



CAPTURING AIR QUALITY DYNAMICS

A Spatio-Temporal Ordinal GAM
Framework for AQI Forecasting
in the Philippines

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AIR POLLUTION IS A PUBLIC HEALTH CONCERN, WHAT IS BEING DONE ABOUT IT?

PH → real-time logging of air quality data, but **no forecasts**

The Metric: 5-tiered ordered Air Quality Index
(Good < Fair < Moderate < Poor < Very Poor)

What do we need?: LGUs require a **day-ahead forecasting window** to execute necessary public health interventions





METHODOLOGICAL GAPS IN CURRENT FRAMEWORKS



Local Gap

- DENR guidelines rely on Gaussian plume physics
- Designed for factory permitting, ignoring regional spillovers

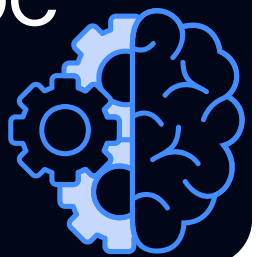


Global Gap

- Use complex partial differential equations
- Fragile under non-linear anomalies (e.g. GFS failing to track Hurricane Sandy)

Machine Learning Gap

- Ignores severe class imbalance
- Flattens extreme categorical spikes
- Relies on post hoc interpretations



OUR SOLUTION: Weighted Ordinal GAM that integrates nonlinear pollutant effects and spatio-temporal factors to create an interpretable, early-warning forecasting model



DATA PIPELINE

Data Acquisition

- 138 Philippine Cities
- Hourly AQI Observations
- Air Pollutants
- Meteorological Variables
- November 2023 – April 2026



kaggle

OpenWeather

Data Processing

- Daily Aggregation
- Maximum AQI
- Missing Value Handling
- Quality Checks

120,328

city-day observations

96.13%

of data retained



Feature Engineering

- Lagged AQI
- Lagged PM_{2.5}, PM₁₀, NO₂, O₃
- Lagged Temperature, Humidity, Pressure, Wind Speed
- Day of Year
- Spatial Coordinates

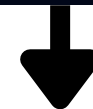


CANDIDATE MODELS

Baseline

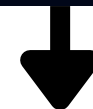
Ordinal Logistic Regression

$AQI \sim PM2.5 + PM10 + NO2 + O3 + \text{Temperature} + \text{Humidity} + \text{Pressure} + \text{Wind Speed} + \text{Longitude} + \text{Latitude}$



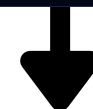
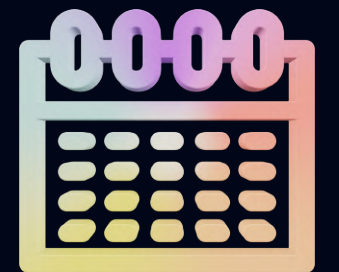
Spatial GAM

$AQI \sim s(\text{Pollutants}) + s(\text{Meteorological Variables}) + s(\text{Longitude, Latitude})$



Dynamic Seasonal GAM

$+ s(\text{AQI Lag}) + s(\text{Day of Year}) + s(\text{Day of Year, City})$



Weighted Dynamic GAMs

$+ \text{Class Imbalance Correction}$





MODEL SELECTION STRATEGY

Stage 1: Baseline Model Comparison

Ordinal Logistic Regression

Spatial GAM

Dynamic **Seasonal** GAM

Selection
Criteria:



Accuracy ↑



Ordinal MAE ↓



Log Loss ↓

Stage 2: Weighting Scheme Comparison

Inverse Frequency Weighting

Square-Root Inverse Frequency Weighting

Selection
Criteria:



Rare AQI Recall ↑



Rare AQI Precision ↑

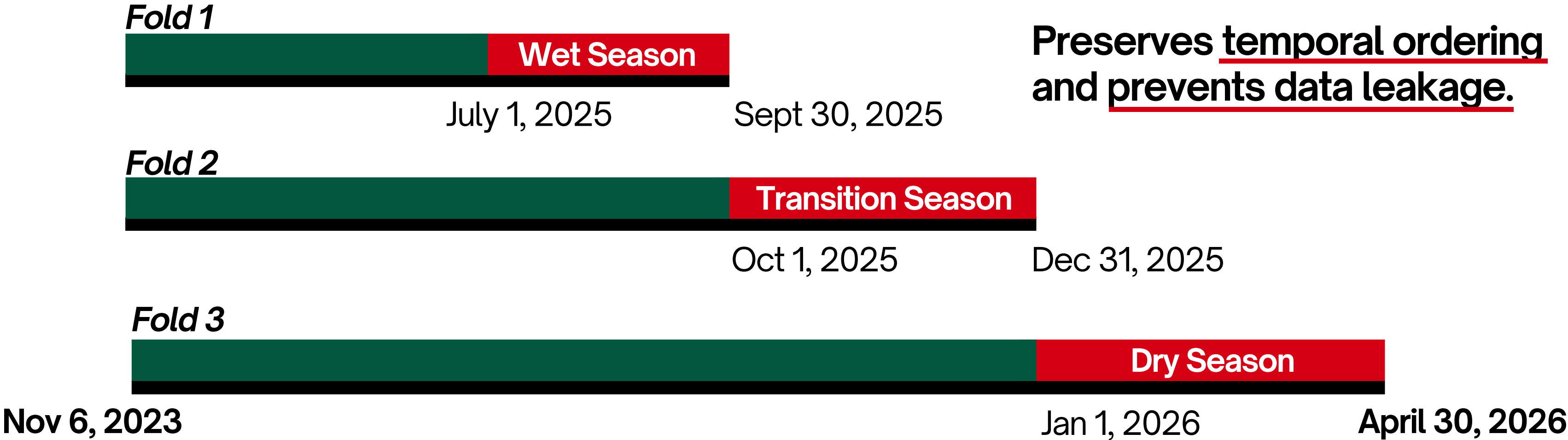
Models were selected using predictive performance
and rare-category detection

VALIDATION FRAMEWORK

1.Out-of-Sample Testing



2.Expanding-Window Cross Validation (3-Fold)



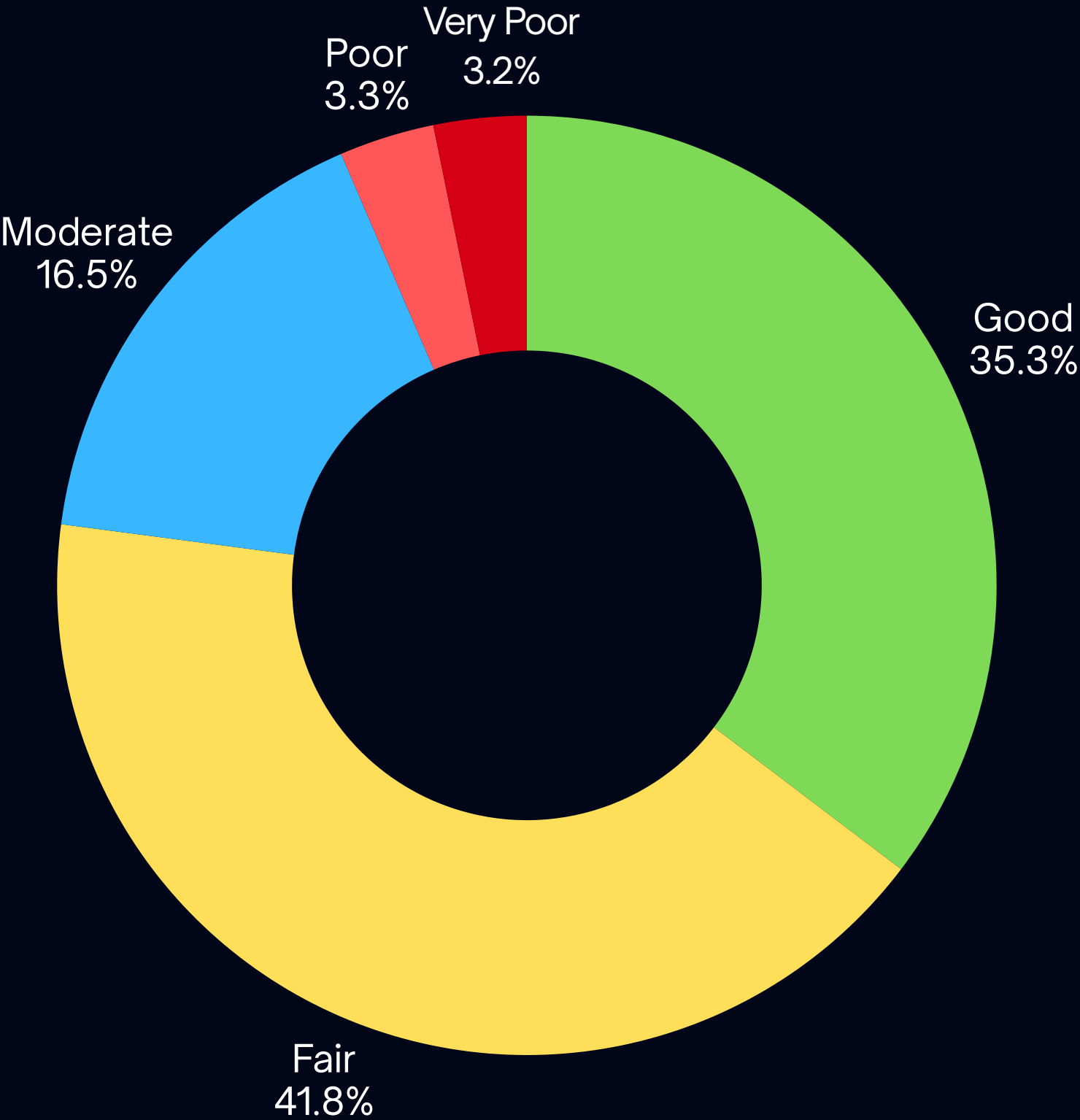


AQI DISTRIBUTION

AQI Classes	Train Set	Test Set
Good	40,686 (39.2 %)	1826 (11.0%)
Fair	41,555 (40%)	8687 (52.5%)
Moderate	14,845 (14.3%)	4953 (29.9%)
Poor	3162 (3.05%)	781 (4.72%)
Very Poor	3520 (3.39%)	313 (1.89%)

Severe AQI classes makes up only about 6% of the data for both the train set and test set

Overall AQI



BASELINE MODELS

Metrics Comparison

Performance Metrics

Model	Accuracy	Ordinal MAE	Log Loss
Ordinal Logit Regression	0.6474	0.3774	0.8244
Spatial GAM	0.653	0.3719	0.7987
Dynamic Seasonal GAM	0.671	0.3527	0.7773

Adding **Seasonal** and **Spatial** terms improved accuracy.

BASELINE MODELS

Best Baseline: Dynamic Seasonal GAM

Class-wise Metrics



Class	Precision	Recall	F1	Balanced Accuracy
Good	0.5802	0.6342	0.6060	0.7886
Fair	0.6926	0.8463	0.7618	0.7159
Moderate	0.6545	0.5064	0.5710	0.6961
Poor	NaN	0.0000	NaN	0.5000
Very Poor	0.8034	0.3003	0.4372	0.6495

The model has **0 recall** for Class 4 (Poor)



What's the Problem?

Confusion Matrix: Class 4 Recall Error

		observed				
predicted		Good	Fair	Moderate	Poor	Very Poor
	Good	1158	831	7	0	0
	Fair	667	7352	2434	161	1
	Moderate	1	504	2508	601	218
	Poor	0	0	0	0	0
	Very Poor	0	0	4	19	94

The model
never predicted
a single **Poor**
AQI day.

WEIGHTING METHODS

Metrics Comparison

Performance Metrics

Weighting Methods	Accuracy	Ordinal MAE	Log Loss	AIC
Square root Inverse	0.6911	0.3180	0.7789	155738.3027
Inverse	0.6711	0.3398	0.8474	190677.1116

Inverse weighting traded a small reduction in overall accuracy for **substantially better detection** of **rare hazardous AQI events**.

Class-wise Metrics

Weighting Methods	AQI Class	Precision	Recall	F1
Square root	Poor	0.263	0.09	0.134
	Very Poor	0.85	0.326	0.471
Inverse	Poor	0.258	0.351	0.298
	Very Poor	0.892	0.342	0.494

Inverse Weighting improved Class 4 Recall from 9% to **35.1%**



How we fix the problem

Confusion Matrix: with Inverse Weighting

predicted	observed					
		Good	Fair	Moderate	Poor	Very Poor
	Good	6197	613	1103	55	0
	Fair	1078	1201	13	0	0
	Moderate	1322	12	3335	442	8
	Poor	90	0	499	274	198
	Very Poor	0	0	3	10	107

The weighting
recovered Poor
AQI days.



FINAL MODEL EVALUATION

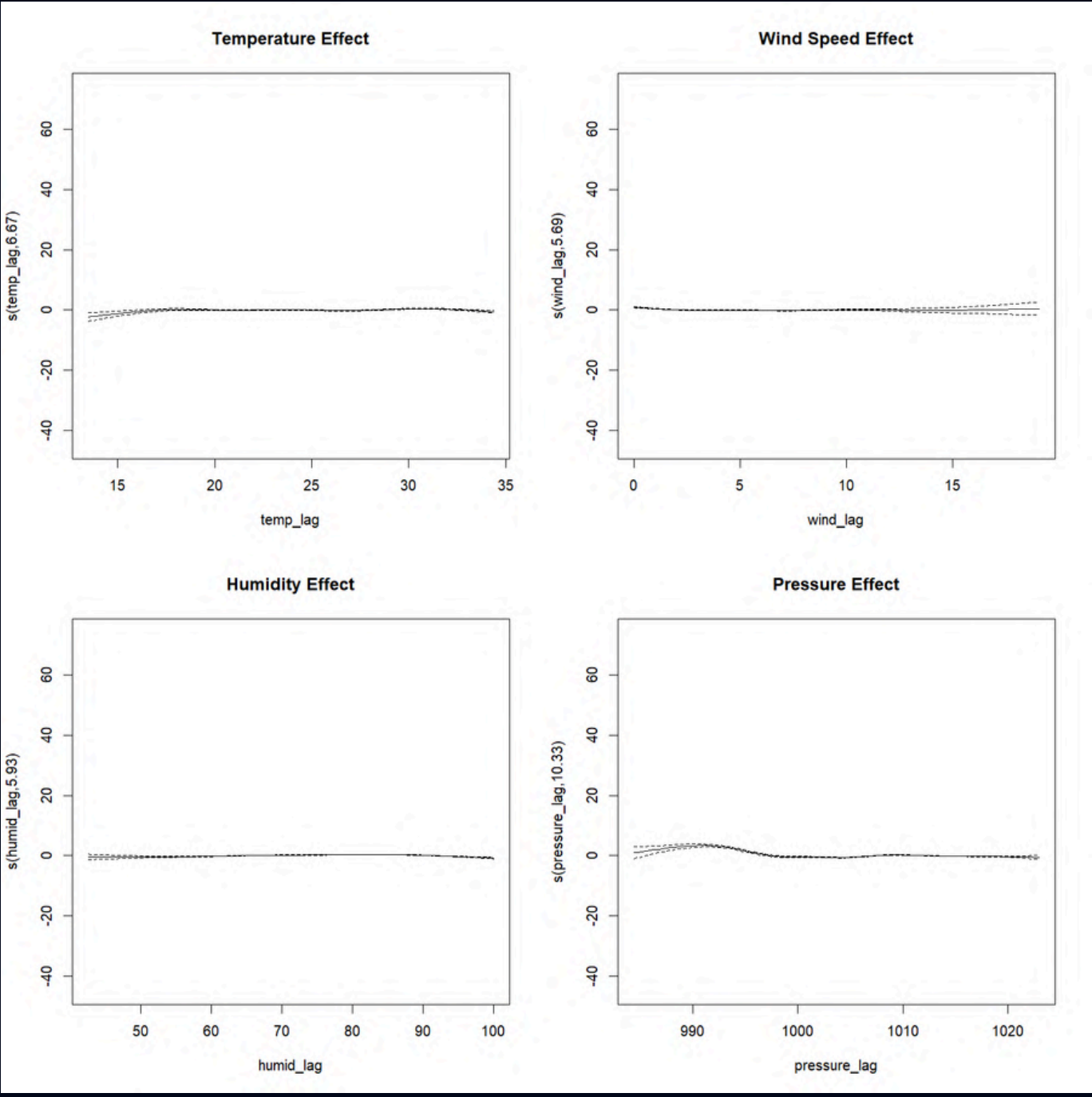
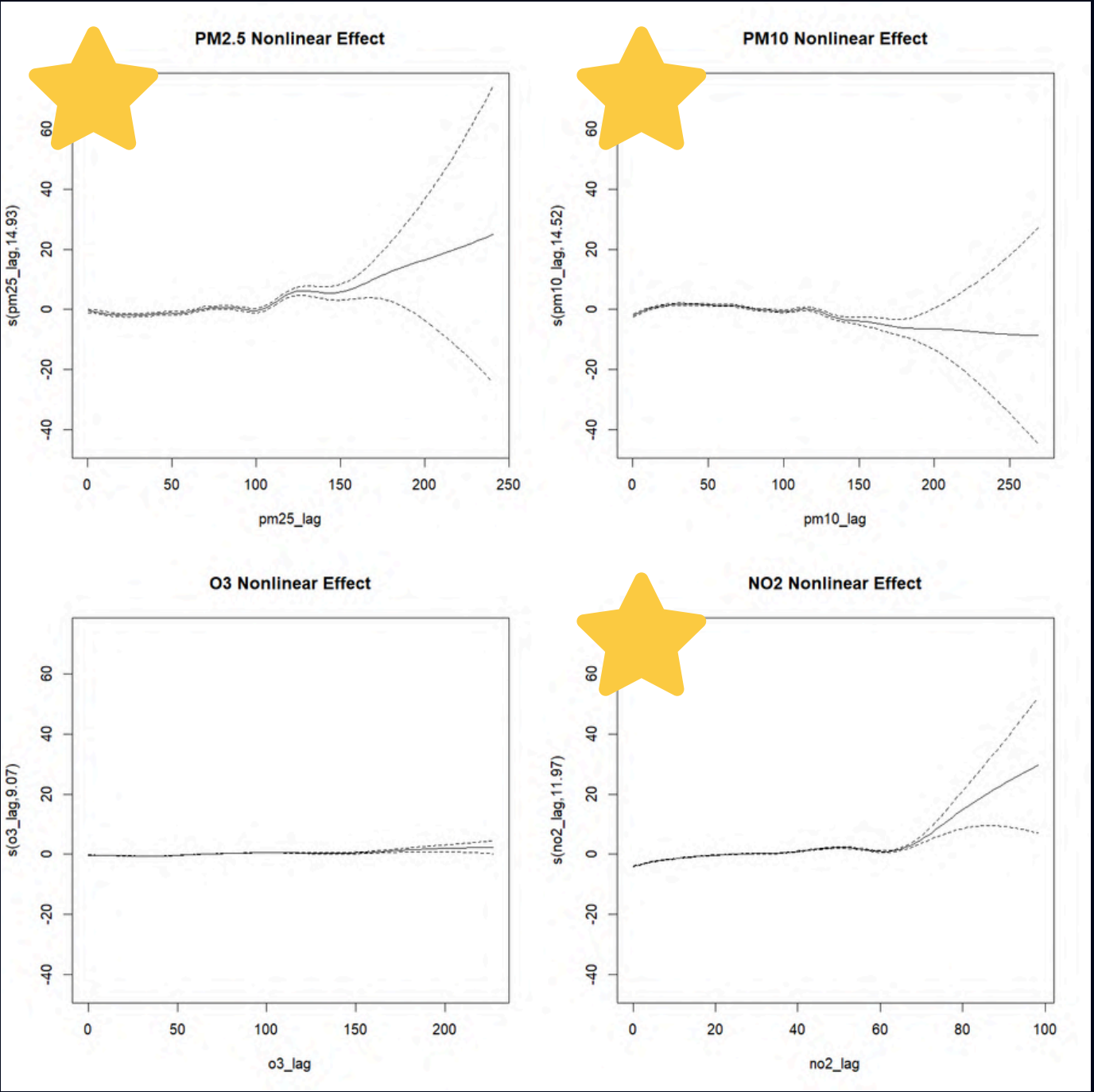
Expanding Window CV

Fold	Accuracy	Ordinal MAE	Log Loss
Fold1 (Wet)	0.7442	0.2824	0.6343
Fold2 (Transition)	0.6468	0.3914	0.8276
Fold3 (Dry)	0.6711	0.3398	0.8474

Performance remained **acceptable** across all seasonal folds.

- ✓ Accuracy exceeded 64% in every validation period
- ✓ Lowest prediction error observed during the wet season
- ✓ Supports model generalizability across changing seasonal conditions

POLLUTANT AND METEOROLOGICAL EFFECTS



Several predictors exhibit nonlinear relationships with AQI, validating the need for a Generalized Additive Model rather than a traditional linear model.

AQI Persistence is Strong, but Not Sufficient

Rank	Variable	F
1	s(aqi_lag)	943.56
2	s(no2_lag)	391.82
3	s(o3_lag)	94.05
4	s(pm10_lag)	72.23
5	s(pressure_lag)	70.15

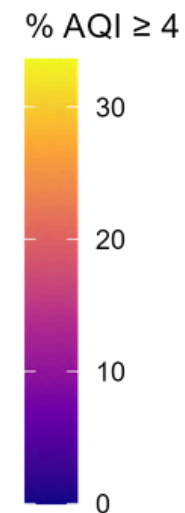
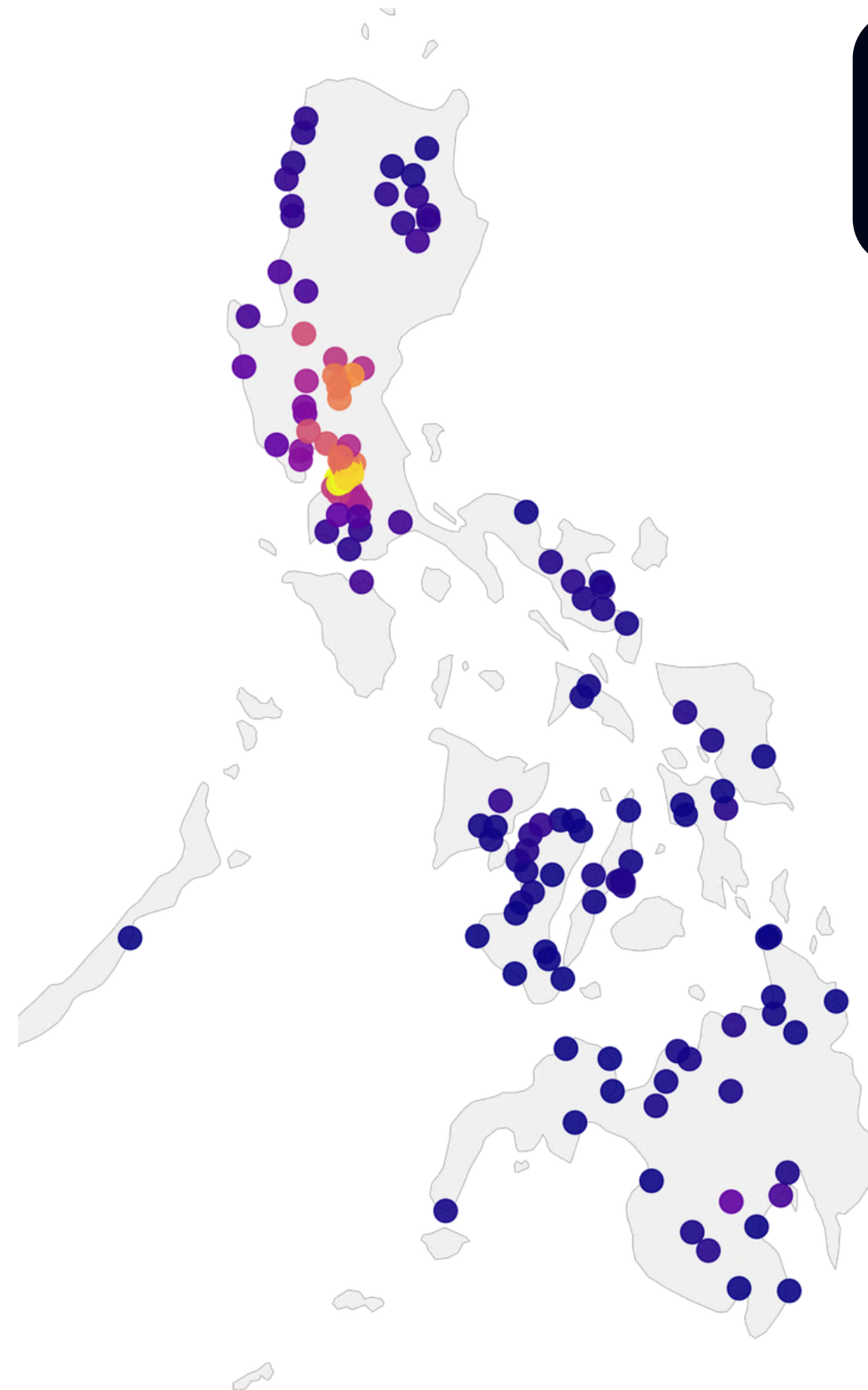
Relative importance based on smooth-term significance

AQI is highly persistent, but environmental conditions still improve forecasting performance.

- NO₂ and O₃ were the strongest environmental predictors
- Seasonal effects ranked lowest, yet adding them improved predictive accuracy



Environmental Signals Behind AQI



NO_2 → indicator of **traffic and combustion emissions**

O_3 → captures **sunlight-driven pollution** that intensifies under **tropical conditions**

The model reflects 2 defining features of the Philippines: **car-centric** and **tropical**.

This explains why unhealthy AQI episodes **concentrate around major urban areas.**

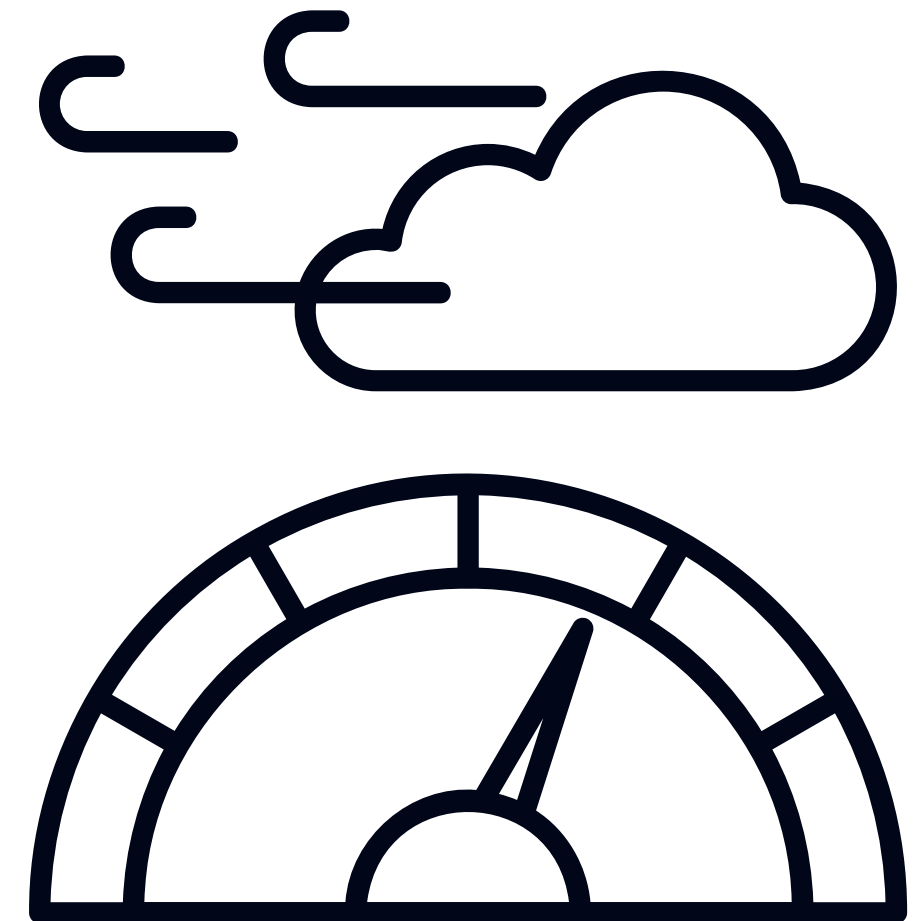
AQI Hotspots in the Philippines

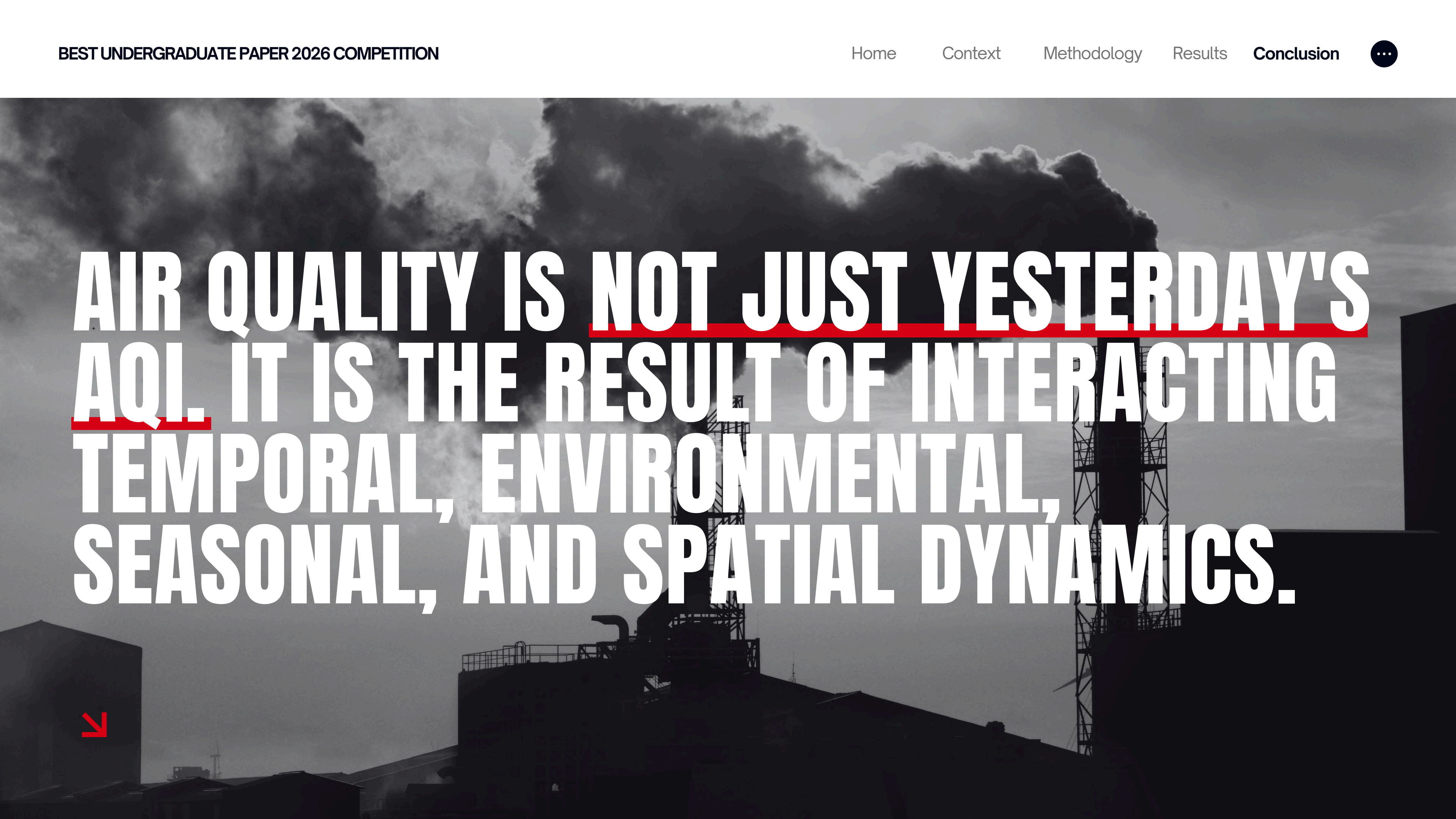


FORECASTING REQUIRES MORE THAN PERSISTENCE

- The previous-day AQI provides the strongest forecasting signal.
- Environmental conditions, seasonal patterns, spatial context, and weighting adjust the risk.
- Weighting recovers rare hazardous events, crucial for early warning.

AQI Forecast = AQI Memory + Space
+ Season + Environment
+ Inverse Freq. Weighting





**AIR QUALITY IS NOT JUST YESTERDAY'S
AQI. IT IS THE RESULT OF INTERACTING
TEMPORAL, ENVIRONMENTAL,
SEASONAL, AND SPATIAL DYNAMICS.**





SO WHAT NOW?

RECOMMENDATIONS

- Validate the proposed model using **official Philippine Air Quality Data (DENR-EMB)**.
- Incorporate **local spatial, socio-economic, and demographic covariates** to better capture community-specific air quality dynamics.
- Explore **alternative weighting strategies** to address class imbalance.
- Develop a **real-time AQI early warning system** to support timely public health interventions.





We may not control tomorrow's
air quality, but we can prepare
for it **today.**



THANK YOU!





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