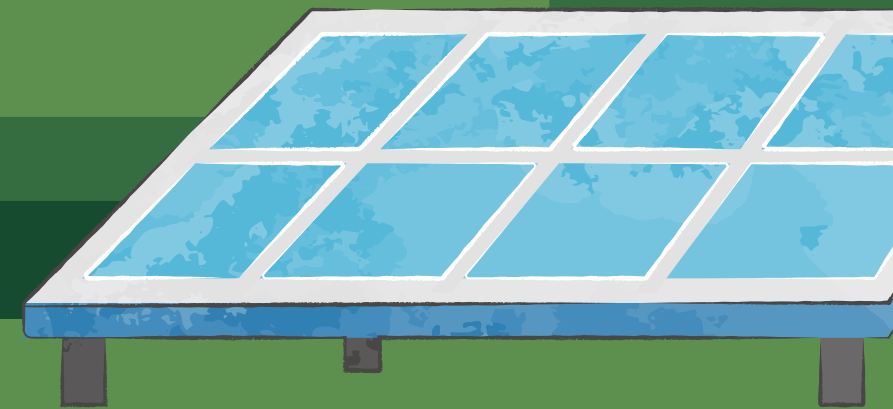
INTRODUCTION

Carbon emissions primarily refer to the release of carbon dioxide (CO₂) and methane (CH₄) into the atmosphere, mainly from burning fossil fuels, industrial processes, and deforestation. Greenhouse gases like CO₂ and CH₄ trap heat in the atmosphere, enhancing the greenhouse effect and causing global warming. According to NASA, atmospheric CO₂ has increased by over 47% since the Industrial Revolution



WHY ARE CARBON EMISSIONS HARMFUL?

- **Increased Global Temperature:** Average global temperatures have risen by about 1.2°C since the late 19th century, leading to record-breaking heatwaves and wildfires.
- **Extreme Weather:** Higher CO₂ levels are linked to more frequent and intense hurricanes, floods, and droughts.
- **Biodiversity Loss:** Many species cannot adapt quickly enough to climate changes, resulting in extinction or forced migration.
- **Human Health:** Air pollution from carbon emissions contributes to respiratory diseases, lung cancer, and cardiovascular problems. According to WHO, 7 million premature deaths occur annually due to air pollution.





CURRENT EFFORTS

Monitoring carbon emissions is essential to track progress on climate goals, such as the Paris Agreement, which aims to limit global temperature rise to below 2°C.

Traditional Tracking Methods:

- Ground-Based Sensors: These provide detailed data in specific locations but have limited geographic reach.
- Industry Self-Reporting: Companies report emissions, but data accuracy varies, making it harder to obtain a reliable global picture.

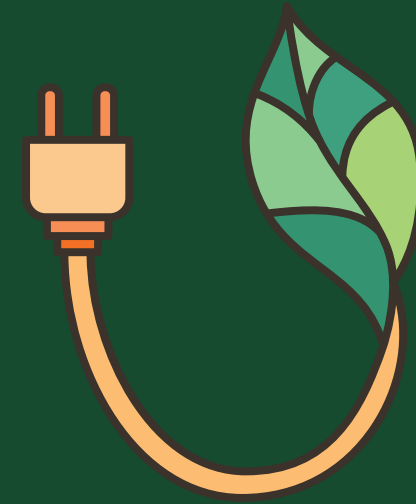
HOW SATELLITE IMAGERY AND AI CAN HELP

Satellite Technology for Emission Tracking:

NASA's Orbiting Carbon Observatory-2 (OCO-2) and the ESA Copernicus Sentinel satellites focus specifically on monitoring greenhouse gases such as carbon dioxide (CO₂) and methane (CH₄). These satellites orbit the Earth, covering both populated and remote areas, and provide consistent data on emissions.

AI for Data Analysis:

The large amounts of data generated by satellites require advanced tools for analysis, and this is where AI comes in. AI algorithms can process satellite data, detect patterns, and identify emissions hotspots. AI can quantify emissions from sources like power plants or urban areas and predict future emission trends based on past data.



LITERATURE SURVEY

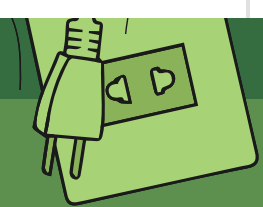


Paper	Key Models	Efficiency	Drawbacks	Improvements in our Project
Machine Learning Algorithms to Forecast Air Quality	Decision Trees, Random Forest, k-NN	Up to 82% accuracy	Limited real-time adaptability; lower accuracy.	Utilizes LSTM for better handling of temporal data and real-time updates.
Application of LSTM Networks for Air Quality Prediction	LSTM	85-90% accuracy	Requires extensive data preprocessing; struggles with extreme weather impacts.	Incorporates diverse environmental parameters to enhance robustness against weather variations.
AQNet: Air Quality Prediction Using Deep Learning and Multimodal Data	CNNs, multimodal data	87-92% accuracy	High computational requirements; data integration challenges.	Aims for efficiency by optimizing data handling and model complexity for real-time processing.
Air Quality Prediction using Deep Neural Networks	DNN	90% accuracy	Generalizability issues; performance varies by location.	Enhances generalizability by integrating localized data and real-time adjustments for varied environments.



PAPER 1

PAPER 1				
Paper Title	Artificial Intelligence-driven Insights: Precision Tracking of Power Plant Carbon Emissions Using Satellite Data			
Problem addressed	Existing carbon emission reporting by power plants relies on self-reporting, which is often inaccurate and lacks real-time data. There is an urgent need for precise, real-time tracking of carbon emissions to better address climate change impacts.			
Soultion proposed	A predictive pipeline was developed that integrates TROPOMI satellite data with power plant attributes and uses AI algorithms. The system utilizes multimodal data processing to map satellite observations of pollutants to specific power plant emissions.			
	<i>Dataset Used</i>	<i>Technologies/Methods</i>	<i>Results</i>	<i>Gaps/Future Work</i>
	Satellite data from the TROPOMI instrument on the Sentinel-5P satellite (covering NO ₂ vertical column densities). Ground-based CEMS (Continuous Emissions Monitoring System) data from the EPA Clean Air Markets Program.	DBSCAN clustering for detecting plumes around power plants to filter data for more accurate modeling. A BERT-based model is employed to establish relationships between pollutant concentrations and plant-specific emissions data.	Achieved significant accuracy with the model, showing high R ² (0.68), SRCC (0.79), and PLCC (0.83) values, indicating strong prediction reliability. The model effectively estimates hourly CO ₂ emissions using satellite and ground data inputs, improving emission tracking accuracy.	Plans to extend the model to include other gaseous emissions and pollutants beyond CO ₂ . Aims to enhance model architectures to improve prediction accuracy and incorporate additional environmental factors.




PAPER 2


PAPER 2				
Paper Title	Near Real-Time CO ₂ Emissions Based on Carbon Satellite and Artificial Intelligence			
Problem addressed	Real-time CO ₂ emission estimates are limited by satellite imaging challenges (e.g., low resolution and significant measurement noise). Current emission monitoring solutions lack objectivity and rely heavily on self-reporting, limiting data reliability for policy and regulatory			
Soultion proposed	Developed a data-driven pipeline, CarbonNet, which integrates carbon satellite data and AI for estimating CO ₂ emissions. Introduced a masked pre-training method to utilize unlabeled data effectively and a linear probing step for more accurate predictions.			
	<i>Dataset Used</i>	<i>Technologies/Methods</i>	<i>Results</i>	<i>Gaps/Future Work</i>
	NASA's OCO-2 satellite data, providing XCO ₂ measurements across specific geographic footprints. Supplementary datasets include CEMS data from the EPA and ERA5 reanalysis data for environmental factors like wind speed.	Transformer-based CarbonNet model for emission estimation, which leverages satellite data and deep learning methods. Compared the proposed model's performance to the Gaussian plume model, a traditional approach used for emission estimates.	The model demonstrated higher Spearman and Pearson correlation values, outperforming the Gaussian plume model in prediction accuracy. Results confirmed that CarbonNet could effectively predict CO ₂ emissions even with noisy and sparse satellite data.	Plans to improve model interpretability, as current deep learning approaches lack transparency in emission prediction processes. Future efforts may focus on refining satellite data resolution and environmental inputs for more accurate model training.

PAPER 3				
Paper Title	Modeling and Spatio-Temporal Analysis of City-Level Carbon Emissions Based on Nighttime Light Satellite Imagery			
Problem Addressed	Challenges in estimating city-level carbon emissions where detailed, localized urban data is lacking. Traditional models often miss urban dynamics and temporal changes.			
Solution Proposed	Developed the NNEnsemble model, which correlates nighttime stable light (NSL) data from DMSP-OLS satellites with carbon emission statistics at the provincial level to predict city-level emissions.			
	Dataset used	Technologies	Results	Gaps
	Nighttime light data from DMSP-OLS paired with statistical carbon emissions data from three northeastern Chinese provinces.	Ensemble neural network model capable of handling non-linear relationships and integrating spatial-temporal data variations.	Outperformed traditional regression approaches, effectively capturing emissions trends over time and across different urban environments.	Less effective for industrial zones. Bright urban areas may face data saturation issues, reducing accuracy. Additional data layers (e.g., industrial output, land use) could enhance model robustness.

PAPER 4				
Paper Title	A Review of Anthropogenic Ground-Level Carbon Emissions Based on Satellite Data			
Problem Addressed	Existing methods for carbon emission estimation face challenges due to limitations in satellite resolution and the need for global-scale data that ground-based methods cannot provide alone.			
Solution Proposed	The review discusses how machine learning and data-driven approaches can enhance satellite and ground data integration for more accurate emission estimates. Evaluates strengths and weaknesses of existing methodologies.			
	<i>Dataset used</i>	<i>Technologies</i>	<i>Results</i>	<i>Gaps</i>
	Diverse satellite data sources (e.g., OCO-2, GOSAT, PRISMA) and ground-based emission inventories	Supervised learning models such as neural networks and data retrieval algorithms like Bayesian Error Subsequent Diffusion (BESD) which interpret satellite measurements.	Demonstrated improved emission estimation when combining satellite and ground-based data, showing the potential for machine learning.	Limitations in satellite data resolution can obscure local emission variations, making it hard to detect smaller emission sources. Ground-based data, while accurate, lacks the global reach needed for comprehensive monitoring.

PAPER 5				
Paper Title	A Carbon-Monitoring Strategy Through Near-Real-Time Data and Space Technology			
Problem Addressed	The lack of real-time, precise, and reliable global carbon monitoring to support climate policy, hindered by limitations in current emission inventory data that rely on energy statistics and lack direct measurements.			
Solution Proposed	Proposes an innovative strategy combining near-real-time emission data with satellite-based CO2 observations. Integrates “bottom-up” inventory data and “top-down” satellite data for enhanced monitoring.			
	Dataset used	Technologies	Results	Gaps
	Combines high-frequency human activity data (e.g., smart meters, grid data) with satellite data from CO2 observation missions such as OCO-2/3, GOSAT, and TanSat.	Satellite CO2 monitoring systems, data assimilation models, machine learning for data synthesis, geographic information systems.	Demonstrated potential for improved spatial and temporal resolution in emission tracking, allowing targeted monitoring of significant emission sources like cities and power plants.	Satellite data accuracy can be affected by background atmospheric noise; satellites need to balance scope and resolution.

PAPER 6				
Paper Title	Estimating CO2 Emissions from Power Plant Water Vapor Plumes Using Satellite Imagery and ML			
Problem Addressed	The high cost and inconsistent availability of direct emissions data from power plants due to limited deployment of continuous monitoring systems.			
Solution Proposed	Uses machine learning to estimate CO2 emissions from power plants by analyzing water vapor plumes detected in satellite images. Provides a scalable, cost-effective alternative for global emissions monitoring.			
	<i>Dataset used</i>	<i>Technologies</i>	<i>Results</i>	<i>Gaps</i> 
	satellite imagery from PlanetScope (3 m resolution), Sentinel-2 (10 m resolution), and Landsat 8 (30 m resolution), combined with reported power plant data from various regions	Machine learning models, including convolutional neural networks (CNNs) for feature extraction and gradient-boosted decision trees for classification and regression.	The model's RMSE is about 0.35% for power generation and 0.22% for CO2 emissions, indicating high accuracy with deviations well under 1%.	Limitations due to the need for visible vapor plumes, which may not always be present; variability in atmospheric conditions affecting visibility; image resolution constraints that reduce accuracy for smaller plants.

PAPER 7				
Paper Title	Tracking Carbon Emissions from Power Plants Using Satellite Imagery and CNN Models			
Problem Addressed	Current methods of tracking carbon emissions from power plants often rely on ground-based measurements, which can be limited by access, coverage, and timely data availability.			
Solution Proposed	Developed a CNN-based model that processes satellite imagery to estimate carbon emissions from power plants, offering a more accessible and potentially global monitoring system.			
	Dataset used	Technologies	Results	Gaps 
	Satellite imagery data focused on large power plant areas, including multispectral and thermal bands.	A CNN model was trained to recognize emissions patterns in satellite images, integrating atmospheric data to improve accuracy.	The model successfully identified high-emission plants, with results comparable to ground-based measurements in controlled environments.	Further refinement is necessary for areas with limited satellite data and complex atmospheric conditions. Enhancements to improve model robustness across different plant types are needed.

PAPER 8

Paper Title

NASA’s Climate and Greenhouse Gas Monitoring Initiatives

Problem Addressed

Limited global monitoring of greenhouse gases, especially in areas without ground-based monitoring stations, restricts comprehensive understanding and tracking of climate change contributors.

Solution Proposed

NASA’s Carbon Mapper program, in collaboration with other agencies, aims to deploy advanced satellite systems for continuous and detailed global greenhouse gas monitoring.

Dataset used

Technologies

Results

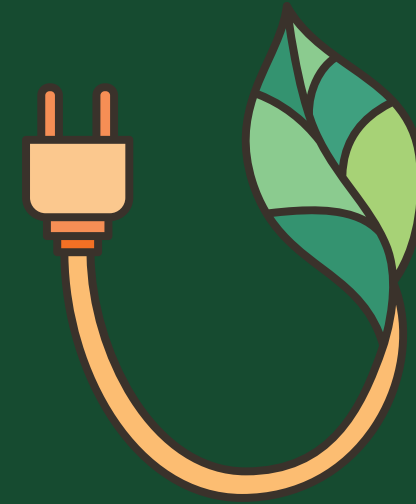
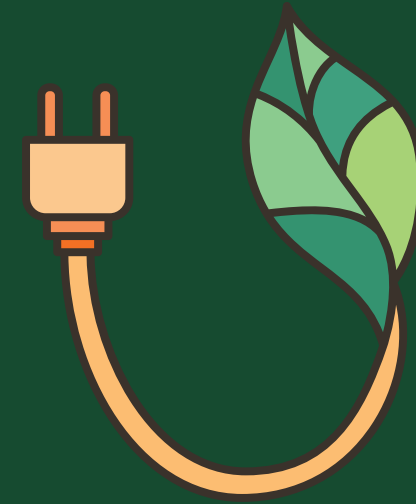
Gaps

Carbon Mapper satellites are equipped with high-resolution spectrometers that detect gases like CO2 and methane in fine detail.

Advanced remote sensing technology uses AI-based data analysis to interpret complex gas emissions patterns.

Early findings demonstrate the capability to accurately pinpoint emission sources, even in remote regions, contributing to real-time emissions monitoring.

Challenges include processing data at scale and ensuring consistency across diverse geographic and atmospheric conditions. More partnerships for ground validation are suggested.



IMPLEMENTATION





THANK YOU

