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Research article

SPATIAL PATTERNS AND METEOROLOGICAL RELATIONSHIP OF AIR QUALITY IN GUJENI MINING ENVIRONMENT, KAGARKO LOCAL GOVERNMENT AREA, KADUNA STATE-NIGERIA

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ABSTRACT

Mining-related air pollution is spatially heterogeneous because emissions from extraction, crushing, haulage and stockpiling interact with wind transport, precipitation and atmospheric stability. This study assessed the spatial distribution of atmospheric pollutants and a screening Air Quality Index (AQI), and examined relationships between AQI and meteorological conditions in the Gujeni iron-ore mining environment, Kagarko Local Government Area, Kaduna State, Nigeria. Atmospheric aerosol and pollutant information for 1986–2025 was obtained from the NASA Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), specifically the M2T1NXAER (tavg1_2d_aer_Nx) Aerosol Diagnostics V5.12.4 collection, which provides hourly time-averaged two-dimensional aerosol diagnostics on a native 0.5° latitude × 0.625° longitude grid. The native hourly observations were temporally aggregated to monthly means for concentration variables and monthly means for aerosol optical depth, after which the resulting monthly gridded layers were clipped to the Gujeni study boundary. The study area, approximately 10°20'–10°35' N and 7°20'–7°40' E, intersects four native MERRA-2 grid cells (2 × 2). MERRA-2 pollutant information was combined with ERA5-Land temperature, rainfall, relative humidity and wind speed. Empirical Orthogonal Function (EOF) analysis and Inverse Distance Weighting (IDW) were used to visualise spatial gradients, while a screening AQI based on PM₁, PM_{2.5}, SO₂, CO and O₃ was used to identify areas requiring monitoring attention. Pearson correlation was used to quantify linear associations between AQI and meteorological variables. Clear spatial heterogeneity was observed. SO₂ showed a south-to-north gradient, SO₄ exhibited a central-western maximum, CO was concentrated in central and southern areas, and AOD displayed a central concentration pattern. The strongest AQI contrast occurred in the central mining zone, particularly around S5, where values approached 200, while northern and southeastern locations generally exhibited lower screening values. Rainfall and relative humidity each showed moderate negative associations with AQI ($r = -0.58$), wind speed was positively associated ($r = 0.36$), and temperature showed a weak positive relationship ($r = 0.11$). The findings support spatially targeted and seasonally adaptive monitoring while emphasising that the relatively coarse MERRA-2 reanalysis fields and derived AQI surfaces are screening products rather than regulatory exposure measurements.

KEYWORDS

spatial air quality; mining pollution; Air Quality Index; IDW; meteorological controls; MERRA-2; ERA5-Land.

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INTRODUCTION

Air pollution remains one of the most consequential environmental determinants of human health, with the greatest burdens increasingly concentrated in low- and middle-income settings. The World Health Organization (WHO) revised its global air-quality guidelines in 2021 in response to accumulating evidence that adverse health effects occur at concentrations lower than those reflected in several earlier guideline values. The guidelines

emphasise particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide as priority pollutants and provide health-based recommendations rather than legally binding national standards (World Health Organization [WHO], 2021). The State of Global Air assessments likewise show that ambient and household air pollution remain major contributors to premature mortality, with a disproportionate burden occurring in low- and middle-income countries (Health Effects Institute [HEI], 2024, 2025).

The air-quality problem is particularly challenging in rapidly changing industrial and extractive landscapes. Mining and quarrying operations can generate dust through drilling, blasting, excavation, crushing, haulage, stockpiling and wind erosion of disturbed surfaces. Combustion from diesel-powered machinery can contribute CO and other combustion-related pollutants, while geological materials and secondary atmospheric processes may influence particulate composition. In open-pit environments, pollutant concentrations can vary strongly with distance from emission sources, wind direction, atmospheric stability, precipitation and activity schedules. Recent evidence from Nigeria has demonstrated high particulate concentrations around quarry operations and potential implications for public health and surrounding vegetation (Ekpa et al., 2025; Oche et al., 2023).

West Africa presents an additional complexity because local anthropogenic emissions interact with large-scale dust transport and seasonal circulation. During the dry season, Harmattan flows can transport mineral dust over large distances, while rainfall during the monsoon season can reduce aerosol loading through wet scavenging and changes in surface conditions. Recent regional modelling indicates that West African PM_{2.5} seasonality is strongly linked to dust and atmospheric circulation, while the magnitude of simulated PM_{2.5} and AOD can differ considerably among models (Toolan et al., 2025). Satellite and reanalysis studies also show strong seasonal AOD variability associated with dust transport and regional meteorology (Ranaivombola et al., 2025). Consequently, an air-quality assessment in a Nigerian mining environment must distinguish local source signals from broader regional atmospheric controls.

Reliable air-quality management normally depends on continuous monitoring. Yet regulatory-grade monitoring networks are often sparse in rural and peri-urban African environments because of equipment costs, maintenance requirements, power limitations, calibration needs and limited institutional capacity. Reanalysis datasets provide a complementary source of temporally consistent information. NASA's Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), assimilates satellite observations within a global atmospheric modelling system and provides long-term atmospheric composition and meteorological information (Gelaro et al., 2017). ERA5-Land provides an enhanced land-surface reanalysis with high temporal consistency and an extended record suitable for environmental applications (Muñoz-Sabater et al., 2021). These datasets can therefore support screening, contextualisation and model development, although they do not replace local measurements at mining-scale spatial resolution.

Despite the rapid growth of machine-learning applications to air-quality prediction, evidence from mining environments in Nigeria remains comparatively limited. Many existing studies focus on urban monitoring stations or use short records, while mining communities can experience source-specific pollution, heterogeneous land surfaces and strong seasonal dust dynamics. A framework that integrates long-term pollutant records, spatial analysis, climate diagnostics and interpretable machine learning could help bridge this gap. The Gujeni mining environment in Kagarko Local Government Area, Kaduna State, provides an appropriate case study. Mining activities occur alongside settlements, agricultural land and exposed surfaces, creating potential exposure contrasts across relatively short distances.

Study objectives

The objectives for this study are to:

- i. To map the spatial trajectory of selected atmospheric pollutants and the study-specific screening Air Quality Index in the Gujeni iron-ore mining environment.
- ii. To quantify the relationships between the screening AQI and selected meteorological variables, including rainfall, relative humidity, wind speed and temperature.
- iii. To evaluate the usefulness and limitations of reanalysis-derived air-quality data for preliminary environmental monitoring in the study area.

MATERIALS AND METHODS

Study area

The study was conducted in the Gujeni Iron-ore mining environment in Kagarko Local Government Area of Kaduna State, northwestern Nigeria. The study area lies approximately between 10°20' and 10°35' N and 7°20' and 7°40' E (See Figure 1). It forms part of the Nigerian Basement Complex and contains geological materials including granite, feldspar, quartz, kaolin, laterite and other industrial minerals. Mining is predominantly open-pit and involves drilling, blasting, excavation, crushing, transportation and stockpiling. These activities have the potential to create both point-like and diffuse particulate sources, with the spatial influence of each source conditioned by topography, wind and atmospheric stability.

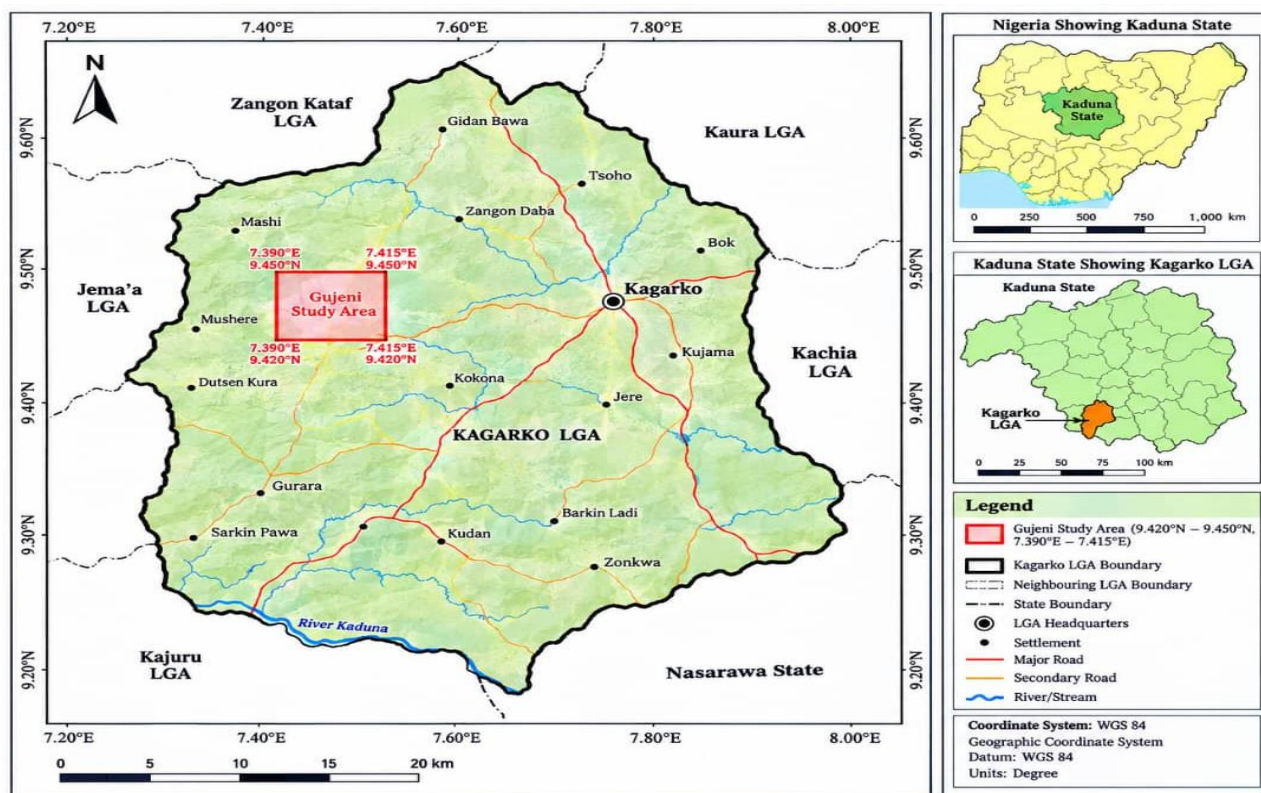


Figure 1: The Study Area

Data sources and preprocessing

Atmospheric pollutant information was obtained from NASA MERRA-2. The source study extracted monthly concentrations for SO₂, SO₄, CO, O₃ and AOD for 1986–2025. Meteorological variables: temperature, rainfall, relative humidity and wind speed were obtained from ERA5-Land. The use of MERRA-2 and ERA5-Land provides a consistent long-term analytical basis, but their spatial scales are coarser than individual mining operations. This distinction is important when interpreting the resulting spatial maps. The gridded datasets were aggregated to monthly resolution and clipped to the Gujeni mining boundary using Google Earth Engine. Extracted values associated with active mining locations were subsequently used for spatial analysis.

Statistical and methodological quality control

Table 1. Atmospheric and meteorological variables used for spatial analysis.

Variable	Resolution	Dataset/source	Role
SO ₂	0.5° × 0.625°	MERRA-2	Sulfur pollutant
SO ₄	0.5° × 0.625°	MERRA-2	Secondary sulfate aerosol
CO	0.5° × 0.625°	MERRA-2	Combustion-related pollutant
O ₃	0.5° × 0.625°	MERRA-2	Secondary oxidant
AOD	0.5° × 0.625°	MERRA-2	Column aerosol loading
Temperature	0.2504°	ERA5-Land	Meteorological predictor
Rainfall	0.2504°	ERA5-Land	Removal/surface condition
Relative humidity	0.2504°	ERA5-Land	Moisture/atmospheric condition
Wind speed	0.2504°	ERA5-Land	Transport and dispersion

Source: Author's Analysis Design, 2026

Spatial analysis

Spatial variability was mapped using Empirical Orthogonal Function (EOF), analysis was performed on the standardised air pollutant and meteorological variables. Prior to decomposition, each variable was standardized using the Z-score transformation.

$$Z_i = \frac{X_i - \mu}{\sigma}$$

Where: X_i is the original observation, μ is the mean, and σ is the standard deviation. The covariance matrix was computed as:

$$C = \frac{1}{n-1} X^T X$$

Where: X represents the standardized climate matrix, and C denotes the covariance matrix. Eigenvalue decomposition was then performed:

$$C = E \Lambda E^{-1}$$

Where: E represents the eigenvectors (EOFs), and Λ represents the corresponding eigenvalues. The principal component scores were obtained as:

$$PC = XE$$

The retained EOF components explained at least 90% of the cumulative variance. Subsequently, Inverse Distance Weighting (IDW) was applied in ArcGIS Pro. IDW assumes that observations closer to a prediction location have greater influence than observations farther away. IDW assumes that nearby observations exert greater influence on prediction locations than distant observations. Predicted concentrations were computed as

$$Z(x) = \frac{\sum_{i=1}^n \frac{Z_i}{d_i^p}}{\sum_{i=1}^n \frac{1}{d_i^p}}$$

Where: $Z(x)$ Predicted concentration, Z_i Measured concentration, d_i Distance between sample and prediction point and p Distance weighting exponent. A power parameter of $p = 2$ was adopted because it provides a suitable balance between local influence and prediction smoothness for environmental variables. We used the resulting surfaces to visualise gradients and hotspots. Because IDW can reproduce local extremes and is sensitive to sampling geometry, the resulting surfaces are interpreted as spatial screening products rather than deterministic maps of regulatory exposure. The spatial analysis is particularly relevant in mining environments because pollution is often heterogeneous. Crushing plants, stockpiles, haul roads and disturbed surfaces may create local maxima, while wind transport can elongate or displace concentration gradients. Therefore, spatially averaged statistics may obscure the highest-exposure locations.

Air Quality Index

The Screen Air Quality Index (AQI) was computed to quantify the combined effects of atmospheric pollutants on ambient air quality. The pollutants considered in the computation included PM_{10} , $PM_{2.5}$, SO_2 , CO , and O_3 in mining environments and are routinely monitored by atmospheric reanalysis systems. The screen AQI was obtained as

$$AQI = \max(AQI_{PM_{2.5}}, AQI_{SO_2}, AQI_{CO}, AQI_{O_3})$$

AQI values were classified according to the US EPA air quality categories.

Climate–AQI correlation

Pearson correlation analysis was used to examine the linear associations between the study-specific screening AQI and the selected meteorological variables, namely rainfall, relative humidity, wind speed and temperature. The Pearson coefficient is expressed as

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Where: r is the Pearson correlation coefficient, X is a climate variable, and Y is AQI. The heatmap provided an initial assessment of the climatic controls on air quality and informed the selection of predictor variables for machine learning modelling.

The correlation matrix consisted of matched monthly observations, with rows representing monthly records and columns representing AQI and the meteorological variables. The study period extended from January 1986 to December 2025, providing 480 potential monthly observations. The actual sample size for each correlation was based on the number of valid paired observations available after data screening. Before correlation analysis, monthly seasonal effects were assessed and controlled by calculating anomalies relative to the corresponding monthly climatological means. Temporal autocorrelation was also examined because serial dependence can reduce the effective sample size of a time series. Statistical significance was evaluated using two-tailed tests at $\alpha = 0.05$. Correlation coefficients were reported with their sample sizes and p-values, and confidence intervals were calculated where appropriate using an autocorrelation-robust or block-bootstrap procedure. The coefficients were interpreted as statistical associations and not as evidence of causal relationships. The results

were presented as a heat map to provide a visual representation of the correlation coefficients among the study variables.

Table 2. Screening AQI categories used in the source analysis.

AQI range	Category	General interpretation
0–50	Good	Little or no health concern
51–100	Moderate	Generally acceptable; sensitive individuals may require caution
101–150	Unhealthy for sensitive groups	Sensitive populations may experience adverse effects
151–200	Unhealthy	Broader population may experience effects
201–300	Very unhealthy	Health alert
301–500	Hazardous	Serious health effects possible

Source: Author's Analysis Design, 2026

RESULTS

The spatial surfaces showed clear heterogeneity across the Gujeni mining environment. Figure 2 presents spatial trajectory of SO₂. The SO₂ exhibited a south-to-north gradient, with higher loadings in southern and central areas and lower loadings toward the northern boundary. The spatial structure suggests that local sources and atmospheric transport jointly shape sulfur pollution. Because SO₂ can also be influenced by regional transport, the map should be interpreted as the spatial distribution of the reanalysis-derived signal rather than a direct source-apportionment map.

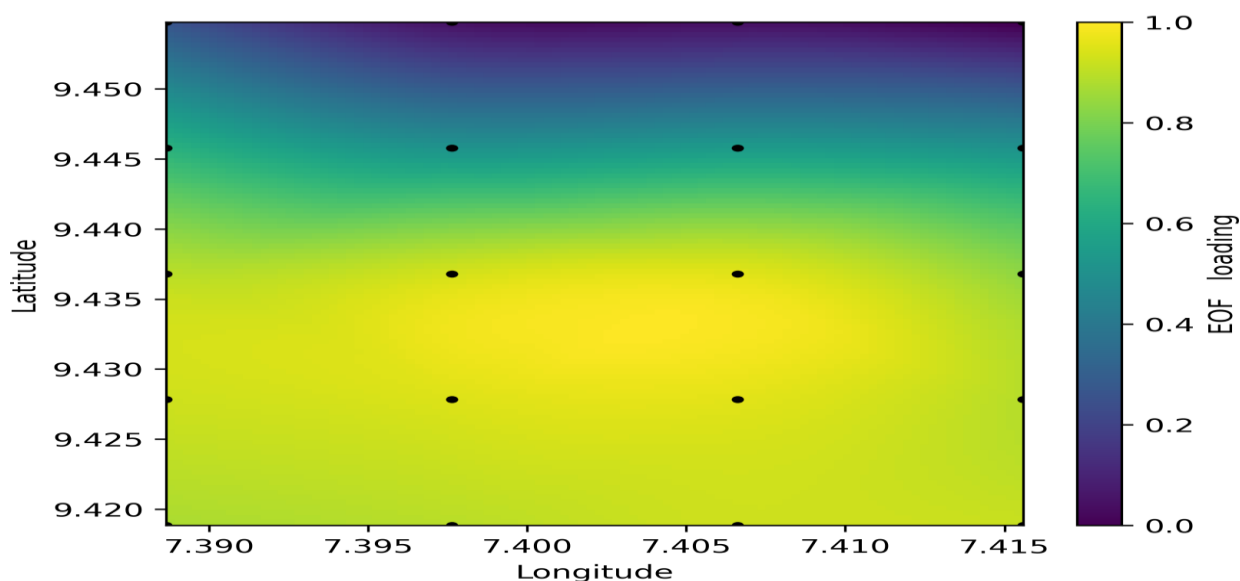


Figure 2: Spatial trajectory of SO₂ in the study area.

Source: Field Analysis, 2026

From Figure 3 it is observed that SO₄ displayed a more localised maximum in the central-western portion of the study area. The concentration decreased toward northern, eastern and western margins. Such localisation is plausible because sulfate formation depends on atmospheric oxidation, aerosol water and humidity, which can vary spatially. It also illustrates the value of mapping secondary pollutants rather than assuming that all pollution gradients follow the location of primary sources.

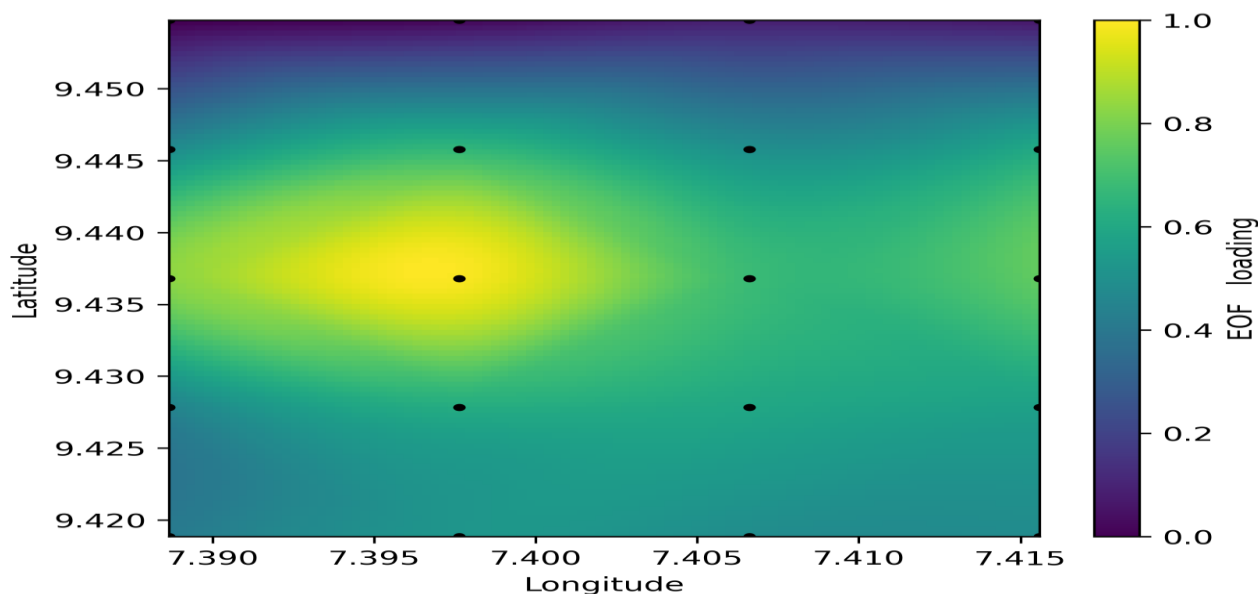


Figure 3: Spatial trajectory of SO_4 in the study area.

Source: Field Analysis, 2026

As indicated in figure 4, CO was concentrated mainly in the central and southern mining environment, with lower concentrations toward the northern and southeastern margins. This pattern is compatible with local combustion sources and transport from mining machinery, although regional combustion and biomass-burning influences cannot be excluded from the reanalysis signal.

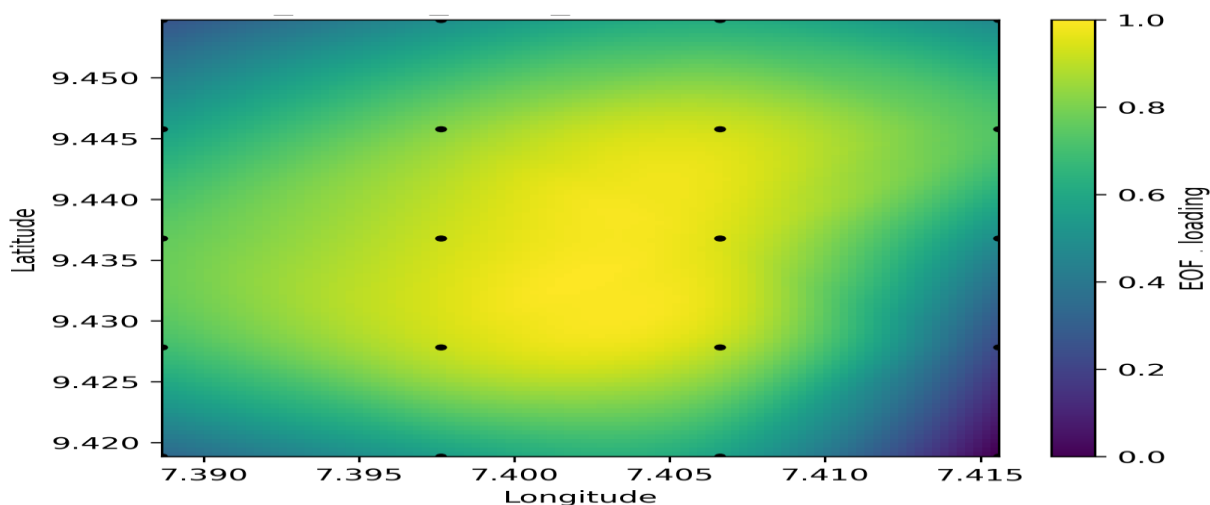


Figure 4: Spatial trajectory of CO in the study area.

Source: Field Analysis, 2026

The AOD depicted in figure 5 showed a central concentration pattern that declined toward the northern and southeastern boundaries. Because AOD represents column-integrated aerosol, its central maximum may reflect a combination of mineral dust, local disturbance and regional aerosol transport rather than surface-level mining emissions alone.

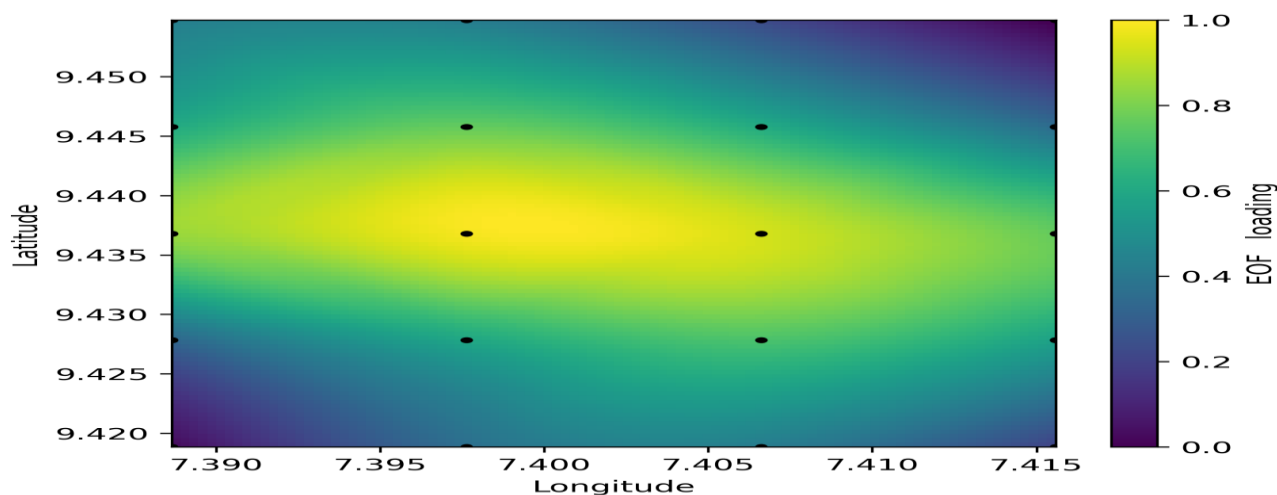


Figure 5: Spatial trajectory of AOD in the study area.

Source: Field Analysis, 2026

The spatial patterns have direct implications for monitoring. A network based only on peripheral locations could fail to detect the highest modelled pollution burden. Conversely, a central hotspot identified from reanalysis and interpolation should be treated as a priority for ground validation rather than assumed to be a confirmed regulatory hotspot. The central zone should therefore receive the first deployment of low-cost sensors or reference-grade instruments, followed by validation of the spatial gradients indicated by the model.

The AQI surface as presented in figure 6 showed the strongest spatial contrast of the study. A distinct central hotspot was centred around sampling point S5, where the AQI reached approximately 200 or slightly above. Elevated contours extended toward S4, S6 and S7, with intermediate values around 120, 140, 180 and 200. In contrast, the northern area around S1–S3 and southeastern locations around S10–S11 showed lower values, generally within Good to Moderate categories. The resulting pattern demonstrates that air-quality deterioration is concentrated rather than spatially uniform.

The central hotspot is consistent with the expectation that active mining and processing zones can have elevated particulate burdens. Recent Nigerian evidence from quarry operations has documented elevated $PM_{2.5}$ and PM_{10} near quarry sites and potential health concerns (Ekpa et al., 2025; Oche et al., 2023). However, the Gujeni AQI values should not be directly compared with regulatory monitoring values because the source data are reanalysis-derived and the index construction includes PM_1 . The value of the map is therefore primarily comparative: it identifies where additional measurement and management attention should be concentrated.

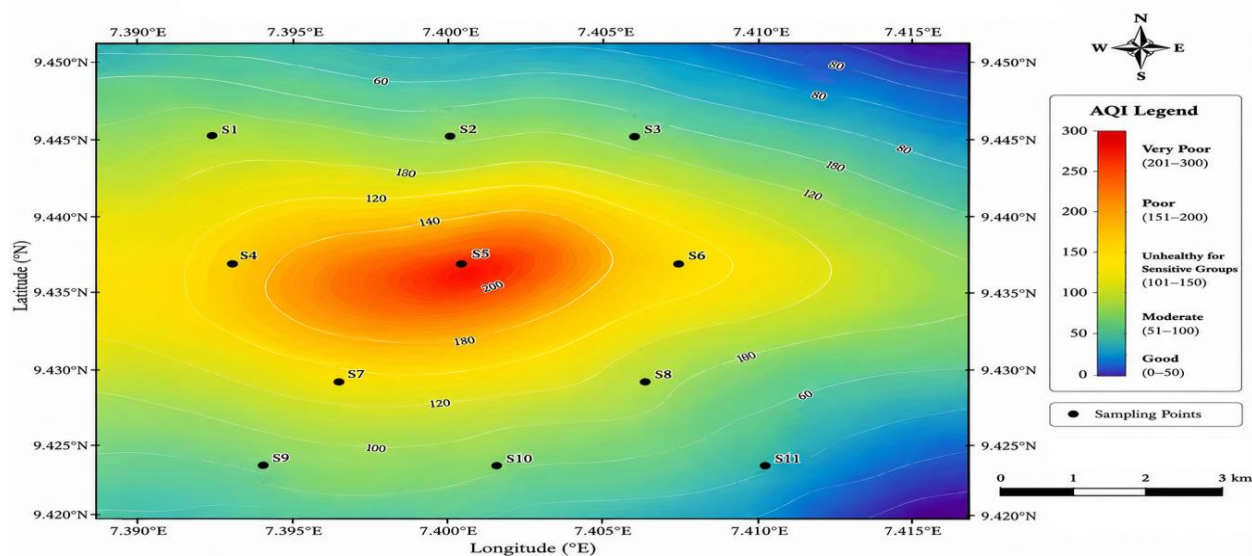


Figure 6: Spatial trajectory of AQI in the study area.

Source: Field Analysis, 2026

Figure 7 presents the relationship between air quality index (AQI) and climatic variables. Rainfall had a moderate negative relationship with AQI ($r = -0.58$). The relationship is consistent with wet scavenging, in which precipitation removes suspended particles from the atmosphere and also wets exposed surfaces, potentially reducing dust resuspension. The result is broadly consistent with African regional evidence that rainfall is associated with changes in $PM_{2.5}$ and aerosol loading (Toolan et al., 2025).

Relative humidity had an equally strong negative relationship ($r = -0.58$). Humidity is a complex predictor because it affects aerosol hygroscopic growth, visibility, cloud formation, deposition and the relationship between dry and wet aerosol mass. The negative association observed here may partly reflect the co-occurrence of high humidity and rainy conditions. It should not be interpreted as a universal rule that higher humidity always improves air quality.

Wind speed was positively correlated with AQI ($r = 0.36$). This result is plausible in a mining environment where stronger winds can resuspend material from exposed surfaces and transport dust from haul roads, stockpiles and disturbed ground. At sufficiently high speeds, however, enhanced dispersion can also reduce concentrations at a receptor. The positive relationship in Gujeni therefore reflects the net effect observed in the dataset rather than a universal monotonic response.

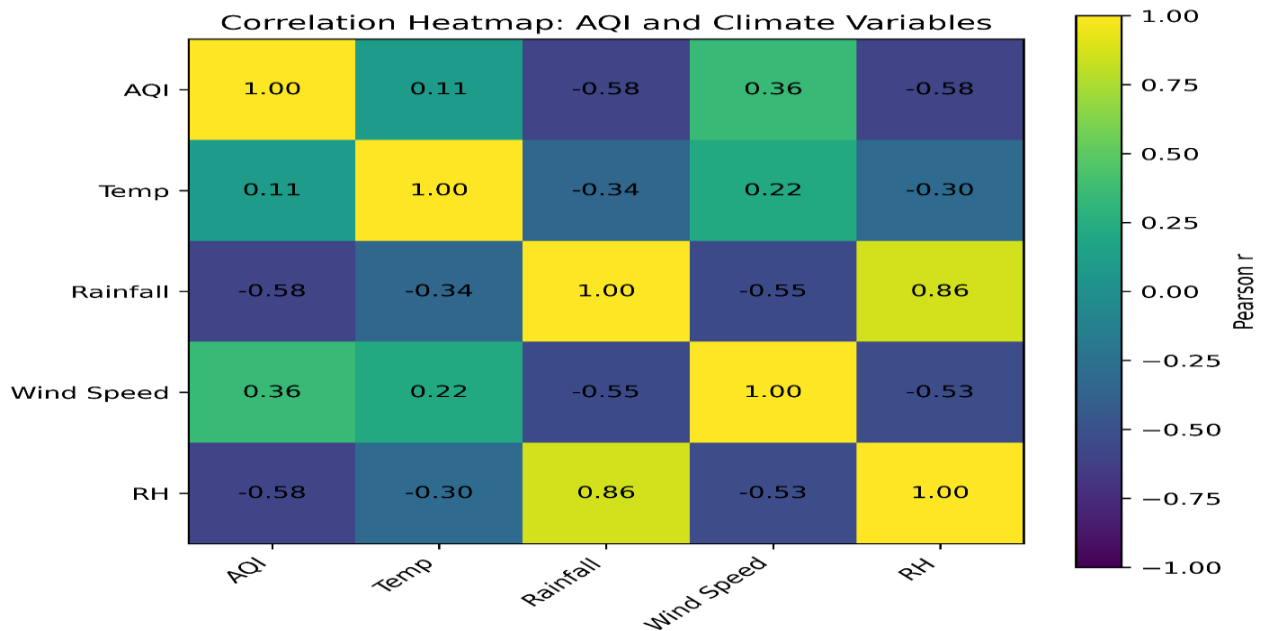


Figure 7: Relationship between AQI and climate variables in the study area.

Source: Field Analysis, 2026

Temperature showed only a weak positive relationship with AQI ($r = 0.11$). Temperature can affect boundary-layer development, chemical reaction rates and atmospheric stability, but its effect is strongly conditioned by other meteorological variables. The weak bivariate correlation therefore does not imply that temperature is irrelevant; rather, it suggests that its information may emerge more clearly through interactions with other predictors, which is one reason for using nonlinear machine learning.

3. Relationship between AQI and climate variables

Variable	R	Interpretation
Rainfall	-0.58*	Moderate negative association
Relative humidity	-0.58*	Moderate negative association
Wind speed	0.36*	Positive association
Temperature	0.11*	Very weak positive association

Note: * significant at the 0.05 level

Source: Field Analysis, 2026

The combined results show that Gujeni's air-quality system around the Iron-ore mining environment is characterised by a mixture of local and regional controls. The spatial concentration of AQI in the central mining zone is consistent with local activity effects, while the annual and sub-annual cycles in O_3 , AOD and particulate matter indicate strong regional and seasonal forcing. This distinction matters because a mining site is not an isolated atmospheric system. Pollutants emitted locally are transported, diluted, transformed and deposited within a regional circulation regime. Recent African studies similarly emphasise that aerosol distributions reflect interactions between local emissions, mineral dust, precipitation and large-scale atmospheric transport (Toolan et al., 2025; Amooli et al., 2025).

The spatial AQI hotspot is perhaps the most directly actionable result. A central high-AQI zone implies that residents, workers and other receptors near active mining operations may not experience the same air-quality

conditions as populations at the periphery. Similar spatial contrasts have been reported around quarry operations in Nigeria, where particulate concentrations can vary strongly with distance from active sources (Oche et al., 2023; Ekpa et al., 2025). The management implication is to prioritise monitoring at the source–receptor interface rather than distributing instruments uniformly across the entire area.

The negative rainfall–AQI relationship is also consistent with the physics of particulate removal. Rain can reduce atmospheric particle loading through scavenging and reduce resuspension by increasing soil and road moisture. However, rainfall may also be associated with changes in boundary-layer depth and humidity, and its effect can differ by particle size. Thus, the correlation result should be understood as an integrated statistical relationship rather than a direct estimate of the efficiency of wet scavenging.

The positive wind-speed association deserves particular attention. In many urban environments, stronger winds can improve dispersion and reduce local concentrations. In a mining environment with large areas of disturbed soil and exposed stockpiles, however, wind can also increase emissions through resuspension. The sign of the relationship therefore depends on the balance between emission generation and dispersion. The positive coefficient observed in Gujeni suggests that resuspension and transport may be important components of the local pollution regime. Field measurements combined with wind-direction data would be required to separate these mechanisms.

The study is also relevant to the wider challenge of environmental data scarcity in Africa. Recent assessments continue to identify large uncertainties in African aerosol and air-quality datasets, particularly for non-dust components and spatial magnitudes (Toolan et al., 2025). Reanalysis and remote-sensing products can help fill temporal gaps, but their uncertainty must be explicitly acknowledged. The most defensible role of the Gujeni framework is therefore as a screening and prioritisation tool that helps determine where field measurements should be concentrated.

The WHO guideline values are health-based recommendations, whereas the AQI values generated here are based on reanalysis-derived concentrations and a study-specific pollutant combination. This study did not estimate dose, exposure duration, population susceptibility or attributable disease. Consequently, it is limited to potential air-quality concern and the need for monitoring. Recent global assessments demonstrate the substantial health burden of air pollution, but site-specific risk assessment requires validated exposure measurements and epidemiological or toxicological evidence (HEI, 2024, 2025; WHO, 2021).

The study contributes to mining-environment research by demonstrating how long-term atmospheric information can be integrated with geospatial and machine-learning techniques. The approach is transferable conceptually to other Nigerian mining and quarrying communities, but transferability should not be assumed automatically. Geological materials, mining intensity, road networks, local meteorology and regional dust regimes differ among sites. Model transfer should therefore be accompanied by local calibration and independent validation.

ENVIRONMENTAL AND POLICY IMPLICATIONS

The central S4–S7 cluster identified by the AQI surface should be prioritised for ground-based validation. Reference-grade monitors should ideally be complemented by calibrated low-cost sensors that can increase spatial coverage. The purpose should be to test whether the reanalysis-derived hotspot corresponds to actual near-surface concentration gradients.

In addition, mining operators should strengthen dust management at crushing, haulage, stockpiling and exposed-surface locations. Practical interventions include road watering where appropriate, surface stabilisation, speed control, enclosure or containment of crushing processes, covered transportation and rehabilitation of inactive disturbed surfaces. These measures should be evaluated using before-and-after monitoring rather than assumed to be effective.

Third, monitoring should be seasonally adaptive. Dry-season conditions can increase regional dust and resuspension risk, while transition periods may show distinct pollutant behaviour. Wet-season monitoring remains necessary because the source analysis identified increases in some pollutant classes and because chemical transformation can change under humid conditions. A fixed single-season campaign would therefore provide an incomplete assessment.

Finally, mining-community communication should focus on understandable indicators and location-specific information. AQI can support communication, but because the present AQI is a screening construct, public communication should clearly distinguish modelled risk indicators from regulatory measurements. Transparency about uncertainty is essential for maintaining public trust.

STRENGTHS AND LIMITATIONS

A major strength of the study is the integration of multiple analytical perspectives. The long 1986–2025 record provides an opportunity to identify persistent temporal behaviour that would not be visible in short monitoring campaigns. The EOF and IDW were used to highlight spatial contrasts. The principal limitation is the dependence on remotely sensed and reanalysis data. MERRA-2 and ERA5-Land are valuable for regional environmental analysis, but their spatial scales can smooth sharp gradients near mining sources. Recent African model evaluations demonstrate that even sophisticated atmospheric models can differ substantially in PM_{2.5} and AOD magnitude, especially for non-dust aerosol components (Toolan et al., 2025). In addition, the use of IDW with a relatively small number of sampling locations. Interpolation results can depend strongly on point configuration and the selected power parameter. A future study should compare IDW with ordinary kriging, empirical Bayesian kriging or machine-learning spatial prediction and should report cross-validation statistics for the interpolation surface.

CONCLUSIONS

Spatial analysis showed that pollution was concentrated rather than uniformly distributed. The central mining zone, particularly the S4–S7 cluster and the area around S5, emerged as the principal AQI hotspot, with values approaching 200 in the study's screening index. Rainfall and relative humidity each had moderate negative correlations with AQI ($r = -0.58$), wind speed had a positive association ($r = 0.36$), and temperature had only a weak positive relationship ($r = 0.11$). These findings indicate that meteorological conditions are associated with air-quality variability in Gujuni. The study provides preliminary air-quality screening in areas with limited monitoring infrastructure. The central zone identified by the screening analysis should therefore be prioritised for environmental implication assessment. Future research should incorporate ground observations, mining activity records, wind-direction data, control locations and source-apportionment methods to improve spatial attribution, exposure assessment and environmental management.

AUTHORSHIP CONTRIBUTION STATEMENT

Ariko, J. D: conceptualization, methodology, software, data curation, formal analysis, visualization, writing original draft.;

Isaac S.: supervision, validation, writing review and editing;

Lass, T.B: Investigation, Resources, Data curation.

DECLARATIONS

Informed consent: Not applicable

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Conflict of interest: The authors declare no conflict of interest.

Data availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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