

Validation of pollution proxy indicators using personal exposure air quality data from 2 sub-Saharan African Countries

Paper No. 364

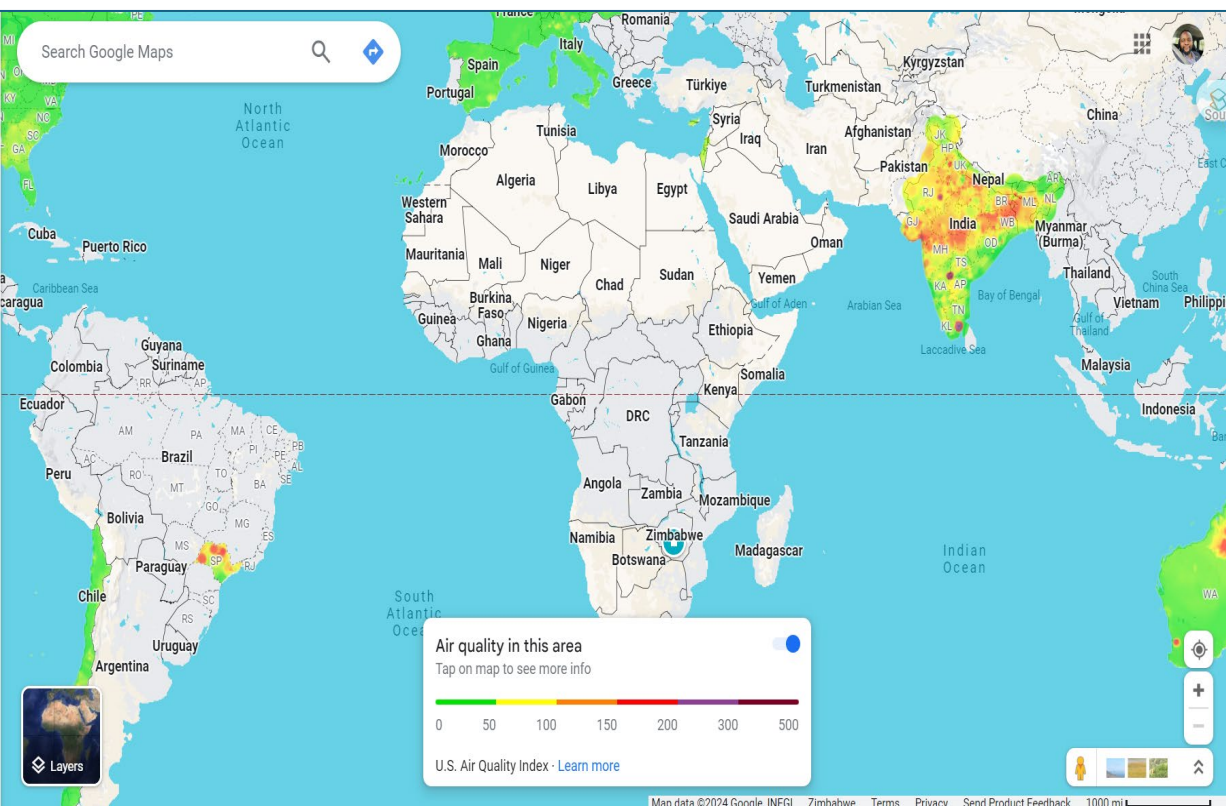
Track B : Health impacts and epidemiology

Handsome Bongani Nyoni

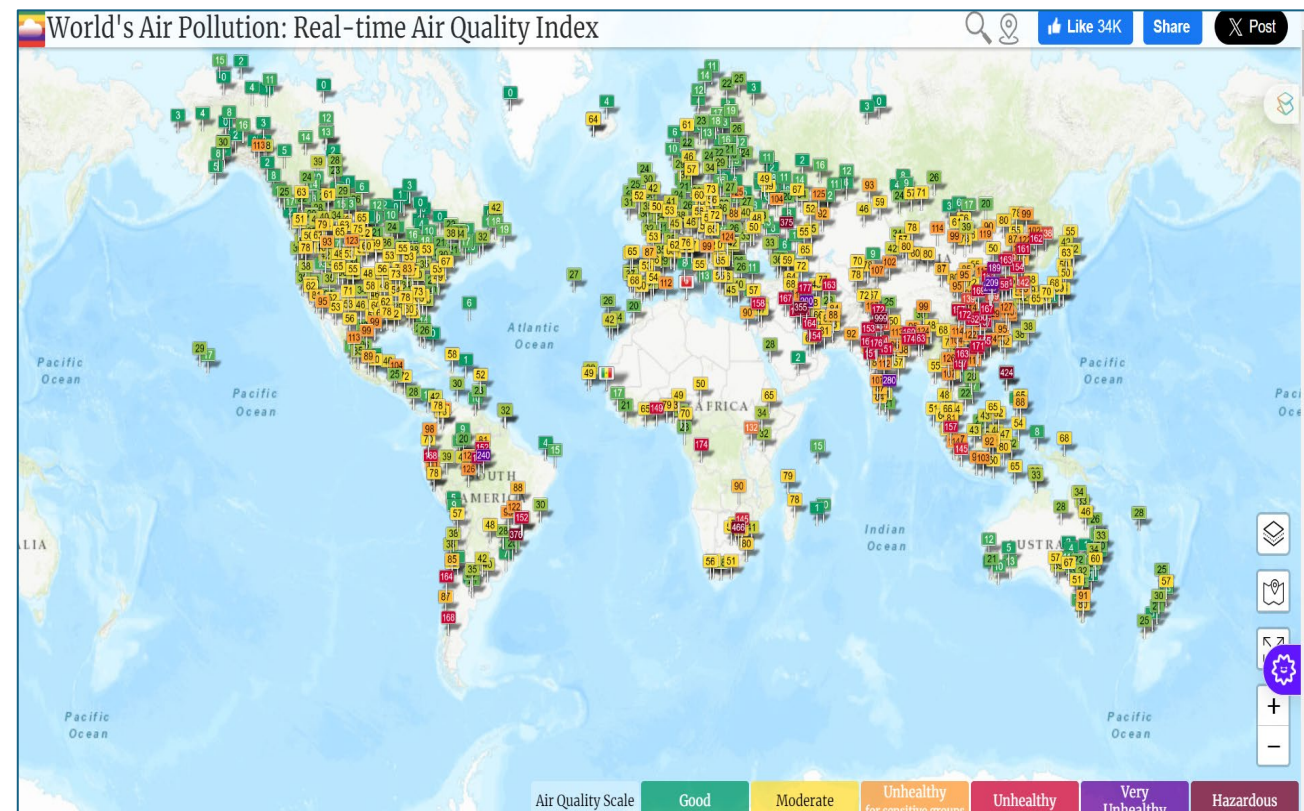
Spatial Data Scientist

Place Alert Labs (PALs)-Midlands State University

+263717929827 nyonih@staff.msu.ac.zw



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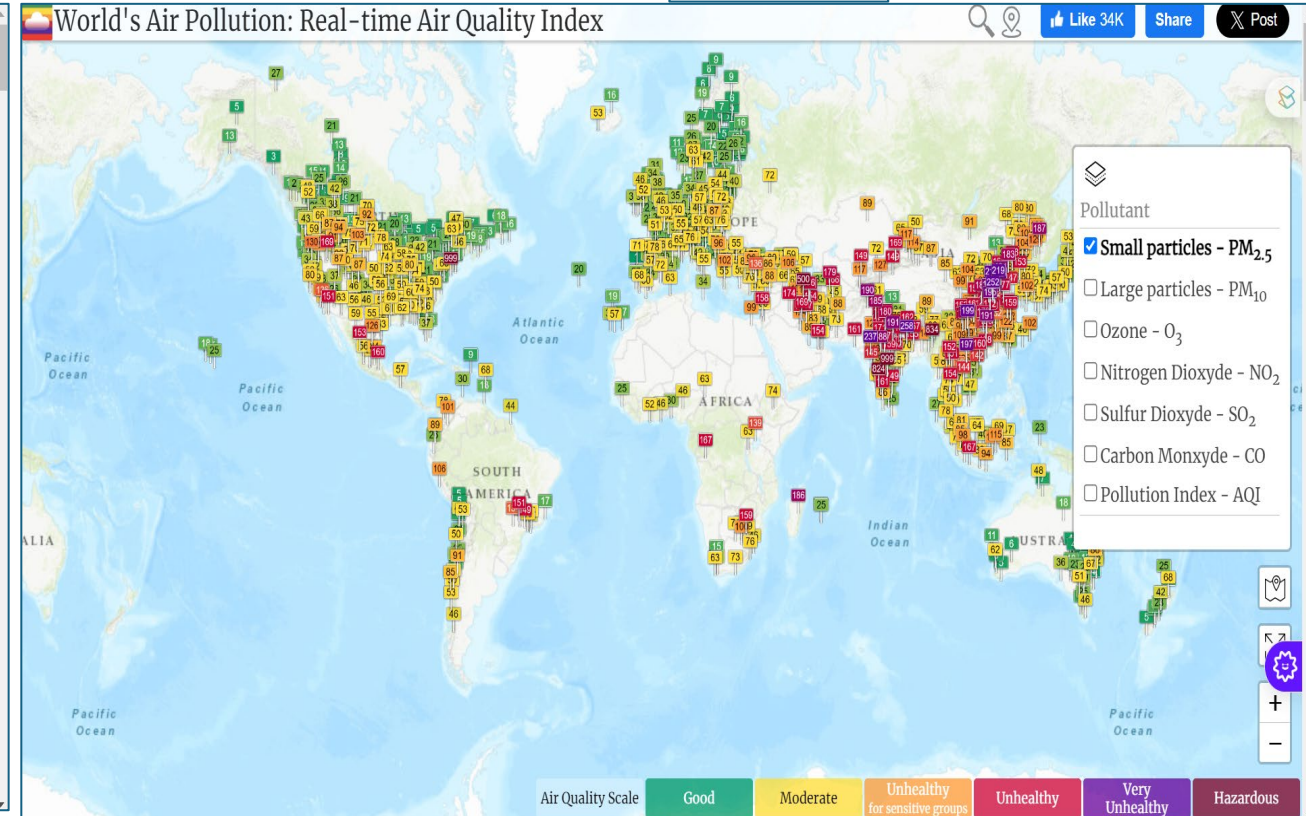
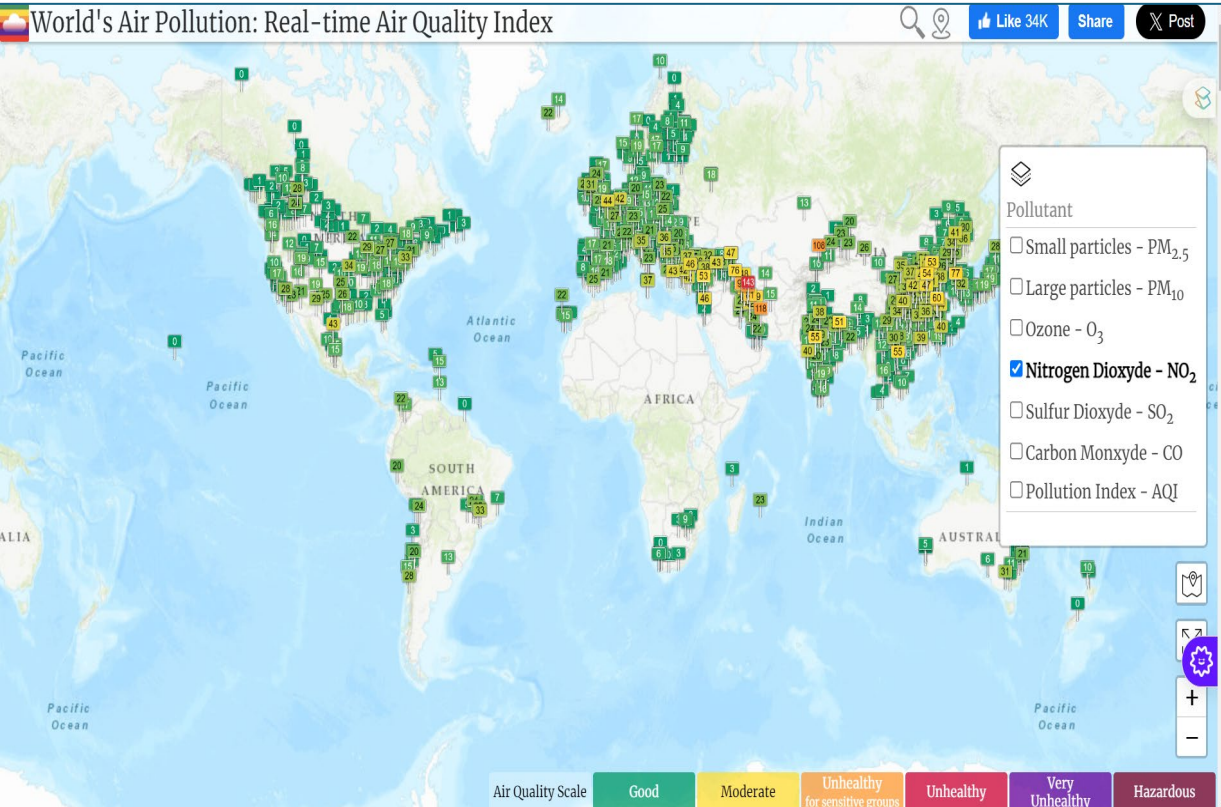


<https://waqi.info/#/c/7.512/0.176/2z>

Background

NO2

PM 2.5



<https://waqi.info/#/c/7.512/0.176/2z>

Introduction



Poor air quality is the 2nd leading risk factor for death worldwide.



Proxy air quality indices offer a vital alternative in areas lacking ground sensor data.



This project focused on validating proxy pollution indicators using extensive personal exposure datasets.



The validation process utilized 1,048,576 multi-dimensional exposure data points recorded by low-cost personal sensors .

Objectives



Develop a validation framework



**Validation criteria ,
methodology and
validation report**



**Assess the
significance of proxy
indicators**



**Scale up proxy
indices**

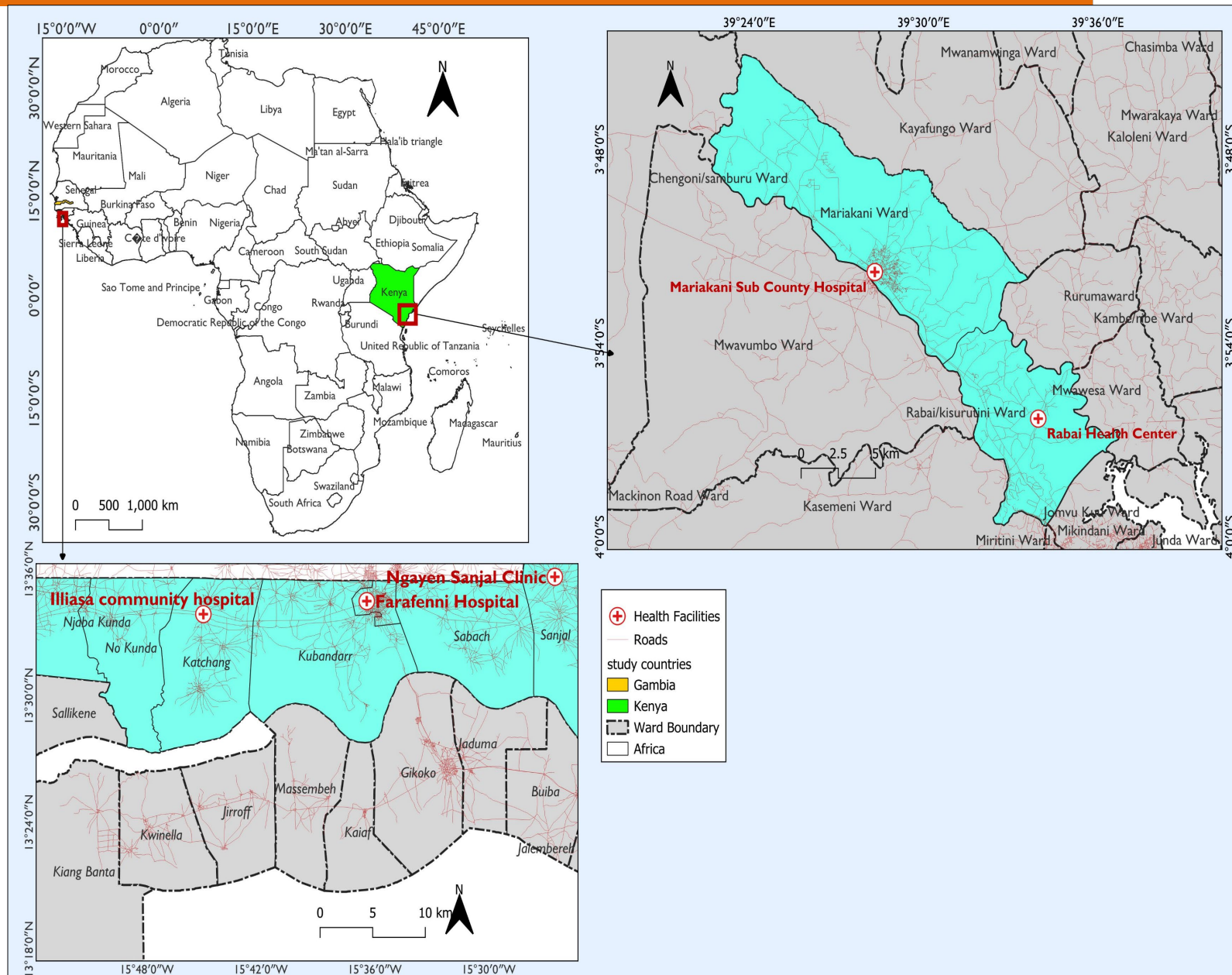


**Support modeling
and upscaling
efforts**

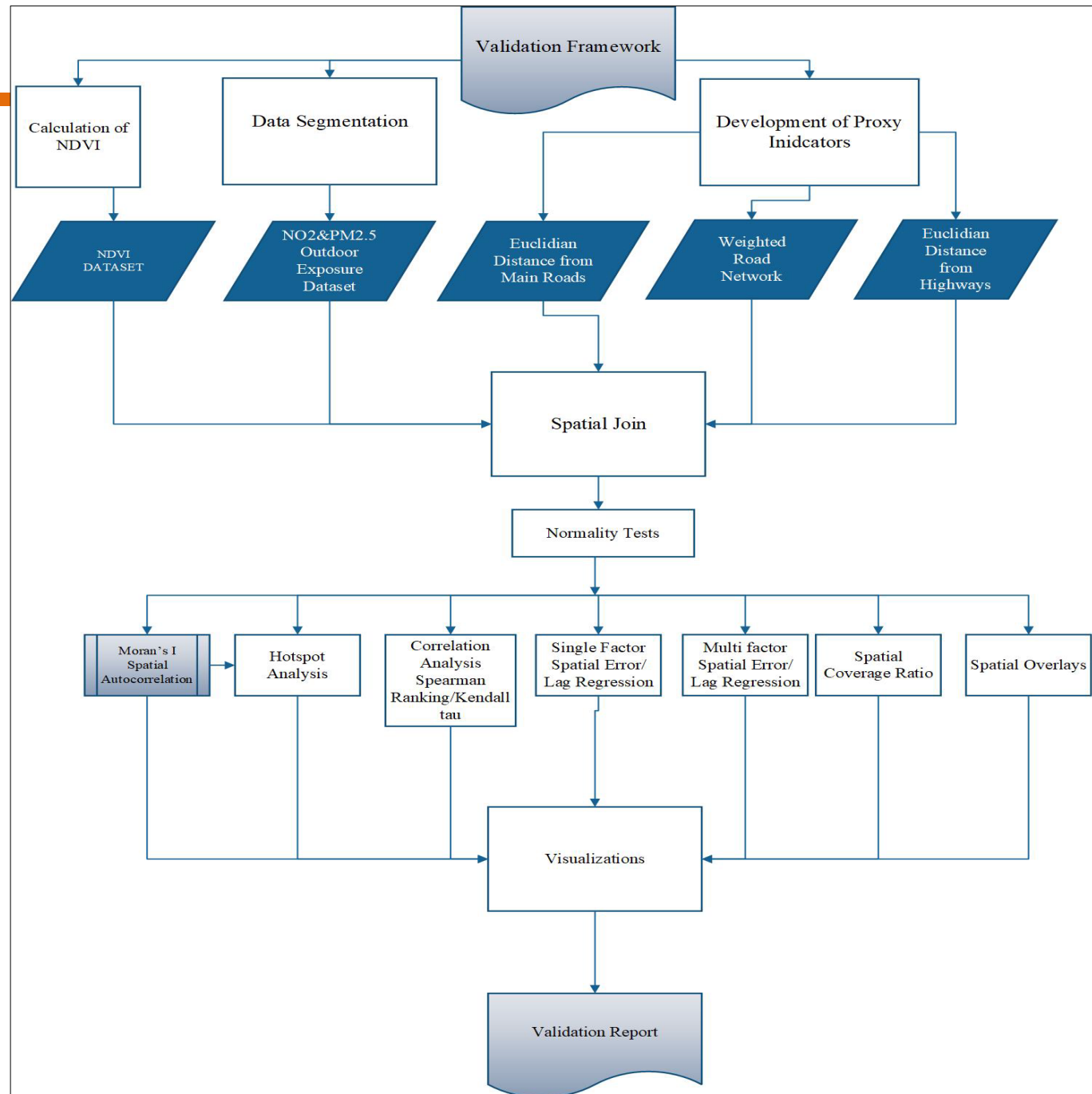


**Enhance
understanding of
pollution drivers**

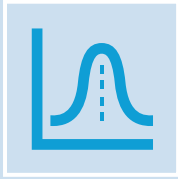
Study Sites



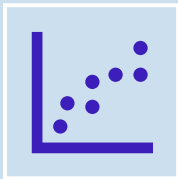
Methodology



Descriptive Statistics



The data did **not follow normal distribution** And there were outliers.

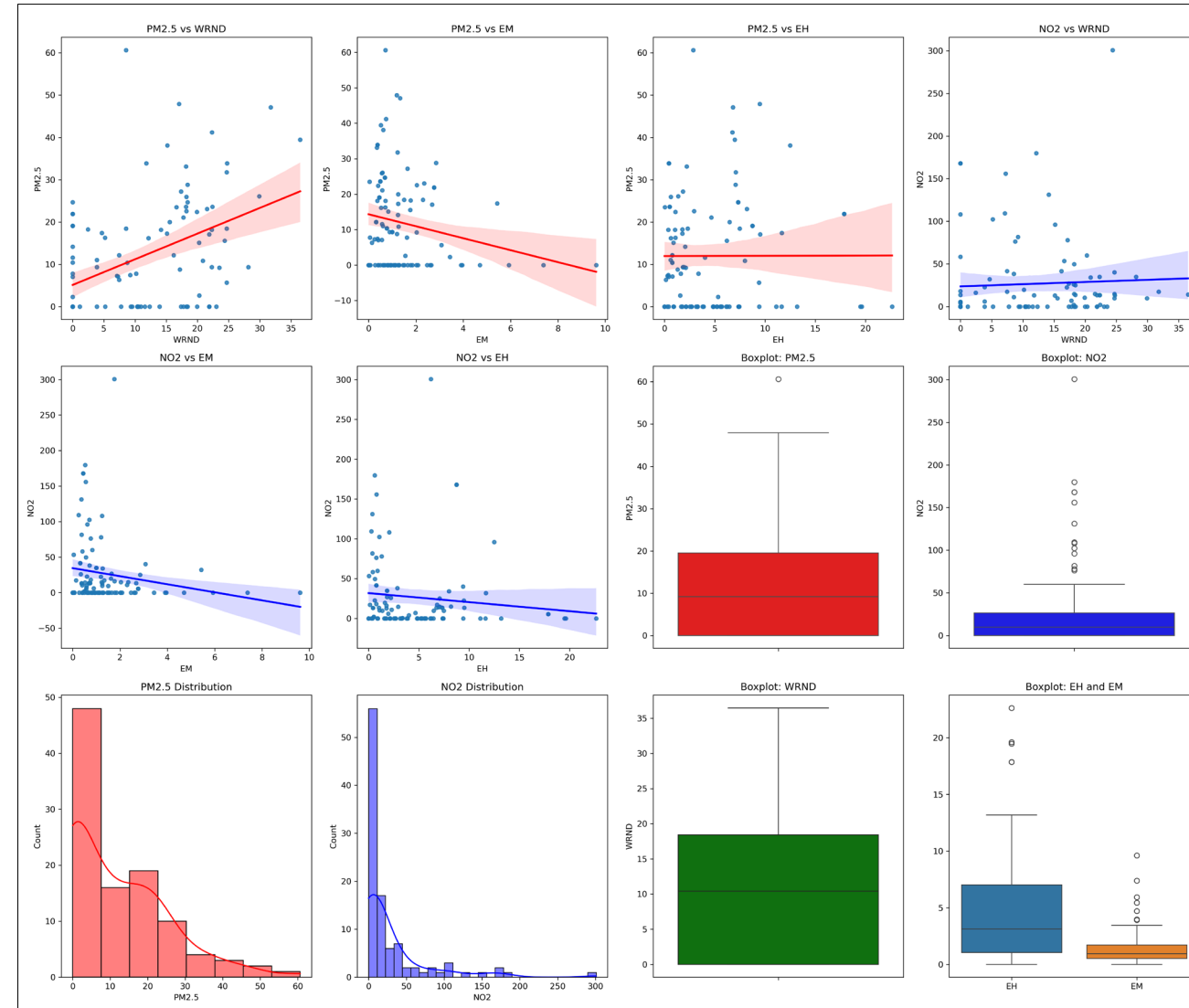


Scatter plots confirm a **positive** relationship between **wrnd** and **exposure**.



Scatter plots also highlight a **negative** relationship between **personal exposure** and **distance** from the main road and highway.

Gambia



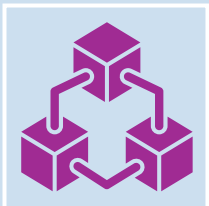
Correlation Analysis



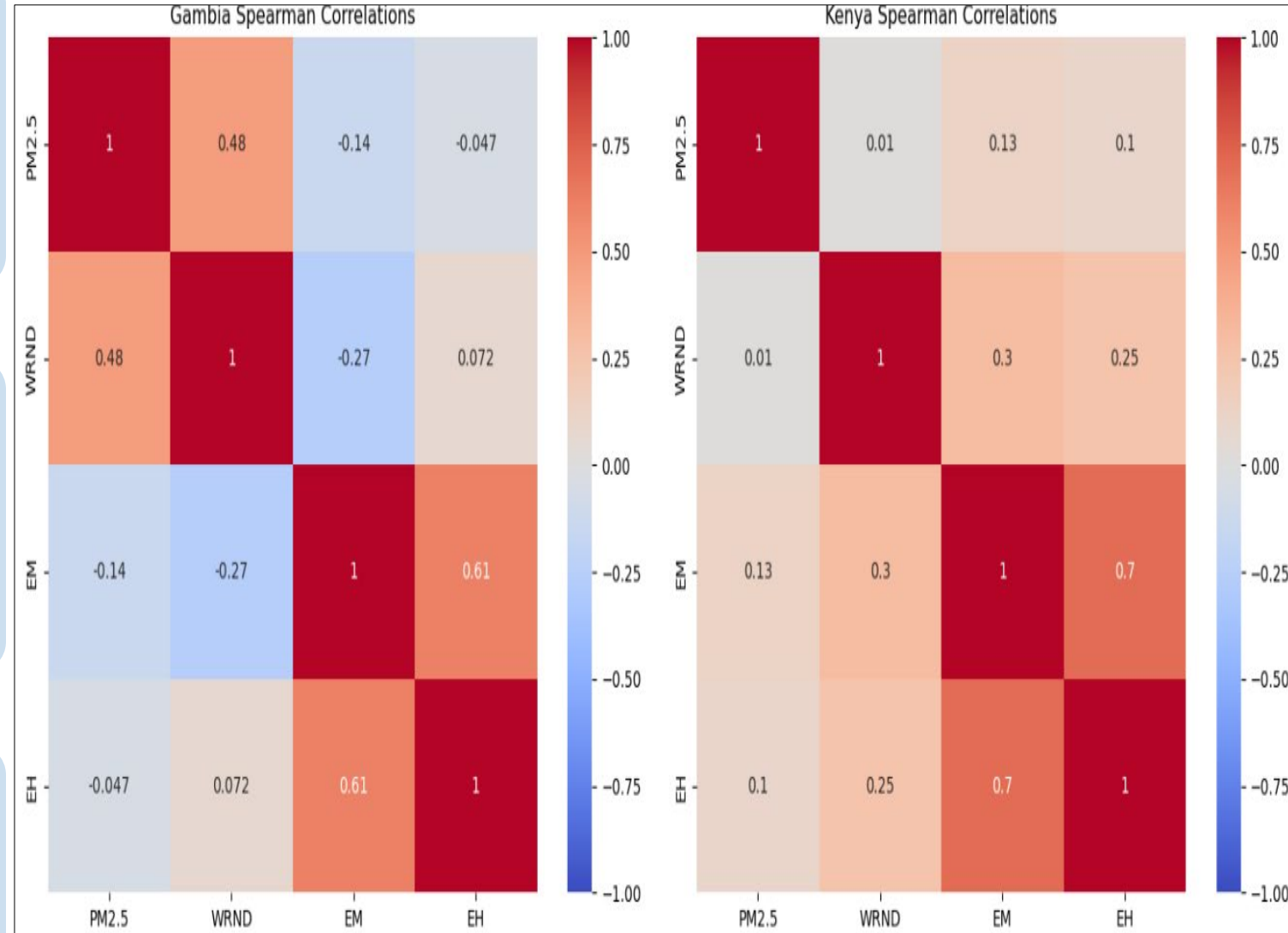
There was **positive association** between **WRND** and **exposure data** in **both countries** confirming initial hypothesis



negative correlations were observed between **EH & EM** and Exposure data in the 2 countries



Weak **Positive correlations** between **EH ,EM, and PM 2.5 data** were observed in **Kenya** suggesting that **other factors** are also contributing to exposure in Kenya .

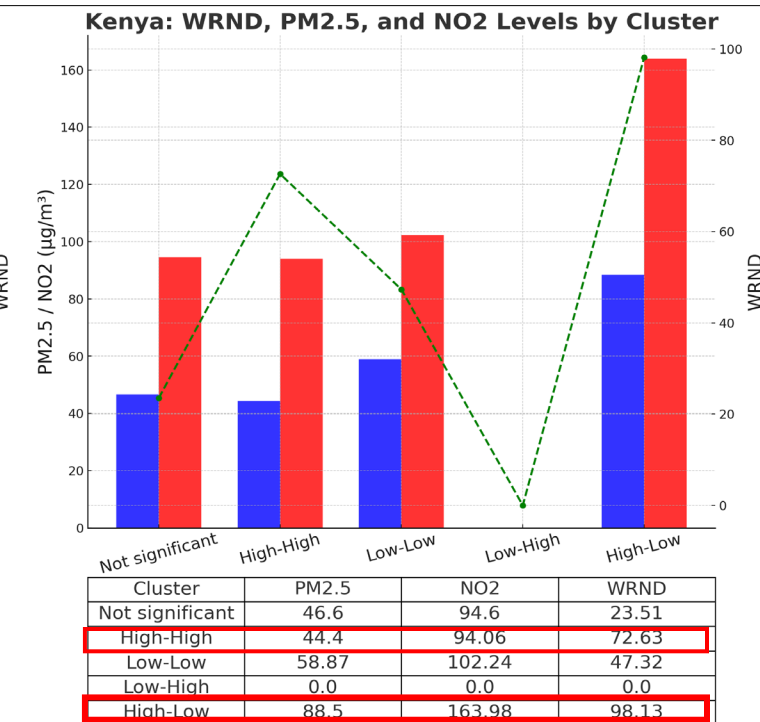
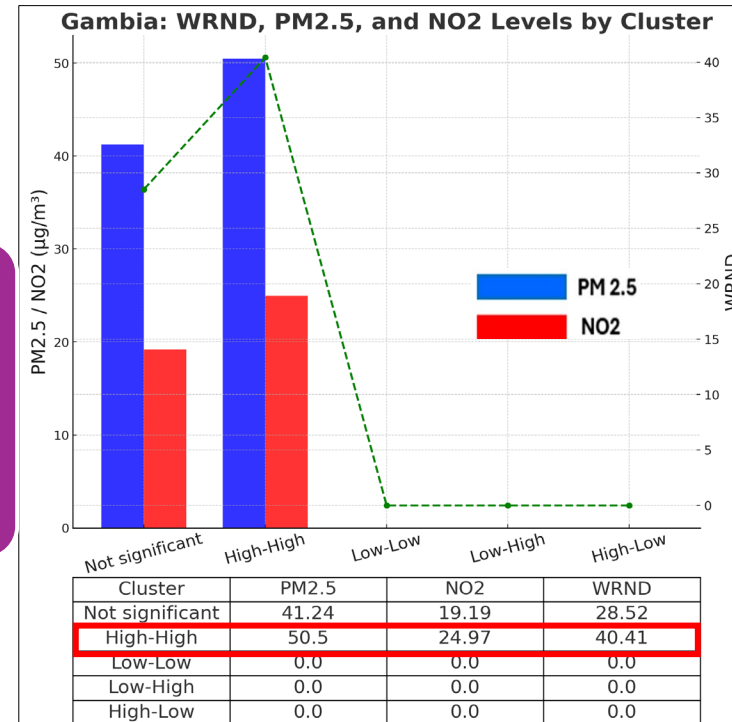
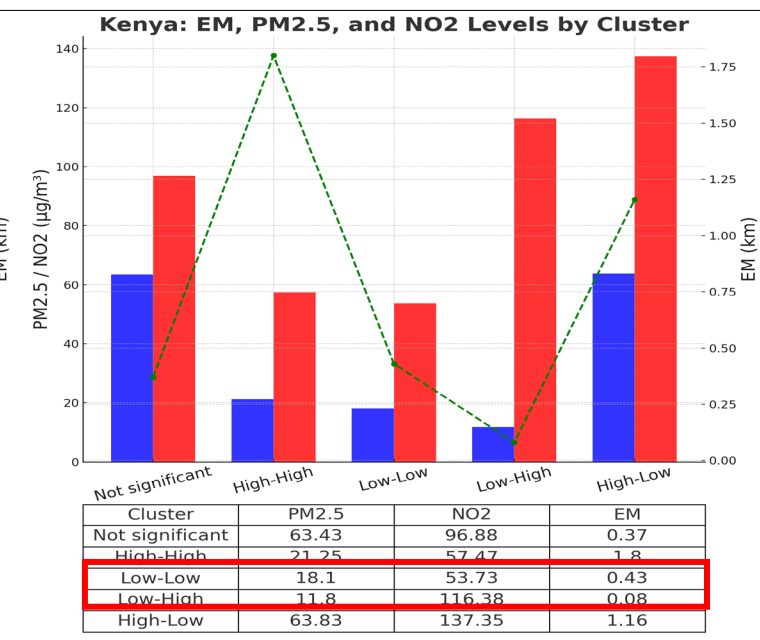
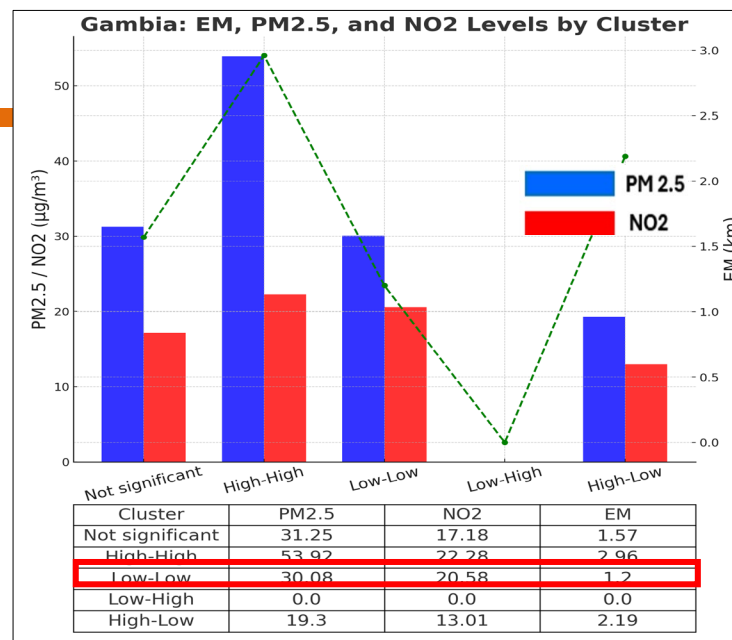


Moran I and Cluster Analysis

All the proxy indicators were autocorrelated.

WRND cluster analysis results confirm that increase in wrnd increases PM 2.5 & No2 exposure

EM cluster analysis confirms that lower values of EM are associated with high values for PM2.5 and No2 exposure.



Single Variable Spatial Regression

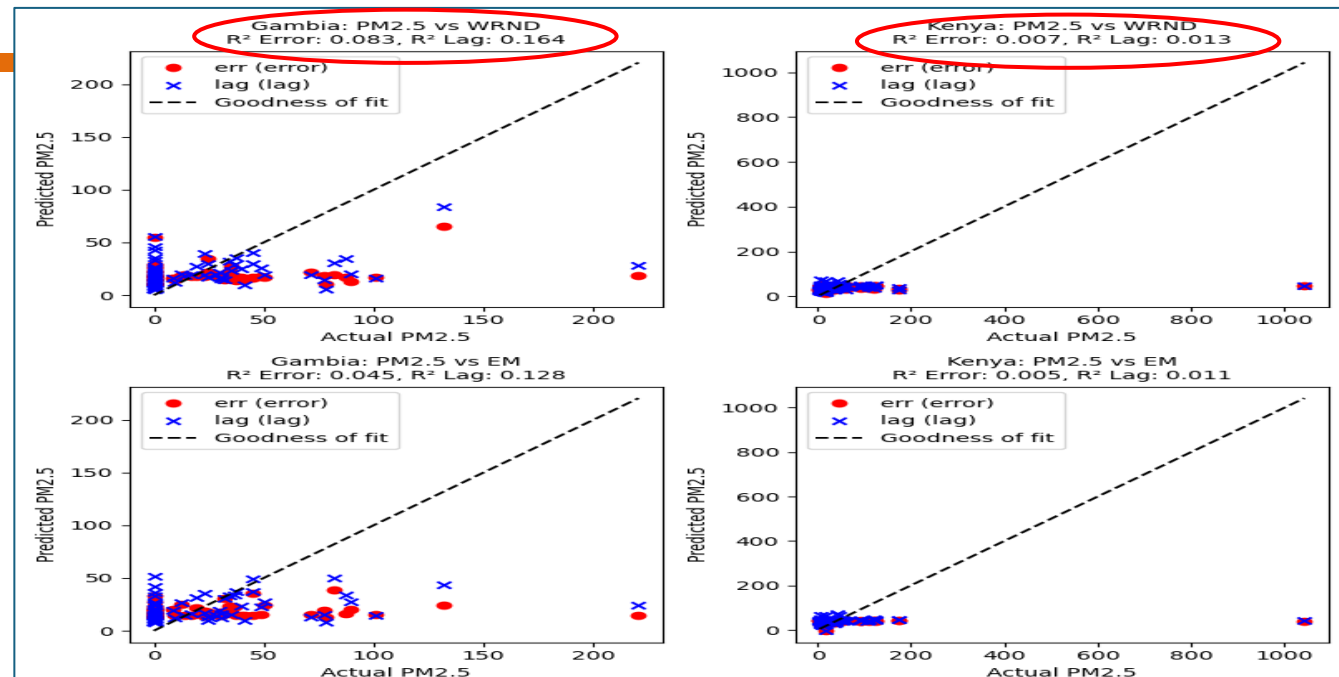
The WRND regression models predicted **PM 2.5** better than other models in **Gambia** ($R\text{-sqr}(0.1\text{-}0.17, p\text{-value } 0.001)$)

The EH and EM regression models predicted **No2** better than other models in **Kenya** ($R\text{-sqr}(0.03\text{-}0.14, p\text{-value } 0.001)$).

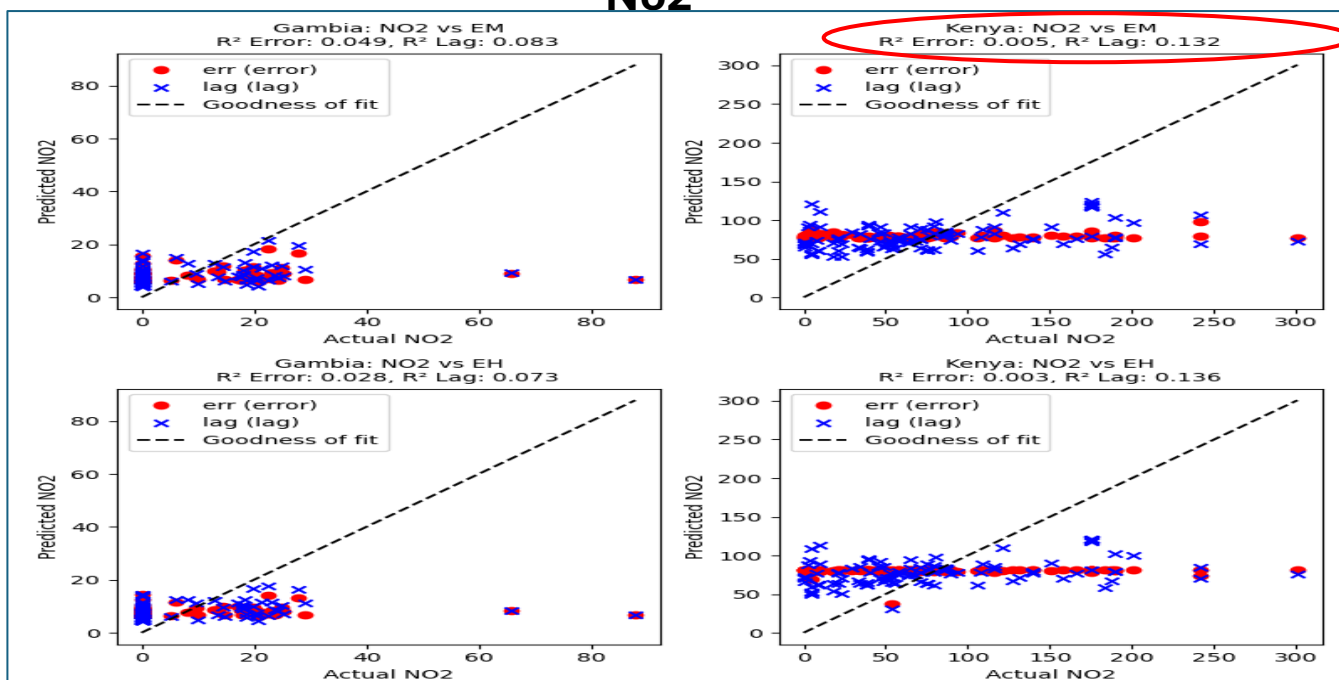
Generally, the **spatial lag model** performed **better** than the spatial error model in the 2 study countries.

Proxy indicators predict **PM 2.5** better than No2 in the two regions.

PM 2.5



No2





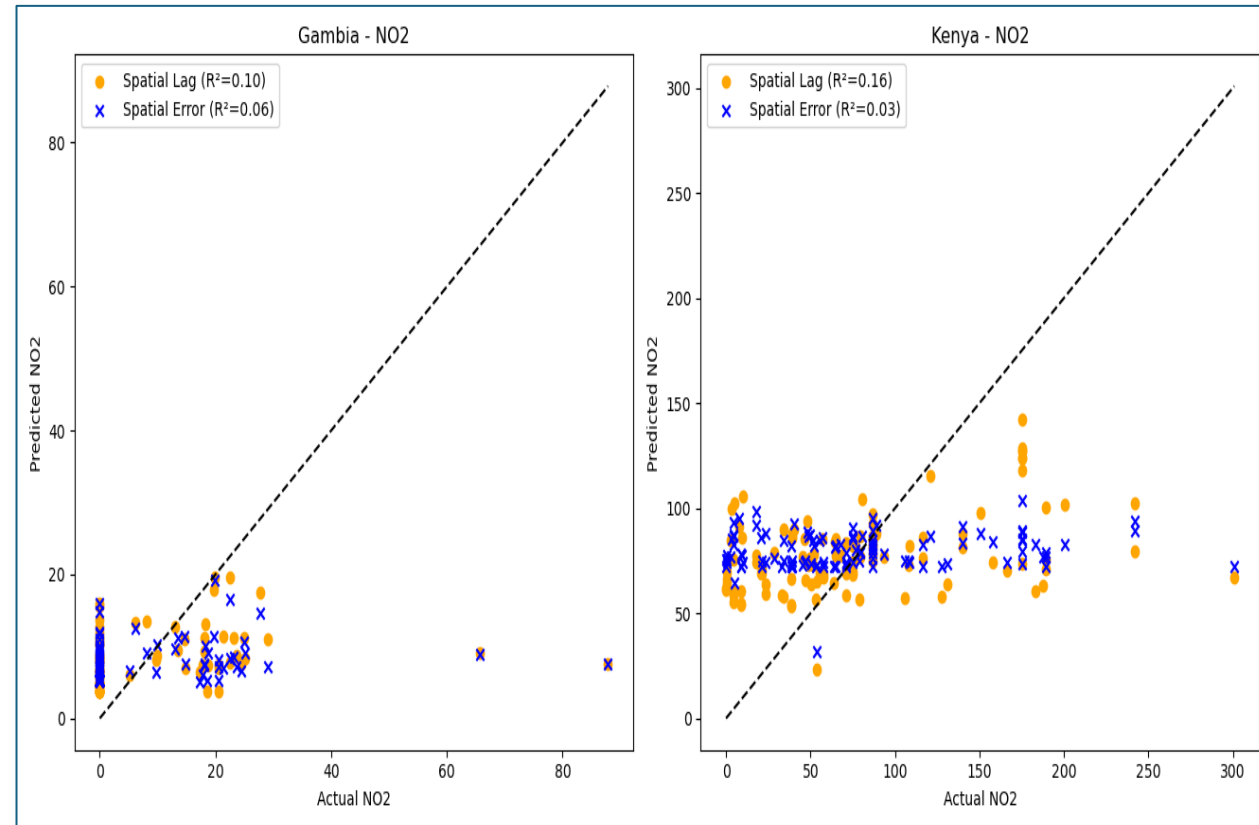
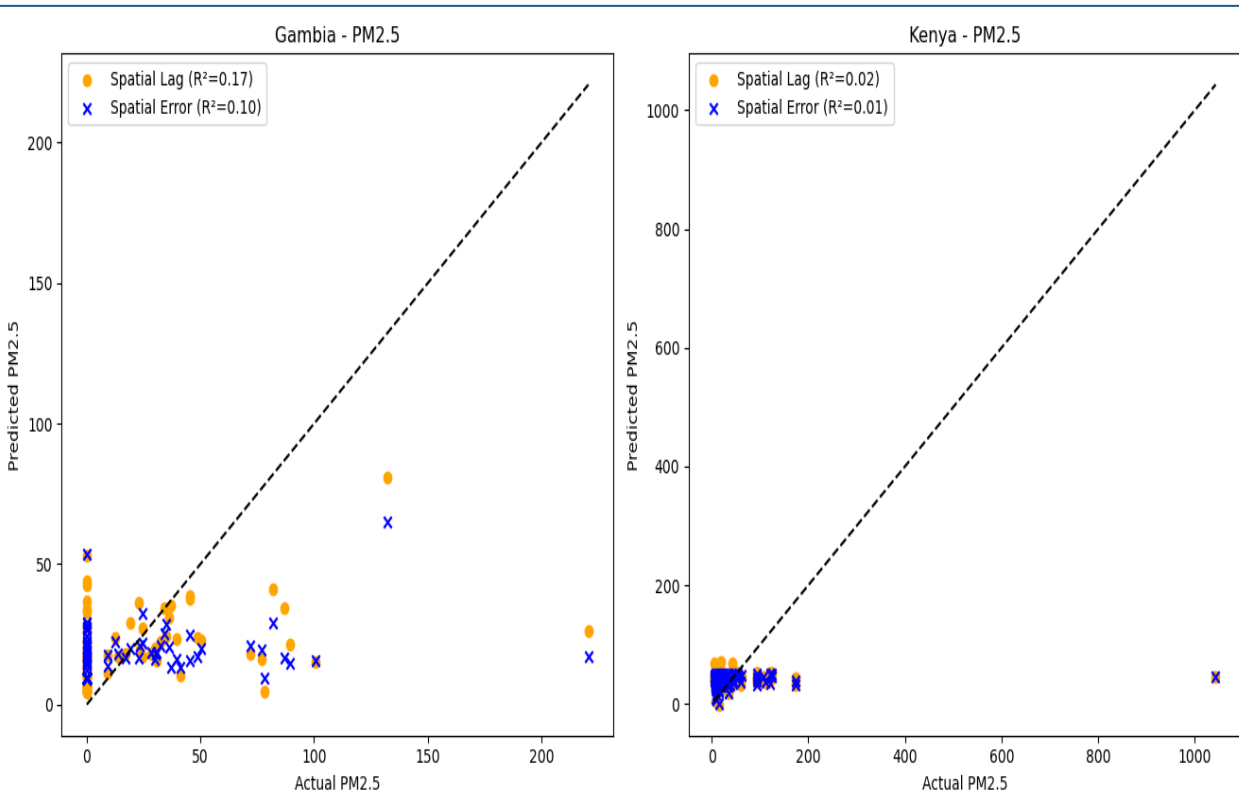
All regression models predicted PM 2.5 better in Gambia (**R-sqr(0.1-0.2, p-value 0.001)**)



All regression models predicted No2 better in Kenya (**R-sqr(0.03-0.2), p-value 0.001)**)



Generally the spatial lag model performed better than the spatial error model in the 2 study countries.



Conclusion and way forward

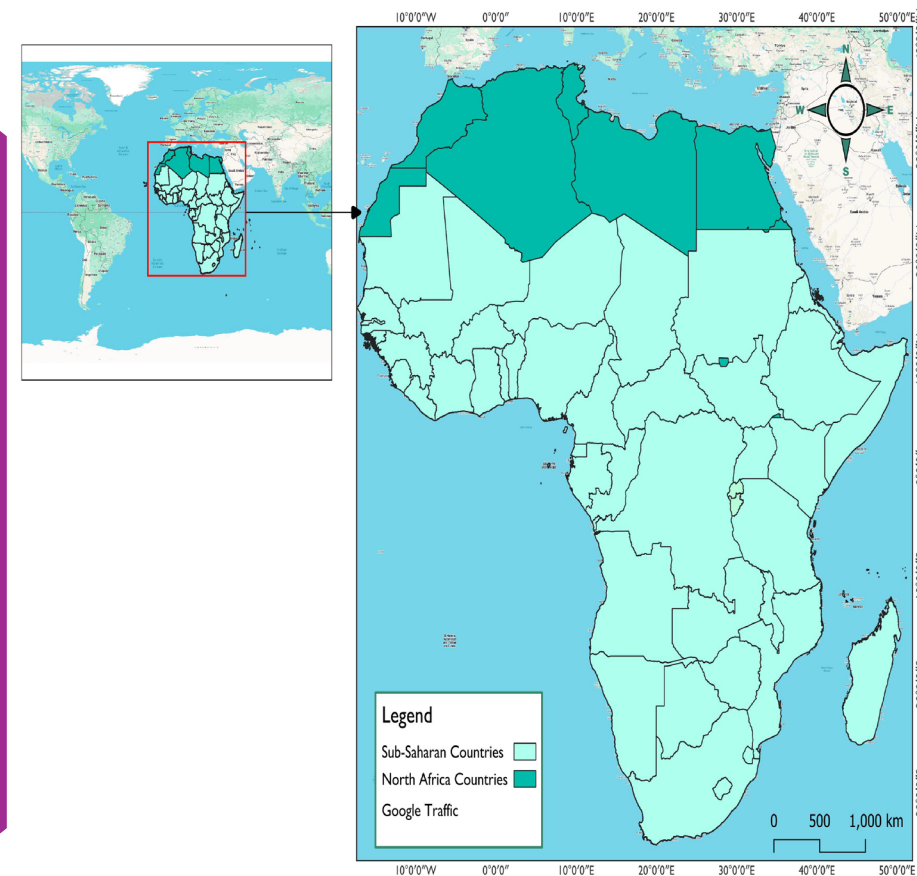
Correlations tests suggest a **positive relationship** between personal exposure and WRND, whilst the EH and EM relationship was **negative**.

Spatial lag model emerges as a more **reliable predictor** for PM 2.5 and NO2 .

LISA analysis suggests that there was **spatial clustering and outliers** ,hence there is a need to **integrate** with other datasets such as **land use**.

Results can be **upscaled** to other countries if Road network density and population datasets are available.

Need to develop and include other proxy indicators such as NDVI , socio-economic factors , AOD, Land use



Acknowledgments

Authors: Handsome Bongani Nyoni¹, Terrence Darlington Mushore¹, Laura Munthali², Sibusisiwe Audrey Makhanya³, Laurine Chikoko¹, Stanley Lutchters², Liberty Makacha^{1,5,6}, Benjamin Barratt⁶, Hiten D Mistry⁵, Marie Laure Volvert⁵, Peter von Dadelszen^{5,7}, Tamara Govindasamy³ Prestige Tatenda Makanga^{1,2,4} The PRECISE Network,

1. Place Alert Labs, Surveying and Geomatics Department, Faculty of the Built Environment Midlands State University, Gweru, Zimbabwe.
2. Climate Environment and Health Department, Center for Sexual Health and HIV AIDS Research, Harare, Zimbabwe,
3. IBM Research Africa, South Africa.
4. Department of International Public Health, Liverpool School of Tropical Medicine, UK
5. Department of Women and Children's Health, School of Life Course and Population Sciences, Faculty of Life Sciences & Medicine, King's College London, Strand, London WC2R 2LS, UK
6. Environmental Research Group, MRC Centre for Environment and Health, Imperial College London, Michael Uren Biomedical Engineering Hub, White City Campus, Wood Lane, London W12 0BZ, UK
7. Department of Obstetrics and Gynaecology, University of British Columbia, Vancouver, British Columbia, Canada.



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(amesegenallo), Na gode, Dalu, E se, Meda wo ase,
Mahadsanid, Kea leboha, Dankie, Merci, Obrigado,
Thank you,) شكرًا shukran).



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