

AI-Enhanced Carbon Emissions Monitoring Framework for Saudi Arabia

Systematic Multi-Modal Integration Approach with Validation Methodology

Mohammad Wajeih Bader | ID: 251000462

Supervisor: Dr. Amjad Qataish

Master of Science in Artificial Intelligence

College of Informatics, Midocean University

Background

- **Global Context:** CO₂ emissions are at record levels → IPCC (2023) emphasizes the need for unprecedented accuracy in monitoring and forecasting.
- **Saudi Commitment:** Saudi Arabia targets net-zero greenhouse gas emissions by 2060 under the Saudi Green Initiative (SGI, 2021).
- **Vision 2030 Investments:** Announced projects exceed \$1.3 trillion (Bloomberg, 2024), with broader estimates reaching up to \$3 trillion (Crédit Agricole, 2024). Reliable forecasting systems are required for evidence-based policy decisions.

Sources: SGI (2021); IPCC (2023); Bloomberg (2024); Crédit Agricole (2024)

Project Overview: This study develops a proof-of-concept framework that combines Saudi Arabia's high-accuracy temporal forecasting ($R^2 \approx 0.989$) with satellite-derived indicators (NO₂ or NDVI) to enhance spatial monitoring. The 3-month Phase-1 focuses on replicating the baseline, integrating one satellite indicator, and validating performance with uncertainty checks — building the methodological foundation for future operational deployment under Vision 2030.

Presentation Overview & Agenda

Two-Part Structure: Completed Work + Future Implementation

Part I: Achievements ✓COMPLETED

-  Background & Motivation
-  Satellite Platforms for Carbon Monitoring
-  Comprehensive LR (20 Studies)
-  Performance Benchmarks Analysis
-  Key Findings from Literature
-  Saudi-Specific Framework Development
-  Research Gaps Identification

Part II: Implementation Plan PROPOSED

-  Evidence-Based Objectives
-  Multi-Modal Data Integration
-  3-Month Implementation Timeline
-  Vision 2030 Integration Strategy

Problem Statement & Research Scope

Core Challenge: Saudi Arabia achieves excellent temporal forecasting ($R^2 \approx 0.989$) but requires systematic investigation of spatial dimension integration potential for comprehensive monitoring capabilities.

Research Focus: This study focuses on proof-of-concept validation of multi-modal integration approaches, establishing foundation methodology rather than operational deployment.

(Nassef et al., 2023)

Research Opportunity

 **Regional Application Study**

Combining proven AI methods with satellite monitoring for arid regions - limited specialized applications identified in literature review.

(Literature gap identified)

Multi-Modal Enhancement

Systematic investigation of satellite data (NO_2 , NDVI) integration with validated ensemble methods for performance improvement.

(Cao, 2023; Zhang et al., 2022)

Research Scope Definition

 **Geographic Coverage**

Focus: Saudi Arabia national-level

Timeline: 1990-2024 training data

 **Technical Scope**

AI Methods: FFNN, LSTM, XGBoost ensemble

Satellite Data: NO_2 , NDVI integration

 **Scope Clarification**

National-level study only (Saudi Arabia).

No sub-national maps or raw satellite image processing in this 3-month study. Outputs are methodological (proof-of-concept), not an operational system.

Importance & Motivation

Triple Impact: Scientific innovation + Policy support + Global scalability

Scientific Importance

Systematic regional application of validated approaches combining proven temporal forecasting excellence with spatial monitoring capabilities

(Nassef et al., 2023; Cao, 2023; Zhang et al., 2022)

Policy Relevance

Vision 2030 Support: Quarterly milestone tracking with uncertainty quantification for large-scale investments (>\$1.3T announced; up to ~\$3T estimated)

(Saudi Green Initiative, 2021)

Global Impact

Regional Application: Validated methodology for arid environment conditions

(Wilson et al., 2025; Venkatappa et al., 2020)

>\$1.3T—~\$3T

Vision 2030 Investments

2060

Net-Zero Target

41%

Global Applicability

(Bloomberg, 2024; Crédit Agricole, 2024; SGI, 2021)

Satellite Platforms for Carbon Monitoring

Key Satellite Platforms: Direct CO₂, proxy gases (NO₂/CH₄), vegetation & temperature — combined for robust monitoring in arid conditions

Platform	Spatial Res.	Temporal Res.	Key Use	Access
TROPOMI / Sentinel-5P	~7 × 3.5 km	Daily	NO ₂ proxy for fossil-fuel CO ₂	Open (ESA)
OCO-2 / OCO-3	~1.3 × 2.25 km	~16-day	Direct CO ₂ columns (targeted)	Open (NASA)
Sentinel-2	10—60 m	2—5 days	NDVI & land cover	Open (ESA)
MODIS	250 m—1 km	Daily—16 d	LST/phenology	Open (NASA)

Scientific Foundation

NO₂ and CO₂ co-emitted during fossil fuel combustion. Strong correlation enables NO₂ as reliable spatial proxy for CO₂ monitoring.

(Cao, 2023)

Proven Performance

CNN-based NO₂ mapping achieves daily R² ≈ 0.89, annual R² ≈ 0.95 - validated for fossil fuel CO₂ estimation.

(Cao, 2023)

Operational Stack (Example): Daily NO₂ (TROPOMI) + seasonal land (Sentinel-2/MODIS) + direct CO₂ passes (OCO-2/CO₂M) → policy-grade monitoring

Sources: See Key References slide

Phase I Achievements: Comprehensive Literature Review

✓ COMPLETED Systematic analysis providing evidence-based foundation for implementation

Research Scope Completed

📄 20 Peer-Reviewed Studies

Coverage: 2016-2024 publications
Focus: Satellite integration for carbon monitoring
Methodology: Systematic review protocol
(Cao, 2023; Couture et al., 2024; Dou et al., 2023)

🌐 Global Performance Analysis

Regions: Saudi Arabia, USA, China, Europe
Methods: 7 distinct analytical architectures
Platforms: 12+ satellite systems analyzed
(Le Brazidec et al., 2024; Rouet-Leduc & Hulbert, 2024)

Key Discoveries

🎯 Performance Benchmarks

Saudi Baseline: $R^2 = 0.989$ (Nassef et al.)
Global Range: R^2 0.70-0.95
Best Methods: Ensemble approaches
(Nassef et al., 2023)

🔍 Research Gaps Identified

Arid Regions: No specialized systems
Uncertainty: Limited quantification
Saudi Context: No multi-modal integration

20

Studies Analyzed

7

AI Methods Reviewed

12+

Satellite Platforms

Literature Review Results: Evidence-Based Performance Tiers

DISCOVERY Three distinct performance tiers identified with clear technical requirements

Tier 1: $R^2 > 0.90$

Methods: Ensemble approaches

Saudi Proven: $R^2 = 0.989$

(Nassef et al., 2023)

Tier 2: R^2 0.85-0.90

Methods: Advanced CNNs

Example: $R^2 \approx 0.89$

(Cao, 2023)

Tier 3: R^2 0.70-0.85

Methods: Single-sensor

Status: Baseline methods

(Zhang et al., 2022)

Key Finding: Saudi Arabia has proven Tier 1 capability but requires spatial enhancement → Our opportunity

Key Findings from Literature (Benchmarks)

BENCHMARKS Tier-1 temporal accuracy is proven; spatial capability is maturing

Saudi Ensemble (Temporal)

Models: FFNN + ANFIS + LSTM
Perf: $R^2 = 0.989$; 6.87% val. error
Use: National forecasting

(Nassef et al., 2023)

CNN NO₂ (Spatial Proxy)

Daily: $R^2 \approx 0.89$ | **Annual:** $R^2 \approx 0.95$
Use: City/region mapping

(Cao, 2023)

Direct CO₂ (CO₂M Sim.)

Task: Power-plant quantification
Error: ~20% abs. rel. error
Note: Improves with CO₂M

(Le Brazidec et al., 2024)

Methane Detection (CH₄)

Method: Vision Transformers
Perf: F1 > 0.8; ↑ sensitivity
Use: Oil & gas plumes

(Rouet-Leduc & Hulbert, 2024)

NRT Systems & Cloud

GRACED: Daily 0.1°; ±19.9% unc.
GEE: >90 PB; ~6× speed-up
Outcome: Policy-grade updates

(Dou et al., 2023; Wilson et al., 2025)

Bottom Line: Saudi temporal performance is Tier-1 ($R^2 \approx 0.989$). The spatial NO₂ proxy is strong (daily $R^2 \approx 0.89$). Direct CO₂ quantification is expected to improve with CO₂M.

Multi-Modal AI Methodology: Literature-Optimized Approach

Design Rationale: Each component selected based on literature performance analysis

Model Architecture (Literature-Proven)

Model	Performance	Application	Reference
FFNN	$R^2 = 0.991$	Baseline replication	Nassef et al., 2023
LSTM	$R^2 = 0.995$	Time dependency	Nassef et al., 2023
XGBoost	$R^2 \approx 0.90$	Non-linear patterns	Literature average
Ensemble	$R^2 = 0.989$	Final integration	Nassef et al., 2023

Data Integration Strategy

**NO₂ as CO₂ Proxy**
Literature: Cao (2023) $R^2 \approx 0.89$
Source: TROPOMI 7×3.5 km daily
(Cao, 2023)

**NDVI Enhancement**
Literature: Zhang et al. $R^2 \approx 0.85$
Purpose: Carbon sink validation
(Zhang et al., 2022)

**LST Calibration**
Critical: 40°C seasonal variations
Source: MODIS thermal bands
(Addas, 2023)

Note: In this 3-month Phase-1, only one satellite indicator (NO₂ or NDVI) will be integrated. LST and any additional indicators are deferred to later phases.

Integration Workflow



Data Collection & Validation Strategy

Comprehensive Coverage: 34 years historical data + literature-validated sources

Multi-Source Data Integration

Source	Coverage	Literature Validation
Our World in Data	1990-2024	Nassef et al. proven
TROPOMI NO ₂	2018-2024	Cao: R ² ≈ 0.89
MODIS NDVI/LST	2000-2024	Zhang: R ² ≈ 0.85
World Bank APIs	1990-2024	Economic indicators

Sources validated through literature review

Validation Framework

**Temporal Cross-Validation**
Training: 1990-2019 (30 years)
Hold-out: 2020-2024 (5 years, untouched)
Cross-validation: 5-fold expanding-window TimeSeriesSplit

**Performance Metrics**
Primary: R² coefficient
Secondary: MAPE ≤ 15%

**Saudi Adaptations**
Dust Filtering: Multi-sensor approach
Validation: Industrial focus
(Addas, 2023)

34 Years
Historical Coverage

4 Sources
Data Integration

5 Years
Hold-out Testing

Proposed 3-Month Implementation Timeline

Implementation Proposal: Literature foundation complete → Ready for systematic execution of proven approaches

Proposed Implementation Roadmap



Month 1: Foundation

Proposed Activities:

- National indicators collection
- Satellite data processing via GEE
- Baseline replication validation

Expected Deliverable: Complete dataset + validated baseline ($R^2 \approx 0.989$)

(Based on Nassef et al., 2023)

Month 2: Integration

Adaptive Development:

- Single-modal enhancement (NO_2 OR NDVI)
- Statistical significance testing
- Performance comparison protocols

Expected Deliverable: Enhanced baseline + initial integration results

(Literature-guided approach)

Month 3: Validation

Proposed Testing:

- Hold-out testing (2020-2024)
- Performance benchmarking
- Methodology documentation

Expected Deliverable: Complete framework + results analysis

Key Advantages

No Exploratory Research: Literature review complete

Proven Methods: Direct implementation of validated approaches

Risk Mitigation: Parallel task execution, modular approach

Timeline Flexibility

Critical Path: Data → Models → Validation

Contingency: Simplify complexity if delays occur

Success: Multiple pathways to valuable contribution

Resources & Implementation Readiness

Full Resource Assessment: Technical infrastructure + Data access + Expert support secured

Technical Infrastructure (Available)

Resource	Specification	Status
Google Colab Pro	GPU/TPU access	Available
Google Earth Engine	Satellite data processing	Free academic
Cloud Storage	~5GB processed datasets	Secured
Local GPU	Backup computing	Available

Data Access & Expert Support

 **Open Datasets**
Our World in Data: CO₂ emissions (free API)
World Bank: Economic indicators
Status: Validated access
(Wilson et al., 2025)

 **Satellite Data**
TROPOMI: NO₂ observations
MODIS: NDVI, LST via GEE
Status: Academic access confirmed

 **Academic Support**
Supervisor: Dr. Amjad Qataish
Literature: 20+ validated references
Methodology: Proven frameworks

Software Stack

Python: scikit-learn, TensorFlow
Data: pandas, numpy, xarray
Viz: matplotlib, plotly

Risk Mitigation

Backup: Multiple data sources
Computing: Cloud + local options
Timeline: Parallel task execution

Readiness Status

Technical: Ready
Data: Accessible
Methodology: Validated

Proposed Performance Targets & Expected Outcomes

Literature-Based Projections: Evidence-informed expectations for proposed implementation

Performance Projections (Literature-Based)



Proposed Success Metrics *Proposed targets based on literature analysis - not achieved results*

Target (3-month study): $R^2 = 0.75\text{--}0.85$ on the 2020–2024 hold-out
Minimum acceptable: $R^2 \geq 0.70$ and $\text{MAPE} \leq 15\%$
Stretch ambition: $R^2 \geq 0.90$ (if feasible)
Validation: 5-fold expanding-window TimeSeriesSplit + final hold-out (2020–2024)
Uncertainty: report 95% CI coverage with a basic calibration plot; full Bayesian UQ deferred to Phase-2

(Conservative projection based on literature)

Expected Deliverables (3 Months)

Proposed Performance Analysis

Multi-modal benefits: Quantified improvement documentation
Hold-out testing: 2020–2024 independent validation
Baseline comparison: vs. Nassef et al. methodology

Technical Framework

Methodology: Complete reproducible integration approach
Pipeline: Data processing + validation protocols
Documentation: Framework for future research phases

Academic Contribution

Literature Foundation: First systematic arid region approach
Saudi Context: Regional environmental adaptations
Future Pathway: Clear extension roadmap established
(Bloomberg, 2024; Crédit Agricole, 2024; SGI, 2021)

0.75–0.85

Target (3 months)

$\geq 0.70 / \leq 15\%$

Min R^2 / MAPE

≥ 0.90

Stretch (Ambition)

Future Research Roadmap: Multi-Phase Program

Strategic Vision: From foundation study to operational deployment and regional leadership

Phase	Duration	Scope	Key Deliverables
Phase 1	3 months	Multi-modal Integration	Methodology framework + validated baseline + single-indicator integration; Target $R^2 = 0.75-0.85$ (Min: $R^2 \geq 0.70$, MAPE $\leq 15\%$).
Phase 2	6-12 months	Bayesian Uncertainty	Confidence intervals, risk quantification
Phase 3	6 months	Saudi Adaptations	Dust storm handling, temperature modeling
Phase 4	12 months	Operational Deployment	Real-time system, Vision 2030 integration
Phase 5	18 months	Regional Expansion	GCC deployment, technology transfer

Research Gaps (Arid Region Focus)



Academic Pathway

Publications: From foundational to comprehensive
PhD Extension: Uncertainty quantification focus

Global Impact

Methodology Development: Regional environmental monitoring
Policy Support: Vision 2030 alignment
(IPCC, 2023)

5 Phases

Research Program

3-5 Years

Total Timeline

GCC Region

Scalability

Success Metrics: Clear & Measurable Criteria

Uncertainty & Calibration: 95% CI coverage $\geq 90\%$ on the 2020–2024 hold-out; basic intervals / ensemble spread in Phase-1; full Bayesian UQ deferred to Phase-2.
Defined Success: Multiple pathways to demonstrate research value and contribution

Primary Success Metrics

🎯 Technical Achievement

Target: $R^2 = 0.75\text{--}0.85$ on hold-out validation with demonstrable integration benefits

Benchmark: Measurable improvement over baseline

Evidence: Statistical significance testing

💡 Innovation Demonstration

Core: Quantified multi-modal integration benefits

Documentation: Feature importance analysis

Reproducibility: Complete methodology framework

🎓 Academic Contribution

Literature: First systematic arid region approach

Foundation: Framework for future research phases

Publication: Clear pathway established

Acceptance Criteria & Fallbacks

✅ Minimum Acceptable Outcomes

Baseline Replication: Nassef et al. methodology validated

Integration Demonstrated: Satellite data successfully incorporated

Performance Documented: Clear improvement measurement

Minimum acceptance: $R^2 \geq 0.70$ & $\text{MAPE} \leq 15\%$ (per proposal).

🛡️ Contingency Success

Even at $R^2 = 0.80$: Valuable contribution achieved

- Methodology framework established
- Multi-modal integration process documented
- Saudi adaptation pathway identified

🕒 Timeline Success

On-Schedule Delivery: Within 3-month scope

Risk Management: Proactive mitigation applied

Future Ready: Clear next-phase roadmap

Bottom Line: Multiple success pathways ensure valuable contribution regardless of exact performance numbers

0.75–0.85

Target (3 months)

≥ 0.70 / $\leq 15\%$

Min R^2 / MAPE

≥ 0.90

Stretch (Ambition)

Risk Management: Proposed Implementation Challenges

Risk Matrix (Likelihood × Impact)

Proactive Planning: Identified risks for proposed implementation with evidence-based mitigation strategies

● High ● Medium ● Low

Risk Category	Likelihood	Impact	Technical Mitigation Strategy
NDVI/NO₂ data gaps / noise Cloud/dust noise; coverage variability (TROPOMI since 2018)	High	Medium	AVHRR NDVI pre-2000 + OMI NO ₂ 2004–2017; dust/cloud filters; annual aggregation if quarterly coverage incomplete.
Model complexity vs. limited data (~30–34y) Overfitting / generalization risk	Medium	High	Start simple (XGBoost / small FFNN) + regularization; expanding-window CV; gradual complexity increase.
Bayesian Model Averaging (BMA) complexity Full UQ pipeline out of scope for Phase-1	High	High	Deferred to Phase-2 (PhD-level); use ensemble spread / simple intervals for basic uncertainty this phase.
Dust storms / extreme temperatures >50 days/year dust; >40°C seasonal variations	High	Medium	Filter high-AOD periods; integrate LST; stress-test hot years; seasonal calibration.
Time pressure / infra interruptions 3-month scope; cloud/colab dependency	Medium	High	Define critical path; parallelize documentation; local GPU / cloud backups; frequent checkpoints / version pinning.

Key Risk Insights:

- Data quality (dust & NDVI/NO₂ gaps) is the most recurrent technical risk.
- Deferring full Bayesian UQ to Phase-2 reduces complexity in this study while preserving value.
- Timeline risk is mitigated via strict critical path and parallel documentation.

Planned Environmental Adaptations

Dust Storm Protocol: >50 days annually (Addas, 2023)
Extreme Heat: 40°C+ seasonal variations
Regional Specificity: Arid environment calibrations

Implementation Readiness

Literature Complete: 20 studies analyzed
Methods Proven: Validated approaches selected
Infrastructure: Computing resources secured

Conclusion: Ready for Implementation

Implementation Ready: Comprehensive foundation established through systematic analysis

Foundation Established

Literature Foundation

- 20 Studies Analyzed** (2016-2024)
- Performance benchmarks established
 - Research gaps identified
 - Saudi-specific framework developed

Technical Readiness

Methods Validated: Tier-1 feasible; target for this study: R^2 0.75—0.85 (stretch ≥ 0.90)
Data Sources: Proven and accessible
Implementation: Clear pathway established
(Literature-validated approach)

Innovation Opportunity

Research Gap: No arid region systems exist
Saudi Context: Multi-modal integration opportunity
Regional Impact: Vision 2030 alignment potential
(Saudi Green Initiative, 2021)

Implementation Request

Ready for Phase II

Literature Foundation: Complete
Methods Selection: Proven approaches identified
Resources: Secured and validated
Timeline: Realistic 3-month scope

Clear Success Metrics

Primary Target: $R^2 = 0.75\text{—}0.85$ (2020—2024 hold-out)
Minimum: $R^2 \geq 0.70$ & $\text{MAPE} \leq 15\%$
Stretch: $R^2 \geq 0.90$ (if feasible)
Innovation: Multi-modal integration benefits quantified
Academic: Reproducible methodology framework

Scope Reminder

Phase-1 (3 months) delivers: baseline replication + single-indicator integration (NO_2 or NDVI) + calibrated validation; no sub-national mapping, no raw image processing, no real-time ops.

Expected Outcome

Deliverable: Saudi Arabia's first multi-modal emissions forecasting framework
Contribution: Foundation for arid region monitoring systems
Impact: Regional monitoring foundation established

Request for Approval: Phase II Implementation - 3 months starting next semester

Note: Methane (CH_4) monitoring, proven in literature with $F1 > 0.8$, is outside the 3-month scope but proposed as a priority for future oil & gas applications.

Phase I ✓

Literature Complete

Phase II →

Implementation Ready

Vision 2030

Policy Support

Key References

Foundation Studies: Core literature supporting methodology and regional context

Key Saudi Studies

Nassef, A. M., et al. (2023). Application of artificial intelligence to predict CO₂ emissions: Critical step towards sustainable environment. *Sustainability*, 15(9), 7648. DOI: 10.3390/su15097648
Performance: R² = 0.989, 6.87% validation error

Addas, A. (2023). Machine learning techniques to map the impact of urban heat island: Investigating Jeddah. *Land*, 12(6), 1159. DOI: 10.3390/land12061159
Regional Context: Saudi environmental challenges

Satellite AI Methods

Cao, E. L. (2023). National ground-level NO₂ predictions via satellite imagery driven convolutional neural networks. *Frontiers in Environmental Science*, 11, 1285471. DOI: 10.3389/fenvs.2023.1285471
Performance: R² ≈ 0.89 for NO₂-CO₂ proxy

Zhang, F., et al. (2022). Estimation of aboveground carbon density of forests using deep learning and multi-source remote sensing. *Remote Sensing*, 14(13), 3022. DOI: 10.3390/rs14133022
Method: Multi-sensor integration approach

Policy Framework

Saudi Green Initiative (2021). Saudi Arabia to achieve net zero emissions by 2060. Available: saudigreeninitiative.org
Context: Vision 2030 policy support requirements

IPCC (2023). Climate Change 2023: Synthesis Report — Summary for Policymakers. Available: ipcc.ch/report/ar6/syr
Global Context: Monitoring accuracy requirements

Bloomberg. (2024, September 10). Saudi Arabia's Vision 2030 projects reach \$1.3 trillion in value. *Bloomberg*.

Crédit Agricole. (2024, September). Can Saudi Arabia afford its ambitions? *Economic Studies*.

Performance Benchmarks

Saudi Proven: R² = 0.989 (Nassef et al., 2023)
Satellite Integration: R² ≈ 0.89 (Cao, 2023)
Target Range: R² = 0.75—0.85 (3-month study); **Stretch:** R² ≥ 0.90

Literature Foundation

Total Studies Reviewed: 20 (2016-2024)
Core References: 6 foundational studies
Regional Focus: Saudi adaptation requirements

Complete bibliography of 20 reviewed studies available in written proposal document



Thank You

Questions & Discussion



Mohammad Wajeesh Bader

Student ID: 251000462



Supervisor: Dr. Amjad Qataish

Master of Science in Artificial Intelligence



College of Informatics

Midocean University

“ *From systematic literature foundation to evidence-based implementation* ”