



# Project Proposal

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

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# 1. Project Overview

## Introduction and Background

The challenge of rising atmospheric CO<sub>2</sub> 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 CO<sub>2</sub> 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 (NO<sub>2</sub> 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 (NO<sub>2</sub> 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 (NO<sub>2</sub> 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 (CO<sub>2</sub> emissions), World Bank (GDP, energy intensity, renewable share).
- Satellite-derived indicators: TROPOMI NO<sub>2</sub> (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 (NO<sub>2</sub> 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 (CO<sub>2</sub>, GDP, energy data).
- Access satellite-derived indicators (NO<sub>2</sub>, 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 (NO<sub>2</sub> 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 <sub>2</sub> data gaps or noise (dust, limited coverage) | High       | Medium | Use AVHRR NDVI for pre-2000 and OMI NO <sub>2</sub> 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 NO<sub>2</sub> 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 + NO<sub>2</sub>/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 ( $\text{NO}_2$ , 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 (CO<sub>2</sub> emissions), World Bank (economic/energy indicators), freely accessible with API integration.
- Satellite Data: TROPOMI NO<sub>2</sub> 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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