



Project Proposal

Title

AI-Based Estimation of Carbon Emissions Using Machine Learning: A
Case Study on Saudi Arabia

Prepared By :

Name: Mohammad Wajeeh Bader

ID No: 251000462

Submitted in fulfillment of the requirements for the degree Master
of Science in Artificial Intelligence

At

College of Informatics

Midocean University

UAE

Supervisor Name: Dr. Amjad Qataish

College of Informatics, Midocean University, Comoros

1. Project Overview

This project aims to solve the problem of accurately predicting Saudi Arabia's annual CO₂ emissions using machine learning techniques. Currently, environmental monitoring relies heavily on manual calculations and traditional methods that lack precision and timeliness. This is important because Saudi Arabia is working toward Vision 2030 environmental goals and needs reliable tools to track emission progress and inform policy decisions.

The project will develop a machine learning framework that uses readily available national economic and energy indicators to predict CO₂ emissions. This approach will make emission forecasting more accessible, accurate, and cost-effective compared to complex satellite-based methods. The resulting tool will help environmental agencies, policymakers, and researchers monitor emission trends and evaluate the effectiveness of environmental policies.

By creating a practical, reproducible framework specifically tailored to Saudi data characteristics, this project will provide decision-makers with an evidence-based tool that supports environmental monitoring and contributes to achieving the country's sustainability objectives.

2. Project Goal

Primary Goal: Develop a model to predict carbon emissions in Saudi Arabia.

Specific Objectives:

- Create a machine learning model that achieves $R^2 \geq 0.80$ accuracy on test data
- Compare multiple algorithms to identify the most effective approach
- Establish guidelines for model selection in emission forecasting
- Deliver a reproducible framework for environmental monitoring applications

3. Approach

Data Collection

The project will use publicly available annual data from two primary sources:

- CO₂ Emissions Data: Our World in Data comprehensive database covering Saudi Arabia's historical emissions
- Economic and Energy Indicators: World Bank Open Data including up to 6 key features:
 - GDP per capita
 - Population and urbanization rate
 - Energy consumption per capita
 - Fossil fuel electricity percentage

- Renewable energy share
- Industrial production index

The data will cover the period from 1990-2024, subject to availability across all sources.

Data Processing

- Data Integration: Align temporal coverage and units across different data sources
- Quality Control: Handle missing values using documented interpolation methods
- Feature Engineering: Create lag features and 3-year moving averages to capture temporal patterns
- Data Validation: Implement quality checks and outlier detection to ensure data reliability

Model/Method Selection

The project will implement and compare multiple machine learning approaches:

- Baseline Models: Ridge and Lasso regression to establish performance benchmarks
- Primary Model: CatBoost regressor, selected for its effectiveness with small tabular datasets
- Optional Extension: XGBoost or LightGBM if time permits

Testing and Evaluation

- Validation Strategy: Time-based cross-validation using expanding window approach (5 folds)
- Hold-out Testing: Reserve final 5-7 years of data for ultimate performance assessment
- Performance Metrics: R^2 , MAE, RMSE, and MAPE to comprehensively evaluate model accuracy
- Analysis: Feature importance analysis, error pattern investigation, and model comparison

4. Project Steps and Timeline

Main Steps (12 Weeks Total)

Data Collection and Preparation (Weeks 1-3)

- Gather CO₂ emission data from Our World in Data
- Collect economic and energy indicators from World Bank
- Clean and integrate datasets from different sources
- Create temporal features and handle missing values

Model Building and Training (Weeks 4-7)

- Implement baseline models (Ridge and Lasso regression)
- Develop primary CatBoost model
- Perform hyperparameter optimization
- Train models using prepared dataset

Testing and Evaluation (Weeks 8-10)

- Execute time-based cross-validation
- Test models on hold-out data
- Compare performance across different algorithms
- Analyze feature importance and error patterns

Final Adjustments and Reporting (Weeks 11-12)

- Make final model improvements based on testing results
- Write comprehensive project report
- Organize code repository and documentation
- Prepare final presentation materials

5. Expected Results

This project aims to achieve the following outcomes:

- Improved accuracy in predicting carbon emissions for Saudi Arabia using machine learning techniques, achieving $R^2 \geq 0.80$ compared to traditional forecasting methods.
- New insights into which algorithms work best for emission prediction using national indicators, providing evidence-based guidance for similar environmental forecasting projects.
- A working tool that can be used for environmental monitoring, specifically supporting Saudi Arabia's Vision 2030 objectives and helping policymakers track emission reduction progress.
- Reproducible methodology and code that other researchers can apply to different regions or adapt for other environmental indicators.
- Clear performance benchmarks showing the effectiveness of different machine learning approaches for carbon emission forecasting in the Middle East region.

6. Resources Needed

Software and Tools

- Programming Environment: Python 3.9+ with data science libraries (pandas, numpy, scikit-learn, catboost)
- Computing Resources: Google Colab (free tier) or standard laptop
- Development Tools: Jupyter notebooks, GitHub for version control

Datasets

- Primary Sources: Our World in Data and World Bank Open Data (both free and publicly available)

- Backup Sources: EDGAR database for validation if needed

Other Support Required

- Expert Guidance: Regular check-ins with thesis advisor
- Computing Resources: Standard university computing facilities if needed

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Project Proposal

AI-Enhanced Carbon Emissions Forecasting for Saudi Arabia: Integrating Multi-Source Data with Advanced Machine Learning

Prepared By

Name: Mohammad Wajeeh Bader

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1. Project Overview

Introduction and Background

The challenge of rising atmospheric CO₂ concentrations continues to define our century, with global emissions reaching unprecedented levels. The IPCC (2023) emphasizes that achieving global climate targets requires unprecedented accuracy in emissions monitoring and forecasting to support evidence-based policy decisions.

Recent breakthroughs demonstrate that AI-satellite integration can achieve remarkable performance improvements: ensemble methods reaching $R^2 = 0.931$ for Saudi national forecasting (Nassef et al., 2023), CNN-based approaches achieving daily monitoring with $R^2 \approx 0.89$ (Cao, 2023), and operational systems delivering near-real-time global coverage (Dou et al., 2023).

Saudi Arabia has emerged as a regional climate leader through the Saudi Green Initiative (SGI, 2021), with net-zero emissions by 2060 commitment and Vision 2030's \$2 trillion investment program requiring sophisticated monitoring capabilities for optimal resource allocation and progress tracking.

Problem Statement

1. Single-modality limitations: National forecasting methods achieve excellent temporal accuracy ($R^2 = 0.931$) but lack spatial validation, while satellite monitoring provides spatial detail but limited national aggregation accuracy.
2. Uncertainty quantification gap: Current systems provide point estimates without confidence intervals, creating critical gaps for policy decision-making requiring risk assessment for billions of dollars in Vision 2030 investments.
3. Regional adaptation challenges: Saudi Arabia's unique environmental conditions (>50 dust storm days annually, >40°C temperature variations, complex oil/gas infrastructure) require specialized adaptations not addressed in existing temperate-region literature.

Core Problem: How can proven high-performance AI forecasting methods ($R^2 = 0.931$) be systematically integrated with satellite-derived environmental indicators to achieve robust, uncertainty-quantified CO₂ emissions forecasting for Saudi Arabia's unique environmental and policy contexts?

Importance and Motivation

- **Scientific Importance:** Develops the first comprehensive multi-modal ensemble approach systematically combining proven temporal forecasting excellence with validated spatial monitoring capabilities, while implementing Bayesian uncertainty quantification for environmental AI applications.
- **Policy Relevance:** Directly supports Vision 2030's quarterly milestone requirements through uncertainty-quantified emissions forecasts enabling risk-adjusted evaluation of renewable energy projects and carbon capture investments. Enhanced monitoring capabilities position Saudi Arabia as regional technology leader while strengthening international climate negotiation credibility.
- **Global Impact:** Establishes methodological foundation for environmental monitoring across 41% of Earth's surface classified as arid or semi-arid, supporting climate monitoring capability building in developing countries worldwide.

Scope Definition

- **Geographic Coverage:** Saudi Arabia national-level emissions (1990–2024 training, 2025–2030 predictions).
- **Technical Scope:** Ensemble AI approaches (FFNN, LSTM, XGBoost) with satellite integration (NO₂, NDVI, LST) and Bayesian uncertainty quantification.
- **Excluded:** Sub-national spatial mapping, raw satellite image processing, real-time operational deployment.

2. Project Goal

The primary goal of this research is to establish the foundational component of an advanced multi-modal forecasting framework by systematically investigating the integration of proven AI ensemble methods with satellite-derived environmental indicators for Saudi Arabia emissions forecasting.

Specific Objectives (3-Month Study)

1. **Core Integration Validation:** Demonstrate systematic integration of ensemble AI methods (FFNN + LSTM + XGBoost) with satellite indicators (NO₂, NDVI) achieving measurable performance improvement over single-modality approaches.
2. **Benchmark Establishment:** Replicate and extend Nassef et al. (2023) $R^2 = 0.931$ benchmark through multi-modal enhancement, targeting $R^2 \geq 0.85$ with documented improvement over baseline.
3. **Methodology Documentation:** Develop reproducible framework for multi-modal integration enabling future research phases and extension to uncertainty quantification and operational deployment.

4. Foundation for Future Work: Establish data pipeline, validation methodology, and performance benchmarks supporting logical extension to Bayesian uncertainty quantification, Saudi-specific adaptations, and regional transferability.

Success Criteria (Achievable in 3 Months)

- Performance: $R^2 \geq 0.85$ on hold-out validation with demonstrated improvement over national-data-only approach.
- Integration: Successful combination of 3 AI models with 2–3 satellite indicators.
- Reproducibility: Complete methodology documentation and code framework.
- Future Readiness: Clear pathway established for uncertainty quantification and operational deployment phases.

3. Approach

Data Collection Strategy

- National indicators: Our World in Data (CO₂ emissions), World Bank (GDP, energy intensity, renewable share).
- Satellite-derived indicators: TROPOMI NO₂ (fossil fuel proxy), MODIS NDVI (vegetation activity), MODIS LST (temperature).
- Policy indicators (exploratory; included if data quality and time permit): Vision 2030 milestone data, oil price impacts.

Temporal Coverage: 1990–2024 (34 years) annual resolution, quarterly for 2015–2024 where available.

Methodology Framework

Tier 1 – Individual Models

- FFNN (baseline replication of Nassef et al. benchmark).
- LSTM (temporal dependency modeling).
- XGBoost (non-linear feature interactions).

Tier 2 – Ensemble Methods

- Weighted ensemble (performance-based weighting).
- Stacking ensemble (meta-learner optimization).
- Bayesian Model Averaging (optional; full uncertainty pipeline deferred to Phase 2).

Tier 3 – Multi-modal Integration

- Early fusion (concatenated features).
- Late fusion (ensemble of modality-specific models).
- Attention-based fusion (learned feature importance; optional, time-permitting).

Validation Strategy

- Temporal cross-validation: Expanding window TimeSeriesSplit ($k=5$) with final hold-out 2020–2024 (5 years).
- The 2020–2024 window is strictly out-of-sample and not used for model fitting.
- Performance benchmarking: Stretch target $R^2 \geq 0.93$ (matching literature); Acceptance: $R^2 \geq 0.85$ and $\text{MAPE} \leq 10\%$.
- Uncertainty validation: 95% confidence interval coverage $\geq 90\%$ with calibration assessment.

4. Project Steps and Timeline

Month 1: Foundation and Baseline Establishment

Week 1–2: Data collection and preprocessing

- Collect national indicators from Our World in Data, World Bank (CO_2 , GDP, energy data).
- Access satellite-derived indicators (NO_2 , NDVI) via Google Earth Engine.
- Validate data completeness for 1990–2024 period and temporal alignment.

Week 3–4: Baseline model development

- Replicate Nassef et al. (2023) benchmark achieving $R^2 = 0.931$ using national data only.
- Implement individual models: FFNN, LSTM, XGBoost.
- Establish single-modality performance baselines and validation framework.

Month 2: Multi-Modal Integration (Core Contribution)

Week 5–6: Satellite data integration and feature engineering

- Process satellite indicators for annual aggregation (2000–2024 coverage).
- Develop feature combination strategies (early fusion approach).
- Create integrated datasets combining national statistics with satellite indicators.

Week 7–8: Ensemble development and multi-modal training

- Implement weighted ensemble approaches combining individual models.
- Train integrated models on multi-modal feature sets.
- Initial performance validation and comparison with single-modality baselines.

Month 3: Validation and Future Work Foundation

Week 9–10: Comprehensive validation and analysis

- Hold-out testing on 2020–2024 independent data.
- Performance comparison: multi-modal vs. single-modality approaches.
- Feature importance analysis and interpretability assessment.

Week 11–12: Documentation and future research framework

- Results analysis and statistical significance testing.
- Complete methodology documentation for reproducibility.
- Future work roadmap development for uncertainty quantification and operational phases.
- Final presentation preparation.

Future Research Phases (Post-Master's)

1. Phase 2: Bayesian uncertainty quantification development (6–12 months, PhD-level).
2. Phase 3: Saudi-specific adaptations and arid region optimization (6 months).
3. Phase 4: Operational deployment and policy integration (12 months, industry collaboration).
4. Phase 5: Regional expansion and GCC technology transfer (18 months, multi-country).

5. Risk Management

To ensure the project remains on track within the 3-month scope, the following risks have been identified along with their mitigation strategies:

Risk	Likelihood	Impact	Mitigation Strategy
NDVI/NO ₂ data gaps or noise (dust, limited coverage)	High	Medium	Use AVHRR NDVI for pre-2000 and OMI NO ₂ for 2004–2017; apply cloud/dust filters; aggregate data annually if quarterly coverage is incomplete.
Model complexity vs. limited data (~30 years)	Medium	High	Start with simple models (XGBoost, small FFNN), apply regularization, and expand gradually; use temporal cross-validation.
Bayesian Model Averaging (BMA)	High	High	Defer full BMA to future phases (PhD-level); in this study use simple ensemble averages or spread-based uncertainty bounds.
Dust storms and extreme temperatures	High	Medium	Filter satellite data during high aerosol periods; integrate temperature (LST) as an input; test stress scenarios with extreme climate years.
Time pressure (3 months)	Medium	High	Strict project management; define a critical path; parallelize documentation and modeling; drop non-essential tasks if delays occur.
Reliance on GEE and Colab Pro	Medium	High	Download processed datasets locally; prepare backup environment (local GPU / cloud credits); save models and outputs frequently.
Internet/Environment instability	Low	Medium	Freeze library versions; document environment; keep backup internet option (mobile hotspot).

Executive Recommendations

Based on the above risk landscape, the following executive recommendations ensure delivery within the 3-month scope.

- **Data Reliability:** Prepare backups of NDVI and NO₂ datasets; ensure cleaning for dust and clouds.
- **Technical Flexibility:** Keep model design modular and simplify if complexity risks overruns.
- **Time Management:** Focus first on baseline replication + NO₂/NDVI integration; defer advanced ensembles if schedule is tight.
- **Operational Continuity:** Maintain redundant computing options (Colab + local GPU/cloud credits) and frequent checkpointing of models/outputs.
- **Regional Adaptation:** Document dust/heat influences and adjust preprocessing or model inputs accordingly.

6. Expected Results

Immediate Results (3-Month Study)

- **Performance Validation:** Demonstration of multi-modal integration benefits achieving $R^2 \geq 0.85$ on hold-out validation with quantified improvement over single-modality approaches. Expected 3–8% performance gain over Nassef et al. baseline through satellite data integration.
- **Methodological Framework:** Complete reproducible methodology for ensemble AI + satellite integration including data preprocessing pipelines, feature engineering protocols, and validation frameworks supporting future research phases.
- **Feature Analysis:** Systematic analysis of satellite indicator contributions (NO₂, NDVI) to forecasting accuracy with interpretability assessment supporting evidence-based data collection prioritization for future operational systems.
- **Baseline Establishment:** Validated replication of Nassef et al. (2023) $R^2 = 0.931$ benchmark providing reliable foundation for multi-modal enhancement evaluation and future uncertainty quantification research.

Foundation for Future Research

- **Research Pipeline:** Established data and methodology infrastructure supporting logical extension to:
 - Phase 2: Bayesian uncertainty quantification (PhD-level investigation).
 - Phase 3: Saudi-specific arid environment adaptations.
 - Phase 4: Operational deployment for Vision 2030 policy support.
 - Phase 5: Regional expansion to Gulf Cooperation Council countries.
- **Policy Relevance:** Framework design explicitly considering Vision 2030 decision-making requirements, enabling seamless transition to policy-supporting applications in future research phases.

- Scientific Contribution: First systematic validation of multi-modal AI-satellite integration for national emissions forecasting in arid regions, establishing foundation for broader environmental monitoring advancement.

Long-term Vision (Multi-Phase Program)

- Comprehensive Monitoring System: Complete uncertainty-quantified, operationally-deployed monitoring framework supporting Saudi Arabia's climate leadership and regional technology transfer (achievable through systematic multi-phase development).
- Academic Impact: Publication pathway from foundational integration study to comprehensive monitoring methodology, supporting PhD research and international collaboration development.

Performance Targets (Current Study)

- Primary: $R^2 \geq 0.85$ with demonstrated improvement over baseline.
- Innovation: Quantified multi-modal integration benefits.
- Reproducibility: Complete documentation enabling future research phases.

7. Resources Needed

Technical Infrastructure

- Computing Resources: Google Colab Pro for model training and validation; Local GPU for intensive ensemble computations; Cloud storage for multi-source data integration (~5GB processed datasets).
- Software Requirements: Python ecosystem (scikit-learn, TensorFlow, PyTorch, pandas, numpy); Jupyter notebooks for development; Google Earth Engine for satellite data access; Statistical packages for uncertainty quantification.

Data Access

- Open Datasets: Our World in Data (CO₂ emissions), World Bank (economic/energy indicators), freely accessible with API integration.
- Satellite Data: TROPOMI NO₂ observations, MODIS vegetation indices and land surface temperature via Google Earth Engine platform (free academic access).
- Validation Resources: Literature benchmarks from Nassef et al. (2023) for performance comparison; International reporting data for independent validation.

Expert Support

- Supervisor Guidance: Dr. Amjad Qataish will provide general academic guidance and ensure proper research methodology.
- Methodological Consultation: Access to ensemble learning and uncertainty quantification literature; Online resources for Bayesian model averaging implementation.

Risk Mitigation Resources

- Backup Data Sources: Alternative temporal aggregations if quarterly data insufficient; Multiple satellite platforms for redundancy.

- Computational Alternatives: Cloud computing credits if local resources inadequate; Simplified ensemble methods if complexity constraints emerge.
- Validation Alternatives: Cross-validation approaches if hold-out testing challenges arise; Multiple performance metrics for robust evaluation.

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Project Proposal

**AI-Enhanced Carbon Emissions Monitoring Framework for Saudi Arabia:
Systematic Multi-Modal Integration Approach with Validation Methodology**

Prepared By

Name: Mohammad Wajeesh Bader

ID No: 251000462

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At

College of Informatics

Midocean University

UAE

Supervisor Name: Dr. Amjad Qataish

College of Informatics, Midocean University, Comoros

Email: [supervisor_email]

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1. Project Overview

Introduction and Background

The challenge of rising atmospheric CO₂ concentrations continues to define our century, with global emissions reaching unprecedented levels. The IPCC (2023) emphasizes that achieving global climate targets requires unprecedented accuracy in emissions monitoring and forecasting to support evidence-based policy decisions.

Recent breakthroughs demonstrate that AI-satellite integration can achieve remarkable performance improvements: ensemble methods reaching $R^2 = 0.989$ with 6.87% validation error for Saudi national forecasting (Nassef et al., 2023), CNN-based approaches achieving daily monitoring with $R^2 \approx 0.89$ (Cao, 2023), and operational systems delivering near-real-time global coverage (Dou et al., 2023).

Saudi Arabia has emerged as a regional climate leader through the Saudi Green Initiative (SGI, 2021), with a net-zero emissions commitment by 2060. Vision 2030 involves announced projects exceeding \$1.3 trillion (Bloomberg, 2024), with broader investment estimates reaching up to \$3 trillion (Crédit Agricole, 2024), requiring sophisticated monitoring capabilities for optimal resource allocation and progress tracking.

Problem Statement

1. Single-modality limitations: National forecasting methods achieve excellent temporal accuracy ($R^2 \approx 0.989$ with 6.87% validation error) and require spatial dimension integration, while satellite monitoring provides spatial detail but limited national aggregation accuracy.
2. Uncertainty quantification gap: Current systems provide point estimates without confidence intervals, creating critical gaps for policy decision-making requiring risk assessment for billions of dollars in Vision 2030 investments.
3. Regional adaptation challenges: Saudi Arabia's unique environmental conditions (>50 dust storm days annually, >40°C temperature variations, complex oil/gas infrastructure) require specialized adaptations not addressed in existing temperate-region literature.

Core Problem: How can proven high-performance AI forecasting methods ($R^2 = 0.989$) be systematically investigated for integration with satellite-derived environmental indicators to develop robust, uncertainty-quantified CO₂ emissions monitoring framework for Saudi Arabia's unique environmental and policy contexts?

Research Focus: This study adopts a systematic validation approach to multi-modal integration, focusing on proof-of-concept demonstration and methodology establishment rather than operational system deployment.

Importance and Motivation

- **Scientific Importance:** Develops systematic regional application of validated multi-modal ensemble approaches, combining proven temporal forecasting excellence with spatial monitoring capabilities while implementing Bayesian uncertainty quantification for environmental AI applications.
- **Policy Relevance:** Directly supports Vision 2030's quarterly milestone requirements through uncertainty-quantified emissions forecasts enabling risk-adjusted evaluation of renewable energy projects and carbon capture investments. Enhanced monitoring capabilities support regional policy frameworks while strengthening international climate negotiation credibility.

Global Impact: Provides validated methodology applicable to arid and semi-arid regions, supporting climate monitoring capability building in developing countries with similar environmental conditions.

Scope Definition

- **Geographic Coverage:** Saudi Arabia national-level emissions (1990–2024 training, 2025–2030 predictions).
- **Technical Scope:** Ensemble AI approaches (FFNN, LSTM, XGBoost) with satellite integration (NO₂ OR NDVI selection) and Bayesian uncertainty quantification.
- **Excluded:** Sub-national spatial mapping, raw satellite image processing, real-time operational deployment.

2. Project Goal

The primary goal of this research is to establish the foundational component of an advanced multi-modal forecasting framework by systematically investigating the integration of proven AI ensemble methods with satellite-derived environmental indicators for Saudi Arabia emissions forecasting.

Specific Objectives (3-Month Study)

1. **Baseline Validation:** Replicate and validate Nassef et al. (2023) $R^2 \approx 0.989$ (6.87% validation error) benchmark as foundation for systematic comparison and enhancement investigation.
2. **Systematic Integration Investigation:** Demonstrate controlled integration of ensemble AI methods (FFNN + LSTM + XGBoost) with single satellite indicator (NO₂ OR NDVI) achieving measurable and statistically significant performance comparison over baseline approaches.
3. **Methodology Documentation:** Develop reproducible framework for systematic integration investigation enabling transparent reporting of both successes and limitations, supporting future research phases.
4. **Adaptive Framework Development:** Establish flexible methodology with multiple successful pathways, ensuring valuable contribution through conservative scope management and robust validation protocols.

5. Contingency Planning: If multi-modal integration proves complex within timeline constraints, project will focus on temporal enhancement using single satellite proxy, maintaining research value while ensuring deliverable outcomes.

Success Criteria (Achievable in 3 Months)

- Performance: Demonstrable improvement over single-modality approaches with statistical significance testing, targeting $R^2 = 0.75-0.85$ on hold-out validation.
- Integration: Successful investigation of satellite indicator integration (NO₂ OR NDVI) with robust uncertainty quantification.
- Reproducibility: Complete methodology documentation and code framework.
- Adaptive Success: Framework design allows scope reduction while maintaining research value - minimum success includes validated baseline replication plus documented integration attempt with lessons learned analysis.

3. Approach

Data Collection Strategy

- National indicators: Our World in Data (CO₂ emissions), World Bank (GDP, energy intensity, renewable share).
- Satellite-derived indicators: TROPOMI NO₂ (fossil fuel proxy) OR MODIS NDVI (vegetation activity) - single indicator selection.
- Policy indicators (exploratory; included if data quality and time permit): Vision 2030 milestone data, oil price impacts.

Temporal Coverage: 1990–2024 (34 years) annual resolution, quarterly for 2015–2024 where available.

Methodology Framework

Tier 1 – Individual Models

- FFNN (baseline replication of Nassef et al. benchmark).
- LSTM (temporal dependency modeling).
- XGBoost (non-linear feature interactions).

Tier 2 – Ensemble Methods

- Weighted ensemble (performance-based weighting).
- Stacking ensemble (meta-learner optimization).
- Bayesian Model Averaging (optional; full uncertainty pipeline deferred to Phase 2).

Tier 3 – Limited Multi-modal Investigation

- Single indicator integration (NO₂ OR NDVI selection).
- Conservative feature combination (early fusion approach).
- Statistical significance testing protocols.

Validation Strategy

- Temporal cross-validation: Expanding window TimeSeriesSplit (k=5) with final hold-out 2020–2024 (5 years).
- The 2020–2024 window is strictly out-of-sample and not used for model fitting.
- Performance benchmarking: Target $R^2 = 0.75-0.85$; Minimum acceptable: $R^2 \geq 0.70$ and $MAPE \leq 15\%$.
- Uncertainty validation: 95% confidence interval coverage $\geq 90\%$ with calibration assessment.

4. Project Steps and Timeline

Month 1: Foundation and Baseline Establishment

Week 1–2: Data collection and preprocessing

- Collect national indicators from Our World in Data, World Bank (CO₂, GDP, energy data).
- Access satellite-derived indicators (NO₂, NDVI) via Google Earth Engine.
- Validate data completeness for 1990–2024 period and temporal alignment.

Week 3–4: Baseline model development

- Replicate Nassef et al. (2023) benchmark achieving $R^2 \approx 0.989$ (6.87% validation error) using national data only.
- Implement individual models: FFNN, LSTM, XGBoost.
- Establish single-modality performance baselines and validation framework.

Month 2: Multi-Modal Integration (Core Contribution)

Week 5–6: Limited satellite data integration and feature engineering

- Process single satellite indicator (NO₂ OR NDVI) for systematic integration investigation.
- Develop conservative feature combination strategies (early fusion approach).
- Create integrated datasets with statistical significance testing protocols

Week 7–8: Controlled integration development and validation

- Implement systematic integration approaches combining individual models.
- Train enhanced models with single satellite indicator integration.
- Conduct rigorous performance comparison with uncertainty quantification.

Adaptive Methodology: If integration complexity exceeds timeline constraints, focus shifts to temporal enhancement using single satellite proxy, ensuring valuable contribution within scope.

Month 3: Validation and Future Work Foundation

Week 9–10: Comprehensive validation and analysis

- Hold-out testing on 2020–2024 independent data.
- Performance comparison: multi-modal vs. single-modality approaches.

- Feature importance analysis and interpretability assessment.

Week 11–12: Documentation and future research framework

- Results analysis and statistical significance testing.
- Complete methodology documentation for reproducibility.
- Future work roadmap development for uncertainty quantification and operational phases.
- Final presentation preparation.

Future Research Phases (Post-Master's)

1. Phase 2: Bayesian uncertainty quantification development (6–12 months, PhD-level).
2. Phase 3: Saudi-specific adaptations and arid region optimization (6 months).
3. Phase 4: Operational deployment and policy integration (12 months, industry collaboration).
4. Phase 5: Regional expansion and GCC technology transfer (18 months, multi-country).

5. Risk Management

To ensure the project remains on track within the 3-month scope, the following risks have been identified along with their mitigation strategies:

Risk	Likelihood	Impact	Mitigation Strategy
NDVI/NO ₂ data gaps or noise (dust, limited coverage)	High	Medium	Use AVHRR NDVI for pre-2000 and OMI NO ₂ for 2004–2017; apply cloud/dust filters; aggregate data annually if quarterly coverage is incomplete.
Model complexity vs. limited data (~30 years)	Medium	High	Start with simple models (XGBoost, small FFNN), apply regularization, and expand gradually; use temporal cross-validation.
Bayesian Model Averaging (BMA)	High	High	Defer full BMA to future phases (PhD-level); in this study use simple ensemble averages or spread-based uncertainty bounds.
Dust storms and extreme temperatures	High	Medium	Filter satellite data during high aerosol periods; integrate temperature (LST) as an input; test stress scenarios with extreme climate years.
Time pressure (3 months)	Medium	High	Strict project management; define a critical path; parallelize documentation and modeling; drop non-essential tasks if delays occur.
Reliance on GEE and Colab Pro	Medium	High	Download processed datasets locally; prepare backup environment (local GPU / cloud credits); save models and outputs frequently.
Internet/Environment instability	Low	Medium	Freeze library versions; document environment; keep backup internet option (mobile hotspot).

Executive Recommendations

Based on the above risk landscape, the following executive recommendations ensure delivery within the 3-month scope.

- **Data Reliability:** Prepare backups of NDVI and NO₂ datasets; ensure cleaning for dust and clouds.
- **Technical Flexibility:** Keep model design modular and simplify if complexity risks overruns.
- **Time Management:** Focus first on baseline replication + NO₂/NDVI integration; defer advanced ensembles if schedule is tight.
- **Operational Continuity:** Maintain redundant computing options (Colab + local GPU/cloud credits) and frequent checkpointing of models/outputs.
- **Regional Adaptation:** Document dust/heat influences and adjust preprocessing or model inputs accordingly.

6. Expected Results

Immediate Results (3-Month Study)

- Performance Validation: Systematic investigation of integration benefits achieving $R^2 = 0.75-0.85$ on hold-out validation with quantified comparison over single-modality approaches.
- Methodological Framework: Complete reproducible methodology for ensemble AI + satellite integration including data preprocessing pipelines, feature engineering protocols, and validation frameworks supporting future research phases.
- Feature Analysis: Systematic analysis of satellite indicator contributions (NO_2 , NDVI) to forecasting accuracy with interpretability assessment supporting evidence-based data collection prioritization for future operational systems.
- Baseline Establishment: Validated replication of Nassef et al. (2023) $R^2 \approx 0.989$ (6.87% validation error) benchmark providing reliable foundation for multi-modal enhancement evaluation and future uncertainty quantification research.

Foundation for Future Research

- Research Pipeline: Established data and methodology infrastructure supporting logical extension to:
- Phase 2: Bayesian uncertainty quantification (PhD-level investigation).
- Phase 3: Saudi-specific arid environment adaptations.
- Phase 4: Operational deployment for Vision 2030 policy support.
- Phase 5: Regional expansion to Gulf Cooperation Council countries.
- Policy Relevance: Framework design explicitly considering Vision 2030 decision-making requirements, enabling seamless transition to policy-supporting applications in future research phases.
- Scientific Contribution: Regional application of multi-modal AI-satellite integration approaches for arid environment conditions, establishing foundation for broader environmental monitoring development.

Long-term Vision (Multi-Phase Program)

- Comprehensive Monitoring System: Complete uncertainty-quantified monitoring framework supporting regional environmental monitoring and methodology development (achievable through systematic multi-phase development).
- Academic Impact: Publication pathway from foundational integration study to comprehensive monitoring methodology, supporting PhD research and international collaboration development.

Performance Targets (Current Study)

- Primary: $R^2 = 0.75-0.85$ with demonstrable integration benefits and statistical significance validation.
- Methodology: Systematic investigation of satellite indicator contributions with transparent uncertainty quantification.
- Adaptive Success Framework: Multiple pathways ensure valuable contribution regardless of integration complexity achieved within timeline constraints.

- Reproducibility: Complete documentation enabling future research phases.

7. Resources Needed

Technical Infrastructure

- Computing Resources: Google Colab Pro for model training and validation; Local GPU for intensive ensemble computations; Cloud storage for multi-source data integration (~5GB processed datasets).
- Software Requirements: Python ecosystem (scikit-learn, TensorFlow, PyTorch, pandas, numpy); Jupyter notebooks for development; Google Earth Engine for satellite data access; Statistical packages for uncertainty quantification.

Data Access

- Open Datasets: Our World in Data (CO₂ emissions), World Bank (economic/energy indicators), freely accessible with API integration.
- Satellite Data: TROPOMI NO₂ observations, MODIS vegetation indices and land surface temperature via Google Earth Engine platform (free academic access).
- Validation Resources: Literature benchmarks from Nassef et al. (2023) for performance comparison; International reporting data for independent validation.

Expert Support

- Supervisor Guidance: Dr. Amjad Qataish will provide general academic guidance and ensure proper research methodology.
- Methodological Consultation: Access to ensemble learning and uncertainty quantification literature; Online resources for Bayesian model averaging implementation.

Risk Mitigation Resources

- Backup Data Sources: Alternative temporal aggregations if quarterly data insufficient; Multiple satellite platforms for redundancy.
- Computational Alternatives: Cloud computing credits if local resources inadequate; Simplified ensemble methods if complexity constraints emerge.
- Validation Alternatives: Cross-validation approaches if hold-out testing challenges arise; Multiple performance metrics for robust evaluation.

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