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Estimation of PM2.5 Particulate Matter Using MATLAB and GWR Models Based on Remote Sensing Data in Baghdad City, Iraq

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Abstract: Precise and effective air quality forecasting plays a crucial role in predicting and mitigating health risks in communities worldwide. This research focuses on estimating particulate matter (PM2.5) concentrations using geographically weighted regression (GWR) and MATLAB models, utilizing remote sensing data in Baghdad city, Iraq. The estimation process incorporates multiple influencing factors, including aerosol optical depth (AOD), population density, normalized difference vegetation index (NDVI), relative humidity, temperature, wind speed, and elevation. The analysis of the relationship between influencing factors and PM2.5 concentration using grey relational analysis revealed that aerosol optical depth (AOD) exhibited the strongest correlation, whereas population density was the weakest. Furthermore, the results indicated that the PM2.5 concentration model developed using MATLAB, based on remote sensing data and incorporating eight influencing factors, demonstrated the highest accuracy, achieving an R^2 value of 0.98 and a root mean square error (RMSE) of 1.7×10^{-10}. The performance of the predictive equation for PM2.5 concentration, derived using MATLAB, was assessed by comparing its estimations with ground station measurements obtained from independent locations and time periods. The model achieved a coefficient of determination (R^2) of 0.77, indicating that it accounts for 77% of the variability in the observed values. This outcome signifies a strong correlation between the predicted and measured concentrations, confirming that the model effectively represents the underlying relationships with a satisfactory degree of accuracy.

Keywords: air pollution, PM2.5, remote sensing data, influencing factors, predictive models

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1. Introduction

The continuity of life on Earth is greatly affected by the quality of air and the extent of its pollution, due to its fundamental impact on the health of living organisms and the progress of economic life [1]. In recent decades, air quality has deteriorated, and air pollution has become widespread worldwide. This issue stems from rapid industrial growth, increased use of personal vehicles, and the burning of fossil fuels [2]. Air pollutants, including carbon monoxide and dioxide, nitrogen oxides, sulfur dioxide, and fine particulate matter (PM2.5 and PM10), pose a serious threat to living organisms and the environment as a whole. Globally, air pollution is recognized as one of the major threats to human health, with an estimated 7 million premature deaths annually. For example, 4 million deaths were recorded due to air pollution in 2019, with Central Europe and East Asia accounting for the largest share [3].

PM2.5 can be described as very small particles with a diameter of approximately 2.5 μm or less and is a group of particles that are small enough to be inhaled [4]. It is well established in numerous scientific studies that PM2.5 has significant negative health effects, and exposure to it is associated with premature death [5–8]. Others have also linked the presence of PM2.5 to increased mortality, with regional variations [9]. There are many studies that have linked PM2.5 to a number of respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), lung microbiome disorders, pneumonia, and lung cancer [10–12]. Recently, studies have shown a strong relationship between high PM2.5 concentrations and COVID-19 infection [13, 14].

PM2.5 sources are divided into natural and anthropogenic sources. There are many natural sources, such as dust storms, forest fires, marine saline aerosols, volcanic eruptions, plants, and biological aerosols [15]. Anthropogenic sources of PM2.5 emissions include transportation, solid fuel combustion, industrial emissions, agricultural activities products, and municipal biomass burning [16]. The level of PM2.5 is influenced not just by local particulate emissions but also by meteorological conditions and altitude.

In Iraq, PM2.5 levels were high, ranking sixth globally at 43.8 $\mu g/m^3$, while Baghdad, the capital, ranked fifth among world capitals at 45.8 $\mu g/m^3$, as recorded in 2023 [17]. These values indicate that Iraq in general, and Baghdad city in particular, has PM2.5 levels that exceed the World Health Organization's PM2.5 standard (5 $\mu g/m^3$). This demonstrates the extent of the deterioration of air quality and pollution levels in Baghdad city, which requires continuous monitoring to find possible solutions to the air pollution threat.

Currently, the methods used to determine PM2.5 levels are ground-based monitoring stations and remote sensing techniques [18]. Ground stations use measuring devices at fixed locations. Although they provide more accurate data, the results have low spatial and temporal resolution and limited scale due to the limited number of monitoring stations. Remote sensing-based estimation depends on image data acquired through a range of remote sensing techniques [19, 20]. Studies have shown that incorporating atmospheric parameters, terrain, and vegetation into the AOD–PM2.5 correlation model increases its accuracy [21]. With the worsening problem of air pollution and the increasing levels of pollution worldwide, the use of remote sensing techniques to estimate PM2.5 levels has become essential in scientific studies. Research has focused on developing remote sensing techniques to represent the relatio nship between AOD and PM2.5. Additionally, incorporating other factors affecting PM2.5 into remote sensing estimation has improved accuracy. Therefore, selecting factors influencing PM2.5 is essential for developing remote sensing estimation methods in this field.

In Iraq, studies on this subject are limited, and this study is among the first to use multiple models based on remote sensing technology to estimate high-precision PM2.5 concentrations.

The primary aims of this study are to:

1) identify the key factors affecting PM2.5 concentrations, including aerosol optical depth (AOD), elevation, relative humidity, temperature, precipitation, wind speed, normalized difference vegetation index (NDVI), and population density, by employing grey relational analysis (GRA);
2) develop a MATLAB-based model for estimating PM2.5 levels in Baghdad city using remote sensing techniques;
3) validate the estimation results by comparing them with ground-based PM2.5 monitoring data.

2. Study Area

Baghdad is the capital of Iraq, situated in the central region of the country within a flat sedimentary plain. Its geographic coordinates range approximately from 32°50′N to 33°46′N latitude and from 43°50′E to 44°58′E longitude, as depicted in Figure 1.

According to the Statistics and Geographic Information Systems Authority of the Iraqi Ministry of Planning, the population of Baghdad Governorate was 8,558,625 in 2020 [22]. The study area is characterized by significant temperature fluctuations, low precipitation, low relative humidity, and high solar radiation, indicating a subtropical desert climate.

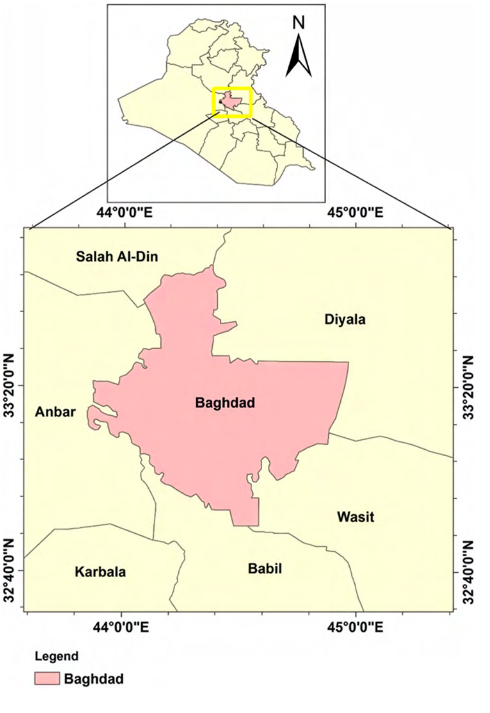

Fig. 1. Location of the study area

3. Methodology and Data Processing

3.1. Data Collection and Processing

A number of methods have been developed in recent years to estimate PM mass from digital data from satellite sensors. In this study, average monthly climatic data obtained from remote sensing were collected from the NASA website. The specifications of the dataset are presented in Table 1. The data was downloaded in the NetCDF format and converted to the shapefile format (Fig. 2). It was then interpolated using the Kriging interpolation method to produce raster data. Finally, to facilitate the use of the dataset in model development programs, 70 reference points were selected and uniformly distributed across the study area (Fig. 3). Subsequently, the data corresponding to these points were extracted and organized into a table. All the data processing was conducted using the ArcGIS 10.8 software.

Table 1. Specifications of the climatic remote sensing dataset

Parameter	Data source	Date	Spatial resolution	Unit	Download link
PM2.5	MERRA 2	January 2024	0.5° × 0.625°	μg/m^3	https://www.nasa.gov/
AOD data	MERRA 2	January 2024	0.5° × 0.625°	–	https://www.nasa.gov/
Precipitation	MERRA 2	January 2024	0.5° × 0.625°	mm	https://www.nasa.gov/
Wind speed	MERRA 2	January 2024	0.5° × 0.625°	m/s	https://www.nasa.gov/
Temperature	MERRA 2	January 2024	0.5° × 0.625°	°C	https://www.nasa.gov/
Relative humidity	AIRS	January 2024	1°	%	https://www.nasa.gov/
Population density	–	2024	–	–	–
NDVI	MOD13A3 vegetation product	January 2024	1 km × 1 km	–	https://www.nasa.gov/
DEM	SRTM V3 data	–	30 m	m	https://earthexplorer.usgs.gov/

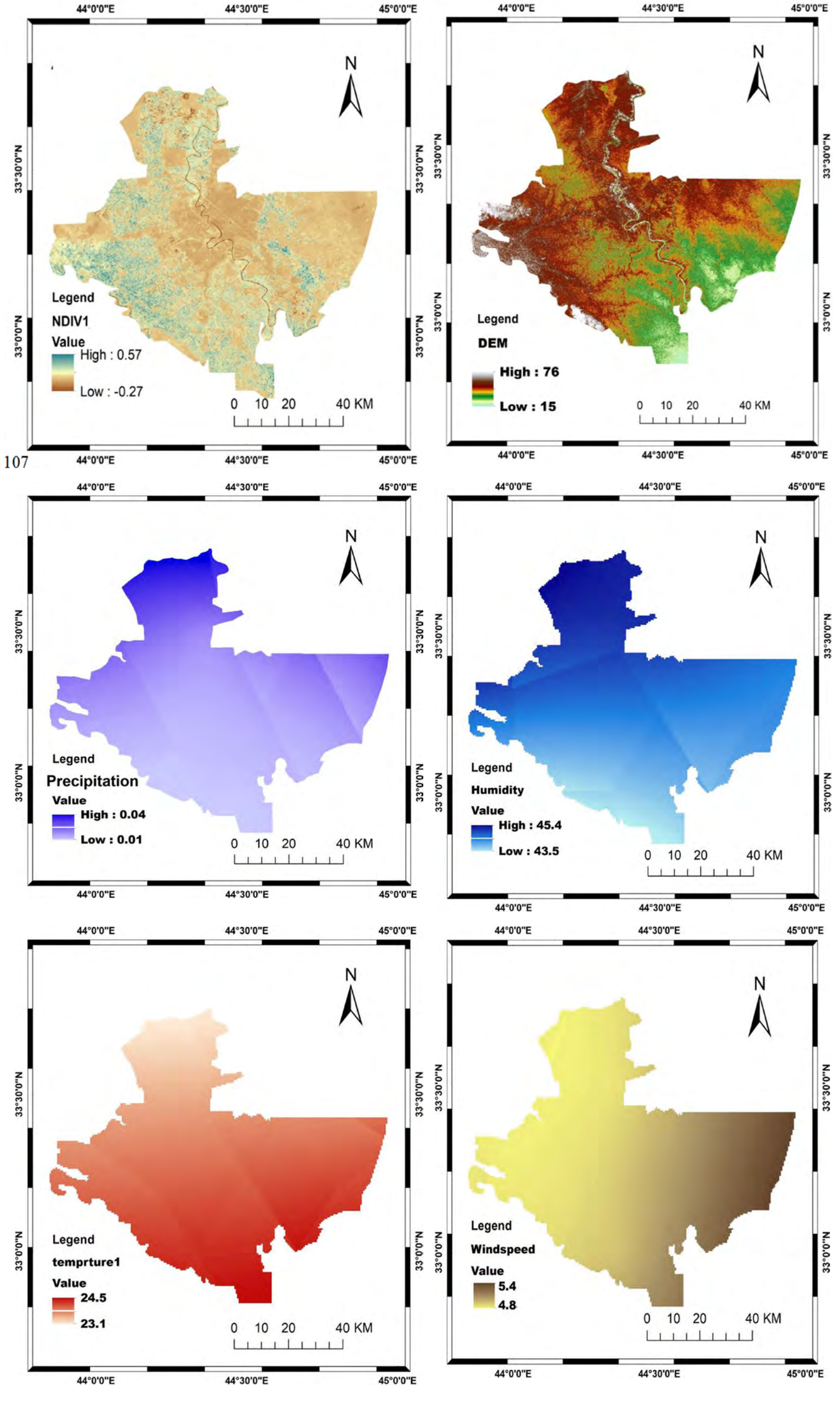

Fig. 2. Conversion of NetCDF data to shapefile format

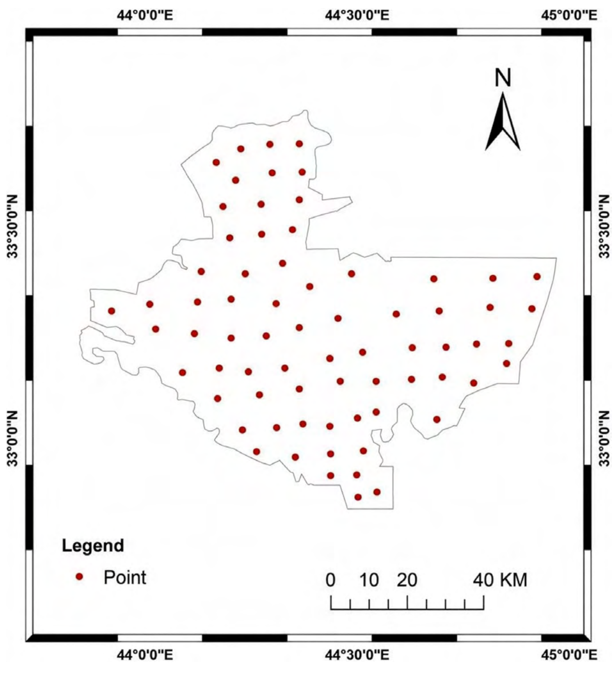

Fig. 3. Distribution of the reference locations in the study area

3.2. Methods

Grey Relational Analysis

Grey Relational Analysis, introduced by Deng in 1982, is a widely utilized approach within the Grey System framework [23]. It can be described as a statistical program through which the degree of association of independent variables with dependent variables is determined based on the degree of similarity [24]. In this analysis, the sample size and distribution are treated as the same value of interest to obtain consistent results for quantitative analysis and qualitative assessment. For this important reason, this analysis was chosen in this study to evaluate the relationship between various factors such as AOD, atmospheric parameters, NDVI, population density, and PM2.5 values.

The grey relational grade is formulated as:

$$\gamma = \frac{1}{m}\sum_{k=1}^{m}\zeta_i(k) \tag{1}$$

where γ is the grey relational grade, ζ_i is the grey relation coefficient at each point, and m – number of variables. For the purpose of analyzing the results, the variables that will have the highest gray relational grade are those with the greatest influence.

Development of a Remote Sensing-Based Retrieval Model

Geographically weighted regression (GWR) is a localized spatial analysis technique that was first introduced in geographical research in 1996. GWR is grounded in statistical techniques commonly employed for curve fitting and smoothing, enabling the analysis of spatially varying relationships within datasets [25]. This method relies on the core principle of estimating localized models by drawing upon subsets of observations surrounding a specific geographic point of interest. GWR constructs spatially localized relationships through the use of a spatial weighting matrix, which assigns weights based on geographic proximity. The model is then fitted and calibrated by accounting for the distance decay effect, wherein closer observations exert greater influence. The correlation within the GWR framework is typically computed as described by Fotheringham et al. [26]:

$$y_i = \beta_{i0} + \sum_{k=1}^{m} \beta_{ik} X_{ik} + \varepsilon_i \tag{2}$$

where y_i represents the dependent variable at location i, while X_{ik} denotes the k^{th} independent variable at the same location. The parameter m signifies the total number of independent variables, the term β_{i0} corresponds to the intercept at location i, whereas β_{ik} represents the local regression coefficient for the k^{th} independent variable at location i. Lastly, ε_i accounts for the random error at location i. The optimal bandwidth for the GWR model was selected using the software's internal optimization process, which works by minimizing the Akaike information criterion (AIC).

MATLAB is a software suite designed for addressing technical computing challenges, incorporating a programming language of the same name [27]. This program is widely used in scientific studies that require data analysis, modeling and algorithm development, and an efficient tool for numerical calculations and programming. The program creates a model that describes the relationship between predictor variables and the response variable. The model formed using linear regression represents the relationship between variables using a linear equation. This approach characterizes the relationship between a dependent variable (response variable), y, and one or more independent variables (predictors), x_1, ..., x_n. In the context of simple linear regression, the model specifically examines the influence of a single independent variable in defining this relationship [28].

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{3}$$

where β_0 is the y-intercept, β_1 is the slope (or regression coefficient), and ε is the error term.

The coefficient of determination (R^2) is one of the most widely used methods for determining a model's suitability and effectiveness in predicting data. Its value ranges between 0 and 1, where the higher the value and the closer it is to 1, the stronger the model's prediction. The root mean square error (RMSE) is a key indicator of a model's effectiveness. The lower the value of this indicator, the higher the model's accuracy, and it should be positive. The values of these indicators (R^2 and RMSE) are calculated using Equations (4) and (5) [28, 29]:

$$R^2 = \sum_{i=1}^{n} \frac{(\hat{y}_i - \overline{y})^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{5}$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\overline{y}$ – mean of the observed values, and n – number of observations.

The software performs internal preprocessing steps during model training, including normalization or standardization of the input variables. Consequently, the calculated error metrics, such as RMSE and MAE, are expressed in the normalized data scale rather than in the original measurement units, unless explicitly stated otherwise.

External Validation of the Estimated Model

A subsequent evaluation was performed to assess the accuracy of the mathematical model or the predictive equation derived from the MATLAB program. This evaluation represents an external validation, wherein the parameters used in the model's calculations – namely temperature, humidity, wind speed, AOD, NDVI, population density, and altitude – were gathered for a time period (from June 1 to June 26, 2024) and locations (three earth stations), different from the one originally used for model development. Although limited, these stations provide the only available reliable measurements within the study area. The PM2.5 concentrations were then calculated using the predictive equation obtained from MATLAB and compared with the corresponding PM2.5 measurements recorded at ground monitoring stations for the same locations and timeframes. Microsoft Excel was utilized to calculate the coefficient of determination (R^2) for the derived equation, thereby assessing the correlation and accuracy of the model. The coefficient of determination (R^2) was used as the primary performance indicator due to the limited number of validation samples.

4. Results and Discussion

4.1. Investigation of the Factors Affecting PM2.5

The accuracy and reliability of the data analysis were enhanced by assessing the correlation between PM2.5 and various factors, including AOD, temperature, relative humidity, precipitation, wind speed, elevation, NDVI, and population density.

Table 2 arranges the variables (influencing factors) according to their degree of correlation or impact on PM2.5. AOD had the highest correlation strength, while population density had the lowest correlation strength among the other variables. These results showed that the correlation strength with PM2.5 for all factors was high, ranging between 0.51 and 0.72. The relational grades of AOD, NDVI, and wind speed exceeded 0.7, indicating their strong impact on PM2.5 within the study area. The moderate effect of humidity, elevation, precipitation, and temperature, and the acceptable effect of population density on PM2.5 values was evident, with their relative relational grades ranging between 0.5 and 0.7 [30].

Table 2. Ranking the influencing factors on PM2.5 according to their relational grades

Factor	Relational grades	Rank
AOD	0.727	1
Wind speed	0.706	2
NDVI	0.702	3
Elevation	0.670	4
Humidity	0.642	5
Precipitation	0.638	6
Temperature	0.601	7
Population density	0.511	8

These results are convincing and consistent with what has been previously found and established by other researchers in this field. Although we cannot directly classify AOD as a parameter for air pollution, it has a strong linear correlation with PM2.5 values [18, 31, 32].

Numerous studies have proven that meteorological conditions have a strong impact on PM2.5 values [33–36]. Liu et al. [37] demonstrated that wind speed and precipitation (depending on its intensity) have a significant effect on PM2.5 pollution, Zhang et al. [38] reported that temperature and wind speed were the main meteorological factors that strongly influenced seasonal variations in PM2.5 values in Kunming. Yang et al. [39] concluded that meteorological factors play a major role in atmospheric particulate matter pollution, alongside emissions from various human activities and the geographical characteristics of the region, which also exert significant impacts. Another study described temperature and humidity as among the most influential meteorological factors on PM2.5 values in Beijing, China [40].

4.2. Modeling PM2.5 Concentrations

A predictive model was created to estimate PM2.5 concentrations using the GWR program, based on eight influencing parameters: temperature, humidity, wind speed, precipitation, AOD, NDVI, population density, and elevation. Remote sensing data from 70 locations across Baghdad city were used. All model properties are shown in Table 3, while the resulting predictive equation was as follows:

$$\begin{aligned} PM_{2.5} &= 23.14 + 0.058T + (-0.021)W + 0.015H + 0.038\mathrm{Pr} + (-0.011)E + \\ &+ 0.026Po + 0.042NDVI + (-0.015)AOD \end{aligned} \tag{6}$$

where: T – temperature, H – humidity, W – wind speed, Po – population density, Pr – precipitation, and E – elevation.

Table 3. Optimal bandwidth and other key parameters of GWR model

Bandwidth type	Bandwidth value	Sigma (σ)	Tau (τ)	RMSE	R^2	Adjusted R^2
adaptive	3.72 km	2.11	0.85	2.51	0.842	0.823

The results indicated that the GWR model demonstrates a good fit to the data, effectively capturing the intricate relationships between PM2.5 and its predictor variables while accounting for spatial variability.

Other spatial diagnostics, such as Moran's I and mapping of local coefficients, were not part of this study, but could be explored in future work to provide a deeper understanding of the spatial patterns.

The PM2.5 levels were estimated through a multivariate linear regression approach implemented in the MATLAB software. The explanatory variables included AOD, NDVI, temperature, wind speed, relative humidity, precipitation, elevation, and population density. Using a dataset comprising the same 70 points and employing 5-fold cross-validation, the resulting predictive model was expressed as:

$$\begin{aligned} PM_{2.5} &= 1 + T \cdot H + T \cdot AOD + W \cdot Po + H \cdot Pr + Pr \cdot AOD + \\ &+ E \cdot NDVI + Po \cdot AOD + NDVI \cdot AOD \end{aligned} \tag{7}$$

A more accurate model is characterized by an R^2 value approaching 1. In this case, the R^2 was 0.98, which is considered outstanding. The RMSE model was 1.7×10^{-10}. It should be noted that the extremely low RMSE values are associated with normalized data and do not reflect the actual error magnitude in micrograms per cubic meter. It indicates an exceptionally high level of accuracy, as the error between the predicted and observed values is nearly negligible. This suggests that the model fits the data extremely well, with minimal deviation in predictions.

The predicted versus actual plot illustrates the model's ability to replicate the observed data. In an ideal regression model, the predicted values match the actual recorded values exactly, resulting in all points aligning along a diagonal line. The vertical distance from the line to any individual point represents the prediction error for that specific observation.

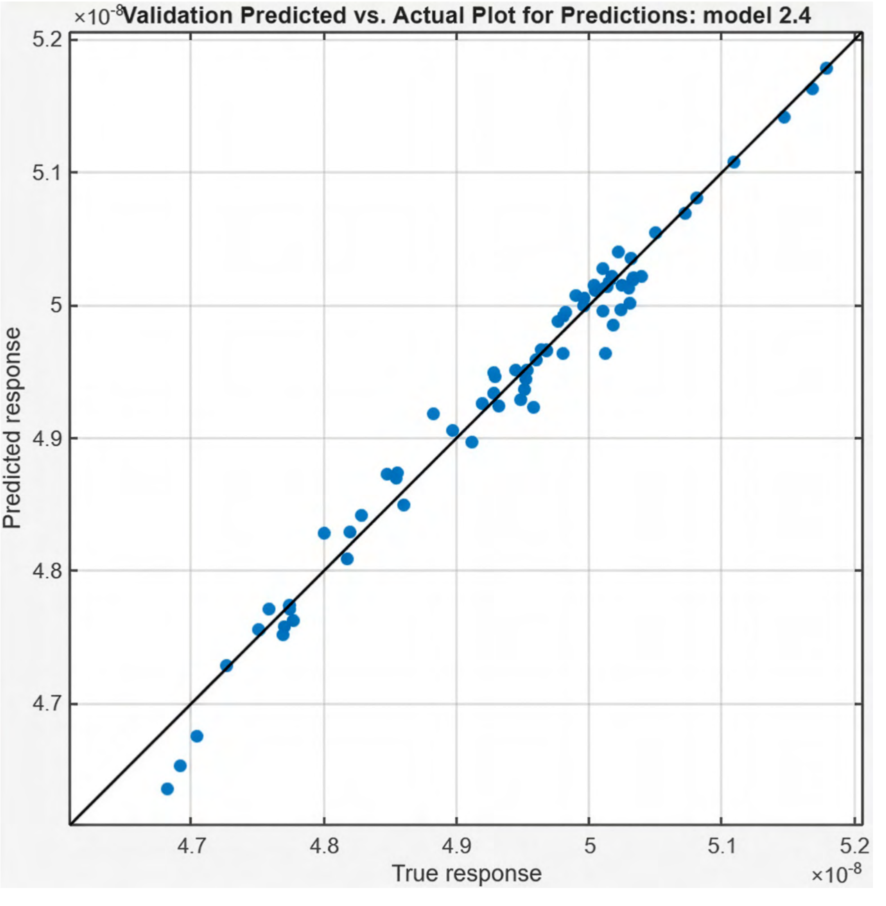

Fig. 4. True versus predicted response

As demonstrated in Figure 4, this model performs exceptionally well, with minimal errors, as the predicted values are closely clustered around the diagonal line.

Figure 5 displays the comparison between the predicted PM2.5 concentrations derived from the regression model and the actual recorded PM2.5 values. The errors are represented by yellow lines, where smaller error magnitudes indicate a more accurate and reliable model.

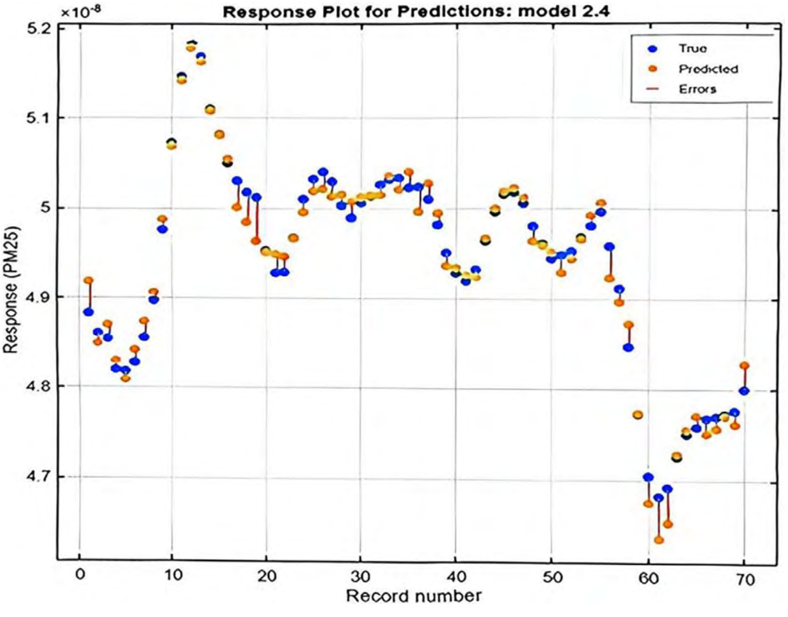

Fig. 5. Predicted versus true values of PM2.5

4.3. External Validation

To evaluate the effectiveness of the predictive equation derived from MATLAB (recognized for its high accuracy and minimal error rate when validated within the program), PM2.5 concentration readings from ground stations at locations and time periods that were not part of the dataset used to develop the model were compared with the PM2.5 concentrations predicted using the estimated equation. The resulting relationship is presented in Figure 6.

The coefficient of determination (R^2) value of 0.77 indicates that the predictive model for estimating PM2.5 concentrations explains 77% of the variance in the measured values. This suggests a relatively strong correlation between the estimated and observed values, reflecting a reasonable level of model accuracy in capturing the underlying relationships.

Figure 6 illustrates the mathematical correlation between the PM2.5 values estimated using the MATLAB program (based on the eight input parameters) and the corresponding ground-based measurements across different locations and time periods. Considering the limited number of official air quality monitoring stations in Baghdad city, which currently consists of only three stations, the development of such an equation capable of providing highly accurate estimates of ground-level PM2.5 concentrations based on the MATLAB-derived values is of significant importance.

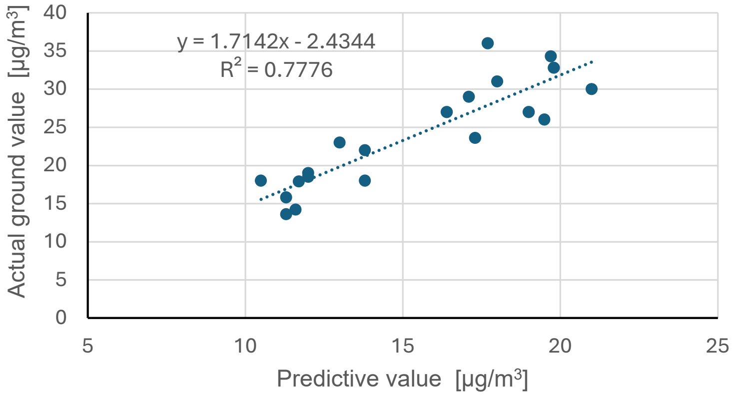

Fig. 6. Comparison of measured and estimated PM2.5 concentrations using the MATLAB model

5. Conclusions

This study aims to establish a correlation between multiple influencing factors and the concentration of PM2.5 in the air over Baghdad city by utilizing remote sensing data. Various analytical programs will be employed to assess their effectiveness, with the objective of identifying the most accurate and representative model for PM2.5 estimation.

Grey relational analysis was employed to enhance the accuracy and reliability of data analysis by evaluating the correlation between PM2.5 concentrations and factors such as AOD, temperature, relative humidity, precipitation, wind speed, elevation, NDVI, and population density. The ranking of parameters according to their degree of influence placed AOD as the strongest correlate, followed by NDVI, then elevation, relative humidity, precipitation, temperature, and finally population density. AOD, NDVI, and wind speed all had grey relational grades above 0.7, so they are described as having a major influence on PM2.5 values. The remaining parameters had a relational grade ranging from 0.5 to 0.7, so their influence can be classified as moderate.

Predictive models for PM2.5 values were developed utilizing two programs, GWR and MATLAB, based on the eight influencing factors. Comparative analysis indicated that MATLAB achieved superior performance, with an R^2 of 0.98 and an RMSE of 1.7×10^{-10}, whereas GWR yielded an R^2 of 0.842 and an RMSE of 2.51.

The efficiency of the MATLAB-derived predictive model for PM2.5 values was assessed by comparing its estimates with ground station measurements at locations and time periods different from those used in the predictive model. The model achieved a coefficient of determination (R^2) of 0.77, indicating that it explains 77% of the variance in observed values. This result demonstrates a strong correlation between the predicted and measured concentrations, suggesting that the model effectively captures the underlying relationships with a reasonable level of accuracy.

However, it is important to note that this study is subject to certain limitations. One of the limitations of this study is that the model was developed using data from a single month (January 2024), which does not account for seasonal variability in PM2.5 concentrations. Future studies should incorporate multi-seasonal or long-term datasets to enhance model robustness and applicability. A further limitation of this study is the relatively small number of spatial samples (70 points), which may influence the model's spatial representativeness and stability. Although each point represents a MERRA-2 grid cell with a resolution of 0.5° × 0.625°, the total number of samples is still modest compared to those typically used in large-scale remote sensing analyses. Expanding the dataset to include more grid cells and higher-resolution data would likely improve the robustness of the model and enhance its ability to generalize spatially. Multicollinearity diagnostics such as VIF were not included and may be considered in future work to further strengthen the regression analysis.

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CRediT Author Contribution

S.T.A.: conceptualization, methodology, formal analysis, softwar, writing – original draft preparation, writing – review and editing.

N.A.A.: data curation, software, investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

All data, models, and code generated or used during the study appear in the published article.

Use of Generative AI and AI-Assisted Technologies

No generative AI or AI-assisted technologies were employed in the preparation of this manuscript.

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