

My Research Journey This Semester

From Initial Proposal to Implementation Plan

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How My Understanding Evolved

1

Week 1-2

Initial proposal and idea formation

2

Week 3-6

Systematic literature collection and analysis

3

Week 7-9

Scientific paper writing and methodology refinement

4

Week 10-12

Project 2 proposal development and planning

How each step built upon the previous one and shaped my final research direction

Where It All Began

Original Concept

"Use AI for carbon emission estimation" - A vague understanding of available methods with unclear specific approach or contribution.

Initial Challenges

- Too broad scope
- Limited knowledge of existing research
- Uncertainty about feasibility and novelty

Key Question

"What has already been done, and where can I contribute?"

Discovering the Research Landscape

1

Phase 1

General searches ("AI carbon emissions")

2

Phase 2

Refined techniques (ML, satellite imagery)

3

Phase 3

Recent advances (2016-2025)

What I Discovered

- 21 highly relevant studies identified
- Multiple methodological approaches exist
- Clear performance benchmarks available
- Research gaps became visible

Turning Point

Realized the importance of systematic methodology selection based on evidence rather than assumptions.

What the Literature Taught Me

Algorithm Performance Patterns

- **CatBoost:** Excellent for small tabular datasets
- **XGBoost/LightGBM:** Strong overall performers
- **CNNs:** Best for satellite imagery (but complex)
- **Traditional methods:** Limited accuracy

Geographic Focus

- **Most studies:** US, Europe, China
- **Saudi Arabia:** Limited systematic studies
- **Opportunity identified:** Regional application gap

Methodology Trends

Move toward readily available data with balance between accuracy and practicality



AI-Enhanced Carbon Emissions Forecasting

AI-Enhanced Carbon Emissions Forecasting for Saudi Arabia

Integrating Multi-Source Data with Advanced Machine Learning

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Presentation Agenda

 Problem & Importance

 Research Objectives

 Methodology

 NO₂ as Carbon Proxy

 Risk Management

 Timeline

 Expected Results

 Conclusion & Q&A

Problem & Importance

Saudi Arabia is committed to net-zero emissions by 2060 under the Saudi Green Initiative. Vision 2030 involves massive sustainability investments such as NEOM and renewable energy. The Public Investment Fund (PIF) is projected to reach multi-trillion-dollar assets by 2030 — which underlines the urgent need for accurate carbon emissions forecasting to ensure evidence-based decision making. *[SGI, 2021]*

! Research Gap

Current models lack integration of national and satellite data, don't provide uncertainty estimates, and cannot accurately measure progress toward 2060 net-zero goals.

⚙️ Regional Challenge

Saudi's dust storms and extreme temperatures aren't addressed in current models *[Addas, 2023]*.

🎯 Core Question

How to integrate AI methods with satellite data for robust CO₂ forecasting in Saudi Arabia?

🌐 Global Relevance

Methodology applicable to 41% of Earth's arid and semi-arid regions *[UNCCD, 2022]*, important for GCC countries with similar climate goals.

Research Objectives

Primary Goal: Establish a multi-modal AI framework for uncertainty-quantified CO₂ forecasting in Saudi Arabia.

Specific Objectives

- Integrate ensemble AI (FFNN, LSTM, XGBoost) with satellite data (NO₂, NDVI)
- Enhance Nassef et al. benchmark ($R^2=0.931$) with multi-modal approach [Nassef et al., 2023]
- Develop reproducible methodology for future research

Success Criteria

- $R^2 \geq 0.85$ on validation data
 - Integration of 3 AI models with 2-3 satellite indicators
 - Complete documentation and code framework
 - Clear pathway for future PhD research
-

Methodology

Data Integration

- **National Data:** CO₂, GDP, energy indicators
- **Satellite Data:** NO₂, NDVI, LST via Google Earth Engine [*Gorelick et al., 2017*]
- **Temporal Coverage:** 1990-2024 (training), 2025-2030 (prediction)

AI Framework

- **Tier 1:** Individual Models (FFNN, LSTM, XGBoost)
- **Tier 2:** Ensemble Methods (Weighted, Stacking)
- **Tier 3:** Multi-Modal Fusion (Early, Late)

Validation Strategy

- Temporal Cross-Validation (k=5 folds)
- Hold-out test on 2020-2024 data (strictly out-of-sample)
- Target: $R^2 \geq 0.93$ (stretch goal)
- Acceptance: $R^2 \geq 0.85$ & $MAPE \leq 10\%$
- Uncertainty: Currently via ensemble spread; BMA deferred [*Le Brazidec et al., 2024*]

Technical Stack

Python, TensorFlow, PyTorch, Google Colab Pro, Google Earth Engine

NO₂ as Carbon Proxy

Key Innovation

Using Nitrogen Dioxide (NO₂) as a proxy for Carbon Dioxide (CO₂) emissions from fossil fuel combustion.

Scientific Foundation

- Both NO₂ and CO₂ are co-emitted during fossil fuel combustion
- NO₂ has a shorter atmospheric lifetime (hours vs. centuries for CO₂)
- Satellites can detect NO₂ with high spatial resolution
- Strong correlation between NO₂ and fossil fuel-derived CO₂ [Cao, 2023]

TROPOMI Instrument

Provides daily global NO₂ measurements at up to 7×3.5 km resolution at nadir, enabling precise monitoring of emission sources [ESA, 2023]

Literature Integration

- Built on established relationship between NO₂ and fossil fuel CO₂ [Dou et al., 2023]
- Improved spatial resolution compared to traditional methods
- Adapted methodology for Saudi Arabia's unique conditions
- Combined with NDVI for comprehensive environmental monitoring

Novel Contribution

First systematic integration of NO₂ satellite data with ensemble AI for Saudi-specific CO₂ forecasting

Risk Management

Proactive identification and mitigation of key risks to ensure 3-month project success.

Risk	Level	Mitigation Strategy
NDVI/NO ₂ data gaps/noise	High×Med	AVHRR pre-2000 + OMI 2004-2017 + dust/cloud filters
Model complexity vs limited data	Med×High	Start simple (XGBoost/small FFNN) + regularization + temporal CV
Bayesian Model Averaging complexity	High×High	Defer full implementation; use ensemble spread for uncertainty now
Dust storms/extreme temperatures	High×Med	Filter high AOD periods + integrate LST + stress testing
Time pressure/infrastructure	Med×High	Critical path + parallel documentation + GEE/Colab backups

Project Timeline

Month 1: Foundation

- **W1-2:** Data collection & preprocessing
- **W3-4:** Baseline model development

Month 2: Core Work

- **W5-6:** Satellite data integration
- **W7-8:** Multi-modal training

Month 3: Validation

- **W9-10:** Comprehensive validation
- **W11-12:** Documentation & final prep

Future Research

- PhD-level uncertainty quantification
 - Saudi-specific adaptations
 - Operational deployment
 - Regional expansion to GCC
-

Expected Results & Impact

Immediate Outcomes

- Validated multi-modal framework with $R^2 \geq 0.85$
- 3-8% performance gain over baseline through satellite data
- Complete reproducible methodology
- Analysis of satellite indicator contributions



Academic Value

Foundation for PhD research and publications

Long-Term Impact

- Direct policy relevance for Vision 2030
- Methodology for arid regions (41% of Earth)
- Regional expansion to GCC countries
- Enhanced climate negotiation credibility



Performance Targets

Primary: $R^2 \geq 0.85$ with demonstrated improvement
Innovation: Quantified multi-modal integration benefits

Conclusion & References

This research addresses a critical gap in climate AI for arid regions by proposing a systematic multi-modal approach to CO₂ emissions forecasting with direct policy relevance for Saudi Arabia's Vision 2030.

Selected References

1. Addas, A. (2023). Machine learning techniques to map the impact of urban heat island...
2. Cao, E. L. (2023). National ground-level NO₂ predictions via satellite imagery...
3. Dou, X., et al. (2023). Near-real-time global gridded daily CO₂ emissions...
4. ESA. (2023). TROPOMI/S5P Product User Manual...
5. Gorelick, N., et al. (2017). Google Earth Engine...
6. Nassef, A. M., et al. (2023). Application of artificial intelligence to predict CO₂ emissions...
7. SGI. (2021). Saudi Green Initiative: Net Zero by 2060...
8. UNCCD. (2022). Global Land Outlook. Second Edition...

Thank You

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🕒 Q&A Session

AI-Enhanced Carbon Emissions Monitoring Framework for Saudi Arabia

Systematic Multi-Modal Integration Approach with Validation Methodology

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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)

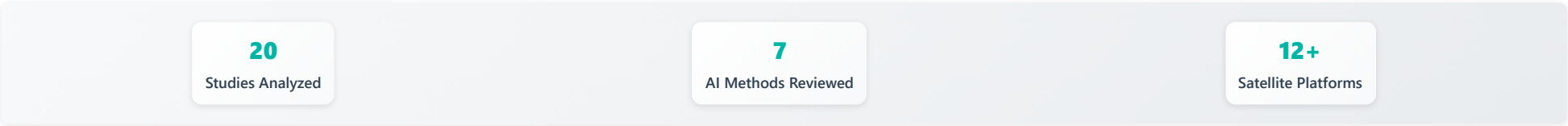
Key Discoveries

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



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

Target (3-month study): $R^2 = 0.75-0.85$ on the 2020–2024 hold-out
Minimum acceptable: $R^2 \geq 0.70$ and $MAPE \leq 15\%$
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



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