



Project Proposal

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

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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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