LOW-COST SENSOR MEASUREMENTS OF ROADSIDE $PM_{2.5}$ AND NO_2

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Introduction - TRAP

Traffic-related air pollution (TRAP) is a major contributor to global disease.

TRAP is associated with fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2).

$PM_{2.5}$ and NO_2 emissions can cause cardiovascular and respiratory illnesses.

Introduction – Health burden

$PM_{2.5}$ is dangerous as it can penetrate deeper in the lungs.

NO_2 is estimated to have caused over 4 million new cases of pediatric asthma annually.

In Australia, asthma estimated to cost AUD 27.9 billion annually.

Introduction – Current measurement techniques

$PM_{2.5}$ and NO_2 are measured using federal reference methods (FRM) or federal equivalent methods (FEM).

FRM and FEM devices are installed at Air Quality Monitoring Stations (AQMS) across Australia.

However, the current AQMS lacks the high spatial resolution.

Low-cost air quality monitors (LCS) are cost efficient and practical alternative.

Introduction – LCS measurement techniques

LCS USE LIGHT SCATTERING TO MEASURE $PM_{2.5}$ CONCENTRATIONS.

ELECTROCHEMICAL LCS MEASURE NO_2 BASED ON REDUCTION POTENTIAL.

Introduction – LCS limitations

Light-scattering and electrochemical LCS are impacted by high relative humidity conditions.

LCS need to be calibrated against a FRM or FEM.

'Calibration' refers to modifying raw LCS measurements based on their relationship with a FRM or FEM device.

Introduction – LCS calibrations

Relative humidity and linear regression calibrations can adjust LCS measurements.

Both calibrations have mixed performances.

Random Forest Machine Learning (RFML) can calibrate complex, non-linear LCS measurements.

RFML uses decision tree algorithm based on patterns and relationships.

Introduction – Aims

Aim 1: To calibrate LCS $PM_{2.5}$ and NO_2 using the Measurement Benchmark Analysis (MBA).

Aim 2: To utilise a LCS risk matrix to assess roadside $PM_{2.5}$ and NO_2.

Introduction – Significance

Confirmation that MBA can calibrate $PM_{2.5}$ and NO_2 concentrations.

LCS risk matrix can assess the likelihood of roadside emission risk to the nearby public.

Methodology - Instrumentation

OIZOM Polludrone use light scattering and electrochemical sensors.

NSW Macquarie Park AQMS use a BAM to measure $PM_{2.5}$ and an API T204 to measure NO_2.

Methodology - Installation

01

LCS 1 was deployed adjacent to a road.

02

LCS 2 was co-located at Macquarie Park AQMS.

03

Both sensors deployed from 26/04/2025 to 26/05/2025.

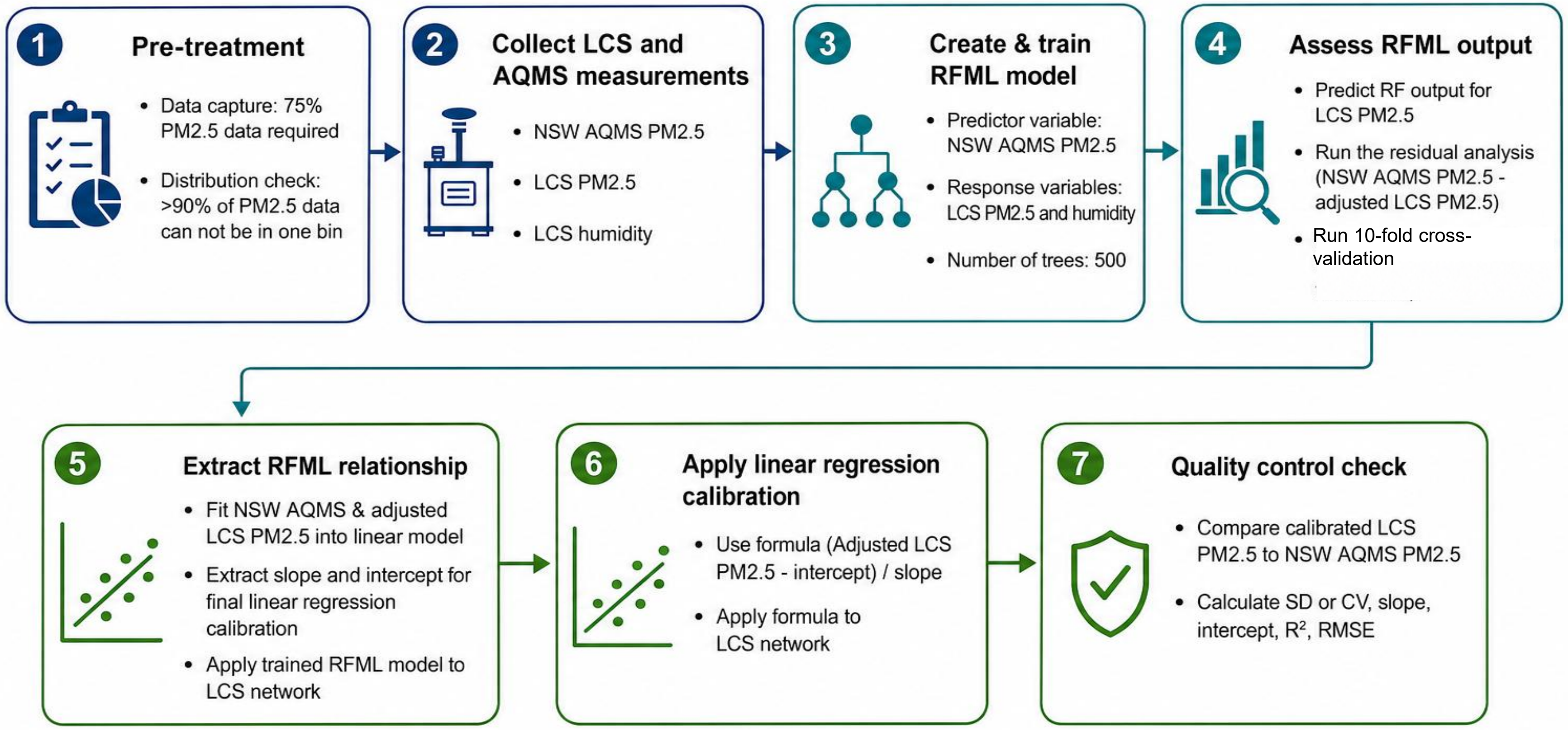
04

Both sensors co-located at Macquarie Park AQMS after the sampling period from 27/05/2025 to 10/06/2025.

Methodology – Data pre-processing

Metric	Parameter	Target	Outcome
Pre-treatment	Data capture	75%	LCS data removed if target is not met
	Distribution	>90% of data in one bin	
Quality control check	SD and CV	≤ 5 µg/m^3 or ≤ 30%	Assigned 20% performance score for each parameter within target
	Slope	1.0 ± 0.35	
	Intercept	-5 ≤ b ≤ 5 µg/m^3	
	R^2	≥ 0.70	
	RMSE	≤ 7 µg/m^3	

Methodology – Measurement Benchmark Analysis (MBA)

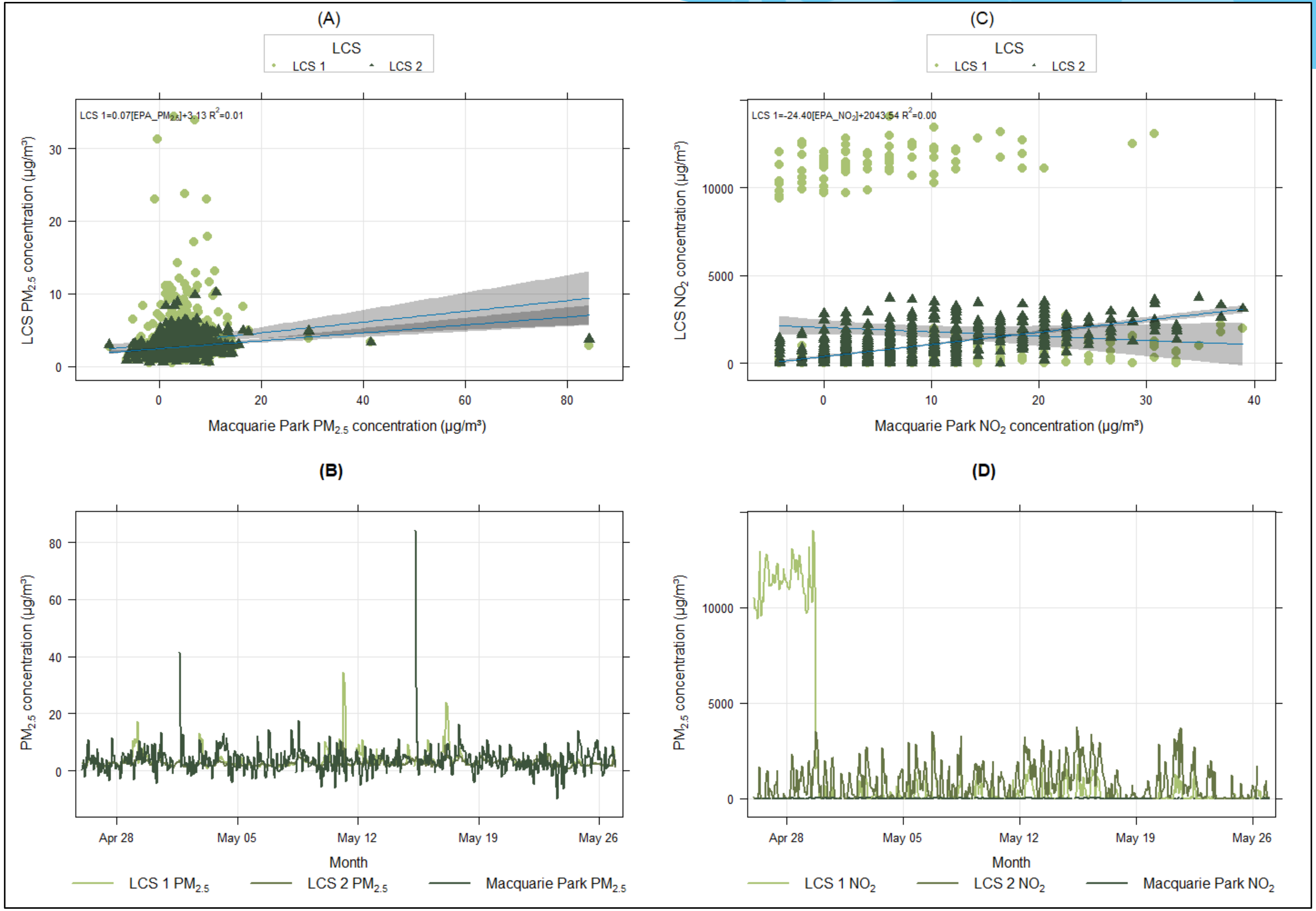


Methodology – LCS Risk Matrix

LCS Risk Matrix	Performance Score (%)				
Air quality thresholds	20	40	60	80	100
Good	N	N	N	N	N
Fair	N	N	L	L	L
Poor	L	L	M	M	M
Very Poor	M	M	H	H	H
Extremely Poor	H	H	E	E	E

Footnote:
$PM_{2.5}$ risk categories were classified Good (<25 μg/m^3), Fair (25–50 μg/m^3), Poor (50–100 μg/m^3), Very Poor (100–300 μg/m^3), and Extremely Poor (>300 μg/m^3).
NO_2 risk categories were classified Good (<110 μg/m^3), Fair (110–164 μg/m^3), Poor (164–246 μg/m^3), Very Poor (246–328 μg/m^3), and Extremely Poor (>328 μg/m^3).

Results – Raw correlations



Results – RFML overview

LCS inter-device variability for $PM_{2.5}$ was good (R^2 = 0.91) but NO_2 was poor (R^2 = 0.44).

Therefore, each LCS was trained separately.

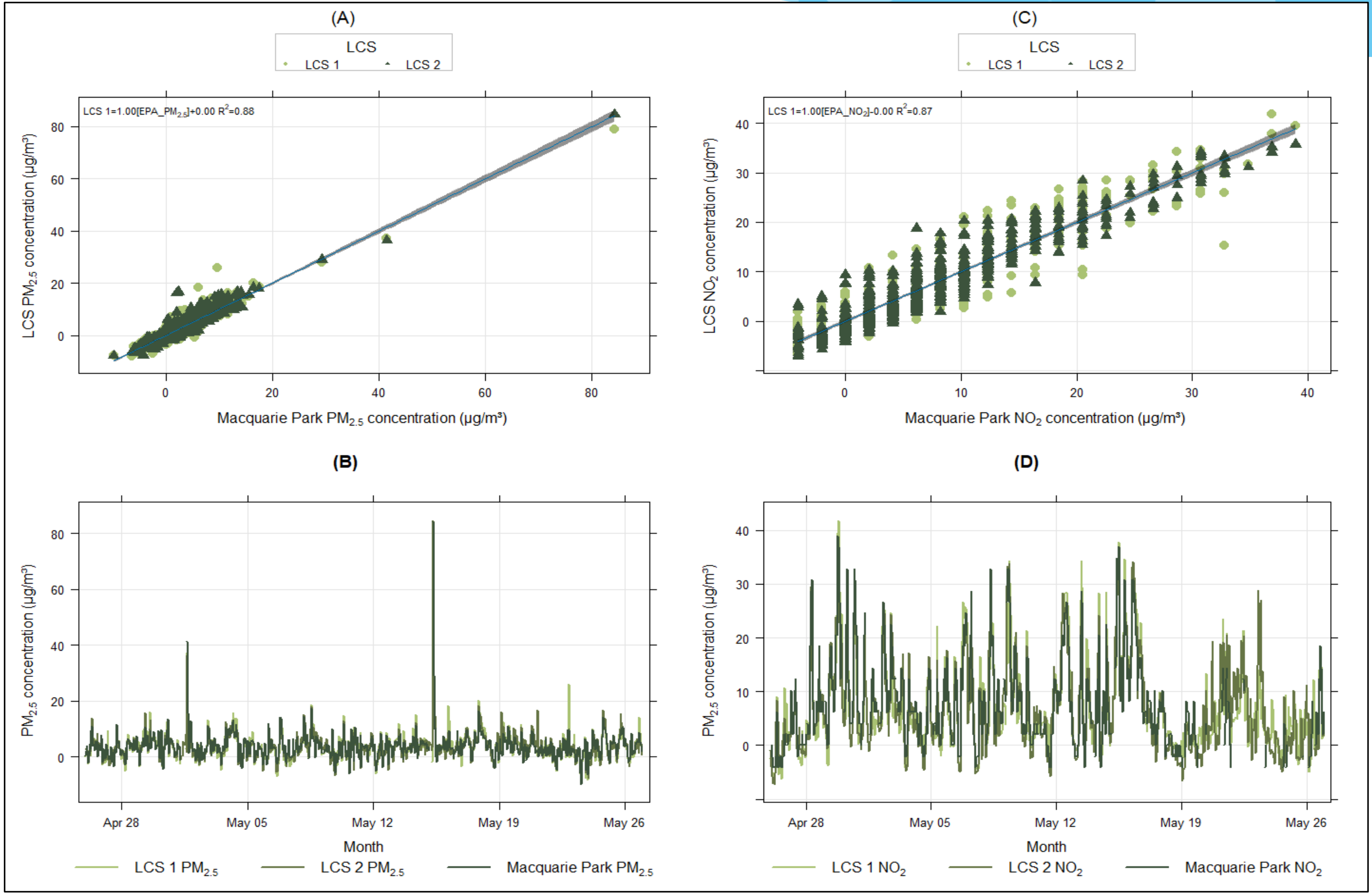
RFML improved R^2 for $PM_{2.5}$ (0.88) and NO_2 (0.87).

The QC control showed the RFML did not overfit the LCS raw data.

Results – RFML training and importance metrics

Training dataset		Importance	
NSW AQMS variables	LCS variables	LCS 1	LCS 2
$PM_{2.5}$	$PM_{2.5}$	12.45	8.85
	Humidity	6.52	7.19
NO_2	NO_2	53.21	61.43
	O_3	33.52	28.34
	Humidity	24.70	25.37

Results – MBA calibration



Results – Calibration overview

Pollutant	LCS	SD or CV	Slope	Intercept	R^2	RMSE	Performance score (%)
$PM_{2.5}$	Raw LCS 1	1.35 & 44.31	0.07	3.13	0.01	3.12	40
	Raw LCS 2	1.35 & 44.31	0.05	2.44	0.05	1.16	40
	Calibrated LCS 1	1.09 & 28.24	1	0	0.88	1.88	100
	Calibrated LCS 2	1.09 & 28.24	1	0	0.89	1.78	100
NO_2	Raw LCS 1	1925.82 & 160.39	-24.4	2043.54	0	3920.95	0
	Raw LCS 2	1925.82 & 160.39	69.31	389.9	0.41	703.5	0
	Calibrated LCS 1	1.88 & 27.01	1	0	0.87	3.28	100
	Calibrated LCS 2	1.88 & 27.01	1	0	0.89	2.92	100

Results – LCS risk assessment

Site	N	L	M	H	E
AQMS $PM_{2.5}$	724	2	1	0	0
LCS 1 $PM_{2.5}$	729	3	1	0	0
LCS 2 $PM_{2.5}$	737	2	1	0	0
AQMS NO_2	590	0	0	0	0
LCS 1 NO_2	733	0	0	0	0
LCS 2 NO_2	740	0	0	0	0

Discussion

MBA successfully calibrated LCS $PM_{2.5}$ and NO_2 measurements.

RFML did not overfit the raw LCS measurements.

The MBA could calibrate LCS networks and expand the current AQMS spatial resolution.

Discussion - Continued

AQMS and LCS risk levels were similar.

LCS risk ranged from ‘negligible-moderate’ for $PM_{2.5}$ and ‘negligible’ for NO_2.

Discussion - Future research

Deploy LCS networks in suburbs with high cases of cardiovascular and respiratory illnesses.

Build $PM_{2.5}$ and NO_2 risk exposure data.

Hourly $PM_{2.5}$ and NO_2 risk categories could be adjusted to reflect significant exposure thresholds.