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ARTICLE

Estimating Chemical Concentrations of Dust $PM_{2.5}$ in Iraq: A Climatic Perspective Using Polynomial Model and Remote Sensing Technology

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ABSTRACT

Air pollution and climate change are interrelated issues, with air pollution levels in Iraq currently exceeding World Health Organization standards. This study aimed to evaluate air quality in Iraq by utilizing climatic data, such as temperature, humidity, and gaseous pollutants for assessing the health effects based on processed and estimated data. The research was conducted between August and November 2020, using remotely sensed images and geographical information techniques. Two methods; Geographic Information Systems GIS-based multiple regression and a polynomial model, were employed to estimate $PM_{2.5}$ levels in the study area. The results showed a significant influence of climatic variables on air pollution in Iraq, with varying effects on $PM_{2.5}$ estimation. The health impact ranged from good to unhealthy, with most provinces experiencing poor air quality. Southern parts of Iraq exhibited $PM_{2.5}$ levels surpassing the healthy threshold. The predictive linear and polynomial model's accuracy was assessed through regression, yielding high correlation coefficients (R^2) of 0.89, 0.95, 0.98, and 0.96 for August to November, respectively. While model validation accuracy ranged between 85–94 %. The study emphasizes the vital role of climate data in understanding the dispersion of air pollutants and their significant impacts on the environment. Addressing air pollution and climate change, as per the SGS-13 "Climate Action", are interconnected and require comprehensive strategies for mitigation.

Keywords: Dust $PM_{2.5}$; Advanced remote sensing; Polynomial model; Health impact; GIS

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1. Introduction

Impact of air pollution on health become a pressing concern for decision-makers involved in hazard management [1,2]. Rapid urbanization and unplanned industrialization have contributed to the degradation of the atmosphere, resulting in adverse effects on both human health and the environment [3].

Plenty of epidemiological studies have proved that air pollution exposure can cause increased death rates and the number of such deaths has reached millions each year [4]. The major indications of air quality abound with particulate matter (PM), ozone (O_3) amount, carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) [5,6]. Although $PM_{2.5}$ is one of many pollutants in the air [7], in current experience it is the most immediate issue for the air quality in Iraq [6]. $PM_{2.5}$ is defined as particulate matter with a diameter of 2.5 micrometers or less and is a major standard by the Environmental Protection Agency (EPA) regarding human health threats [8,9]. The concentration of $PM_{2.5}$ is highly dependent on the dynamic of diverse weather phenomena; hence, we need to consider the impacts and interventions that may address the air pollution menace [10]. The nature of climatic factors deserves full attention in air pollution forecasting as provocateurs of higher concentrations of pollutants are more active in the warm season periods [11]. Regression analysis is a technological estimation technique that examines the connectivity between different variables, to find the most suitable regression equation capable of being used to project the required values [12]. Also, modeling methods like multiple linear regression offer a way of linking the air pollution variable representing the space variability with the predictor variables [13]. Additionally, as regards the applied work of air quality modeling, the most used statistical operations are linear regression models [14]. Even though GIS systems and AI could also work very efficiently, this however also clearly indicates that these air quality models can predict the air quality based on special parameters such as air pollutants and real data [15].

GIS holds a variety of important tools that not only help to describe spatial relationships but also a manipulation that is being used productively and effectively [16–18]. One of the key roles of remote sensing data in this context is the implementation of air pollution monitoring and management [19,20].

In the statistical models, the investigation using regressions indicates a set of statistical analyses for assessing the relationships between a reliant variable, frequently called the 'result' or the response variable, and at least one autonomous factor, regularly called indicators or illustrative factors [21]. The most widely recognized type of regression model is the linear model which defines a line or more complicated linear set that closely fits the information data based on a specified mathematical standard [22]. For example, Ordinary Least Squares (OLS) computes the hyper-plane which is the unique line that reduces the sum of squared differences between the real and hyper-plane data and thus allows estimation of the conditional prediction of the dependent factor when the independent factors have specific values [5].

Regressions are mainly used for two conceptually specific goals. In the first place, regressions are broadly used for expectation and estimation. Secondly, in certain circumstances, regressions can be utilized to conclude causal associations among the independent and dependent factors [21].

This investigatory research is based on different types of remote sensing images to analyze air quality based on $PM_{2.5}$ and climatic data with some gaseous pollutants to identify health effects. The study is based on an ArcGIS-based modeling approach and a polynomial model. Four models for dust $PM_{2.5}$ estimation were introduced. The role and impact of climate were analyzed and visualized.

2. Materials and methods

2.1 Study area

The study was conducted in Iraq, which lies between (38° 45' and 48° 45') longitudes and (29° 5' and 37° 22') latitudes as shown in **Figure 1** which represents the remotely sensed dust $PM_{2.5}$ samples in the study area (Iraq).

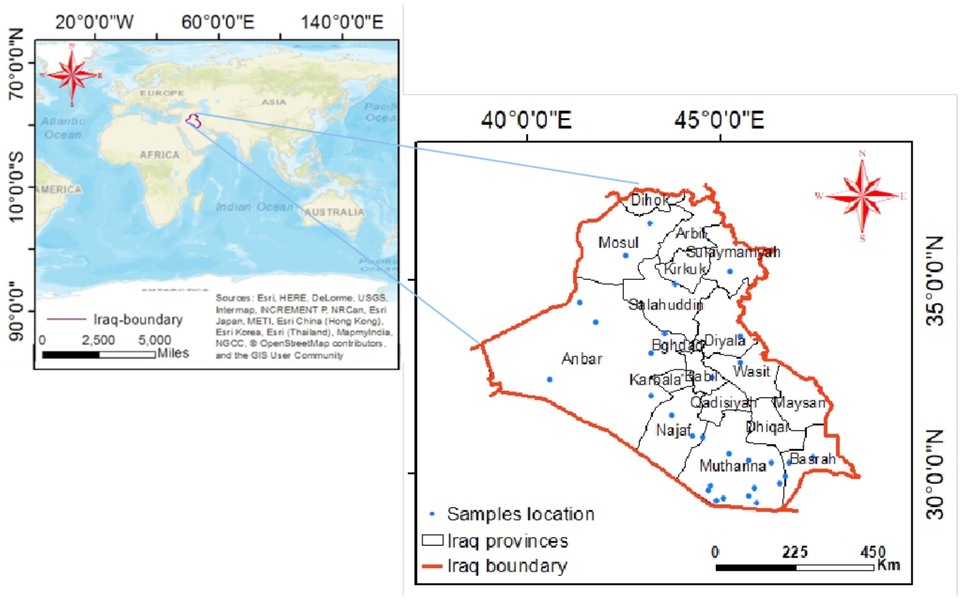

Figure 1. Remotely sensed samples location in the study area (Iraq).

Iraq's topography is characterized as mountainous in the north, desert areas in the west, swamps in the south, and plain lands in the center [23]. Temperatures range from 0°C to 50°C, and annual precipitation varies from 100 to 180 mm [22].

2.2 Satellite imagery data

The data used are reported in **Table 1** which represents the used satellite data characteristics.

Pollutant factor values of Iraq for the period of August-November 2020 were extracted from satellite images downloaded from an online source via NASA Worldview application [24]. The average monthly dust $PM_{2.5}$ and SO_2 from Modern-Era Retrospective analysis for Research and Applications (MERRA-2), weather data from Aqua/Atmospheric Infrared Sounder (AIRS), O_3 from Aura/Ozone Mapping and Profiler Suite (OMPS), and NO_2 from Aqua/Ozone Monitoring Instrument (OMI). The data evaluated was in a raster layout and was extracted from satellite imagery. A maximum of thirty points were randomly selected in the study area to build the models. The data of these sites were extracted from remote sensing images based on ArcGIS and Geoprocessing tools.

Table 1. The used satellite data characteristics.

No.	Data	Image source	Element details	Temporal coverage
1	Dust $PM_{2.5}$	MERRA-2	Display dust surface mass of $PM_{2.5}$ layer	1980–Present
2	RH	Aqua/AIRS	Display surface relative humidity over 2m above sea level	2002–Present
3	T	Aqua/AIRS	Display surface air temperature over 2m above sea level.	2002–Present
4	SO_2	MERRA-2	Display SO_2 column mass density	1980–Present
5	O_3	OMPS	Display the quantity of O_3 in the total column	2012–Present
6	NO_2	Aura/OMI	Display tropospheric element of NO_2 column	2004–Present

2.3. Methodology

Based on the examined datasets, user operations are identified in **Figure 2**, which represents the study procedures. ArcGIS/version 10.8 was used to examine and process the data. Two methods were used to calculate $PM_{2.5}$ dust levels in the study area. The GIS-based OLS Model and a statistical Polynomial Model were used in prediction and validation. In order to validate the selected data after modeling we used some station data (historical data of $PM_{2.5}$) that was collected in 2020 from ground stations.

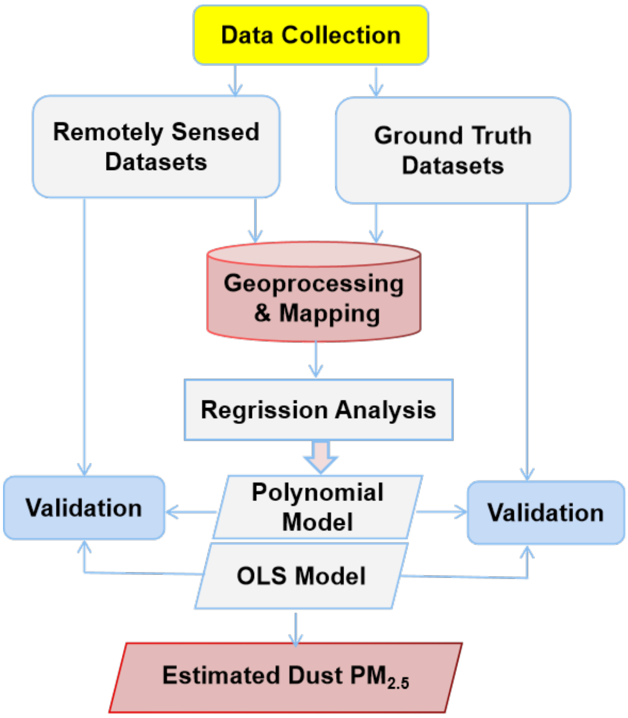

Figure 2. The study methodology.

Essentially, regression analysis by itself just reveals correlations among a dependent factor and a set of independent factors in a given dataset. It is necessary to know that there must be adequate records to predict the regression model. In this case, one dependent and five independent factors (Dust $PM_{2.5}$, T, RH, SO_2, O_3, and NO_2), are used to estimate the model via linear regression below in equation (1) [5,10,21];

$$\text{Dust } PM_{2.5(EST.)} = \beta_O \pm \beta_T * T \pm \beta_{RH} * RH \pm \beta_{SO_2} * SO_2 \pm \beta_{O_3} * O_3 \pm \beta_{NO_2} * NO_2 \pm e_i \quad (1)$$

Where, Dust $PM_{2.5(EST.)}$ is the dependent estimated factor, is the intercept, T and RH are the independent climate factors (Temperature and Relative Humidity). β_T and β_{RH} are climate factor coefficients, β_{SO_2}, β_{O_3}, β_{NO_2} are the independent factors of gaseous pollutants (SO_2, O_3, NO_2) respectively, and e_i is an error term.

The polynomial model is a type of regression technique where the correlation between the factor x and the factor Y is displayed as an nth degree in x. In this case, the equation (2) that proposes the model can be written in the form [22];

$$Y = \beta_0 + \beta_1 x + \beta_2 x^2 + e \quad (2)$$

Where Y is the dependent variable, Dust PM2.5(EST.), and x represents the independent variables. β is an unknown parameter, represents a scalar, and e is a random error. In this regression model, for any unit changes in the value of x, the restricted prediction of y changes by β_1 units.

The polynomial model is linear from the point of view of prediction, meanwhile, the regression equation is linear in terms of the unknown factors β_0, and β_1. Thus, the calculations and concluded issues are entirely performed by the multiple regressions technique, and this can be achieved by considering x and x^2 as individual independent factors [22,25].

3. Results

3.1 GIS and RS-based modeling results

Upon ArcGIS mapping tools, the remotely sensed datasets were mapped and the spatial distribution of dust $PM_{2.5}$, RH, T, SO_2, O_3, and NO_2 was mapped.

Figure 3 represents the remotely sensed datasets' spatial distribution maps of dust and meteorology. The distribution of factors and the produced maps have been displayed per variable in the study region. While gaseous pollutants of SO_2, O_3, and NO_2 spatial distribution maps are shown in **Figure 4**.

To hypothesize the modeling equations, the relationship has been practiced for rating the linear regression potentials of dust $PM_{2.5}$ and climatic data with gaseous pollutants. Based on equation (1), the multiple linear OLS model was employed. The analysis involved the correlation among the independent factors (T, RH, SO_2, O_3, and NO_2) with the dependent factor dust $PM_{2.5}$. We attained the equations (3), (4), (5), and (6) from regressions results to estimate dust $PM_{2.5}$ in each month (August to November respectively);

$$\text{Dust } PM_{2.5(EST.\ AUG)} = -585.4 + 12.9T - 2.7RH - 0.8SO_2 + 8.6O_3 - 1.3NO_2 \quad (3)$$

$$\text{Dust } PM_{2.5(EST.\ SEP)} = -189.2 + 7.2T - 6.8RH + 0.7SO_2 + 2.4O_3 - 0.3NO_2 \quad (4)$$

$$\text{Dust } PM_{2.5(EST.\ OCT)} = -70.2 + 6.1T - 4RH - 0.1SO_2 - 0.8O_3 - 0.003NO_2 \quad (5)$$

$$\text{Dust } PM_{2.5(EST.\ NOV)} = 296.7 + 3.9T - 6RH + 0.1SO_2 - 4.5O_3 + 1.6NO_2 \quad (6)$$

Where, Dust $PM_{2.5(EST.)}$; is the computed $PM_{2.5}$ levels in µg/m^3 for August-November 2020. T in °C; Temperature, RH %; is Relative Humidity, SO_2; Sulfur Dioxide in µg/m^3, O_3; Ozone in µg/m^3, and NO_2; Nitrogen Dioxide in µg/m^3 are the independent factors of August-November 2020 models.

Moreover, **Table 2** represents the regression summary for August-November 2020. Statistical Metrics have been calculated for regression models of each month. The Standard Error (SE) of each factor for model performance was reported. Also, the Standard Deviation (StD) of measured and estimated $PM_{2.5}$ data has been calculated. Moreover, Normalized Mean Square Error (NMSE), Mean Bias Error MBE, and Root Mean Square Error RMSE were calculated based on measured and estimated data used in the model. The estimated model correlation coefficients (R^2) for August to November, are also shown in the table with values of 0.89, 0.95, 0.98, and 0.96 respectively.

Furthermore, **Table** 3 represents EPA air quality standards. The classifications of predicted and range of pollutants were based on the levels reported in the table.

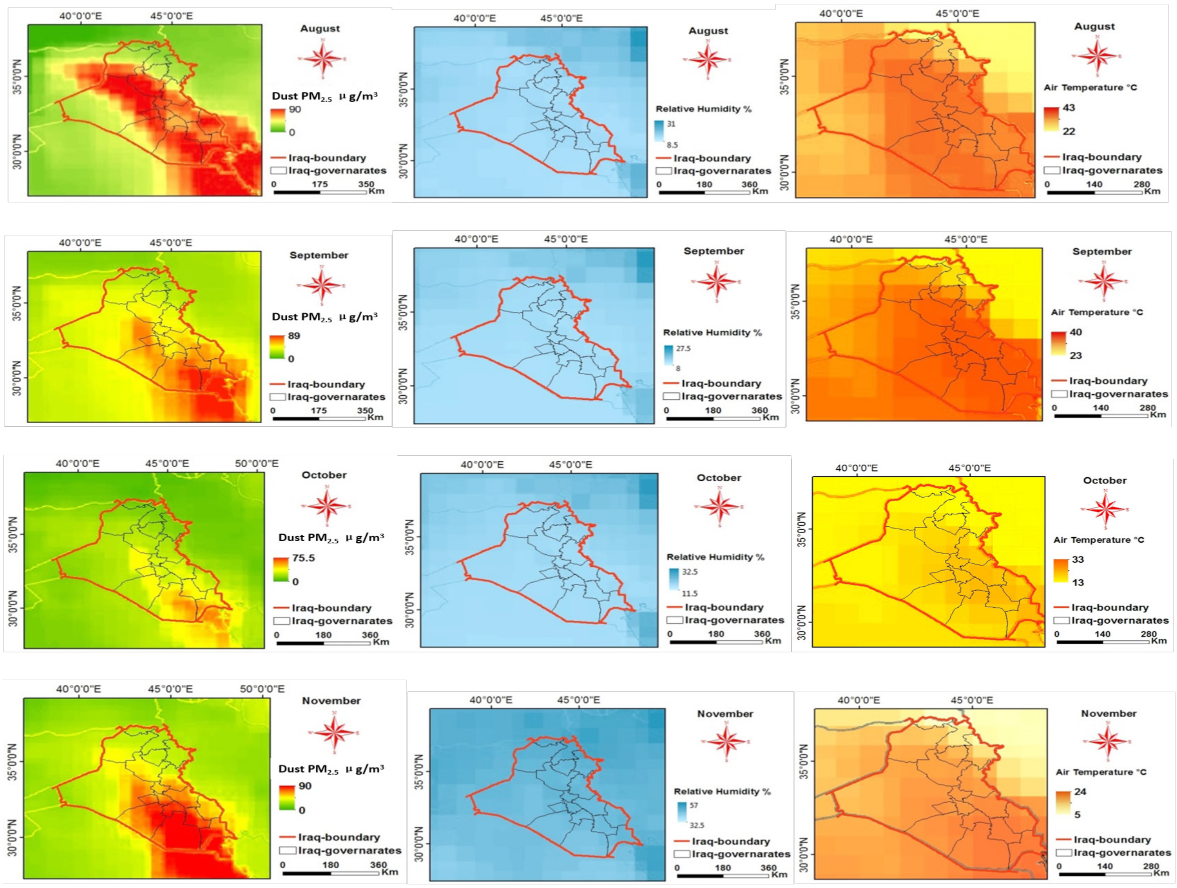

Figure 3. Remotely sensed datasets spatial distribution maps of dust and meteorology.

Commonly, the attained distributed dust $PM_{2.5}$ measure ranged from about 0 to 90 µg/m^3 in August-November 2020. While RH values were extended from 8%–57% in August-November 2020. On the other hand, T values ranged from 5°C–43°C in August-November 2020.

Moreover, the attained distributed NO_2 measure ranged from about 0 to 9.6 µg/m^3 in August-November 2020. While O_3 values were extended from 19.90–23.31 µg/m^3 in August-November 2020. On the other hand, SO_2 values ranged from 1–45 µg/m^3 in August-November 2020.

Furthermore, based on OLS the ArcGIS spatial statistic modeling tool, the estimated dust $PM_{2.5}$ levels from August to November 2020 were mapped in **Figure 5**. The predicted data ranged from 7.96 to 98.66 µg/m^3.

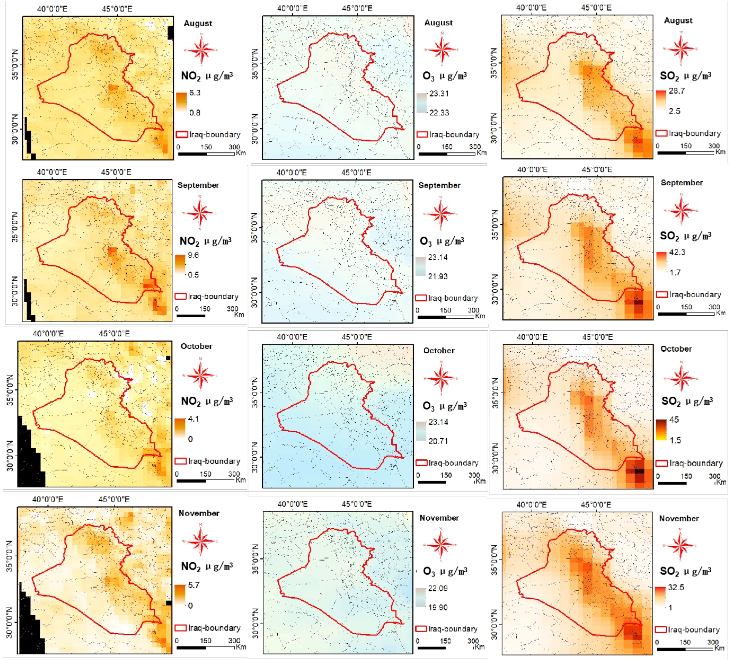

Figure 4. Remotely sensed datasets spatial distribution maps of gaseous pollutants.

Table 2. Regression summary for August-November 2020.

Time	Equation	Factor	Coefficient	Statistical Metrics	
August 2020	Equation (3)	β_0	–585.4	R^2	0.89
		T	12.9	StD Measured	22.3784
		RH	–2.7	StD Estimated	21.2694
		SO_2	–0.8	NMSE	0.0977
		O_3	8.6	MBE	1.2486
		NO_2	–1.3	RMSE	6.9950
September 2020	Equation (4)	β_0	–189.2	R^2	0.95
		T	7.2	StD Measured	22.6388
		RH	–6.8	StD Estimated	22.1864
		SO_2	0.7	NMSE	0.0435
		O_3	2.4	MBE	–0.0411
		NO_2	–0.3	RMSE	4.7222
October 2020	Equation (5)	β_0	–70.2	R^2	0.99
		T	6.1	StD Measured	18.9941
		RH	–4	StD Estimated	18.7871
		SO_2	–0.1	NMSE	0.0150
		O_3	–0.8	MBE	0.8045
		NO_2	–0.003	RMSE	2.3297
November 2020	Equation (6)	β_0	296.7	R^2	0.96
		T	3.9	StD Measured	28.0076
		RH	–6	StD Estimated	27.7258
		SO_2	0.1	NMSE	0.0338
		O_3	–4.5	MBE	0.2281
		NO_2	1.6	RMSE	5.1518

Table 3. EPA air quality standards.

AQI I_{Low}–I_{High}	**$PM_{2.5}$ (μg/m^3)** D_{Low}–D_{High}	**PM_{10} (μg/m^3)** D_{Low}–D_{High}	**NO_2(PPB)** D_{Low}–D_{High}	**SO_2(PPB)** D_{Low}–D_{High}	**Air Quality**
0–50	0–12.0	0–54	0–53	0–35	Good
51–100	12.1–35.4	55–154	54–100	36–75	Moderate
101–150	35.5–55.4	155–254	101–360	76–185	Unhealthy for sensitive groups
151–200	55.5–150.4	255–354	361–649	186–304	Unhealthy
201–300	150.5–250.4	355–424	650–1249	305–604	Very Unhealthy
301–500	250.5–500.4	425–604	1250–2049	605–1004	Hazardous

Source: Jumaah et al [6].

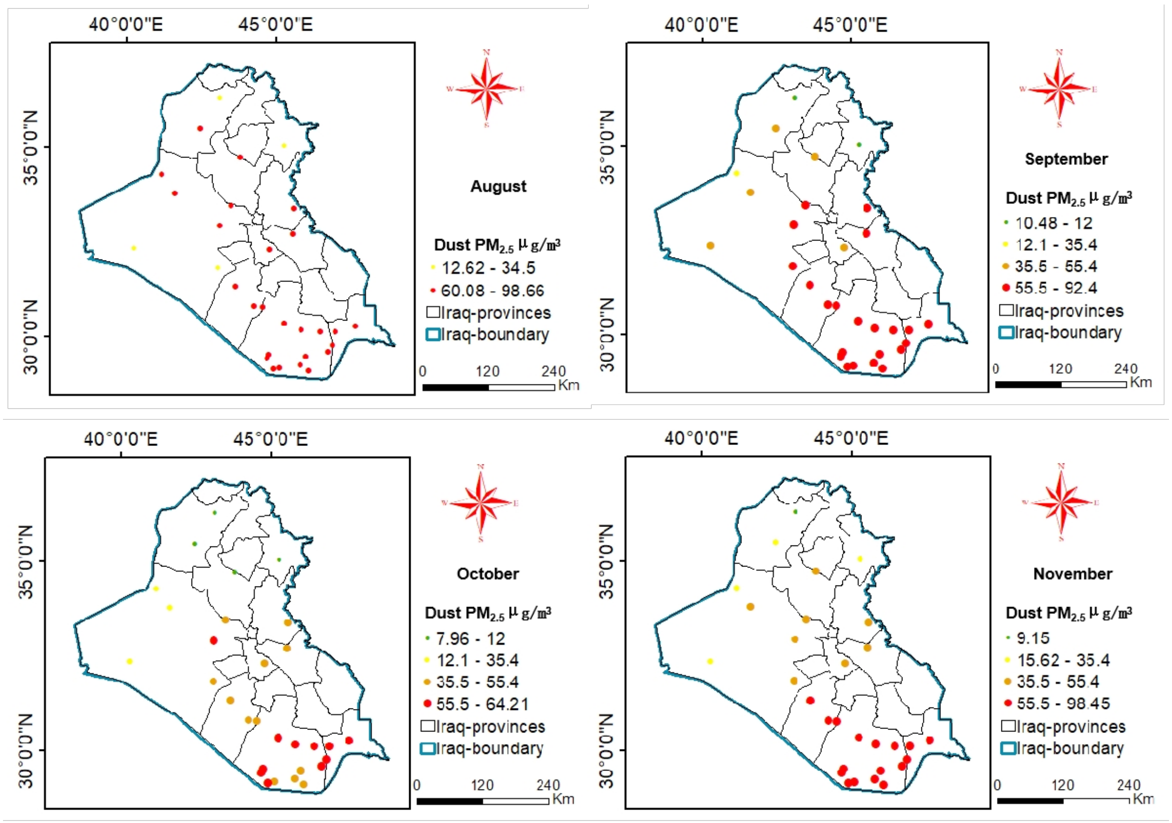

Figure 5. Estimated dust $PM_{2.5}$ levels from August to November 2020.

3.2 Validation

Researchers use the fitting method, involving mathematical equations and non-parametric techniques to model the info. Two processes of validation were applied; one represents the model performance generated in modeling that correlates remotely sensed data of dust $PM_{2.5}$ with the estimated dust $PM_{2.5}$. The second validation represents the model evaluation using additional datasets, and correlates the ground truth of dust $PM_{2.5}$ with the estimated dust $PM_{2.5}$. Researchers use 30% of trained data for evaluating models, here we used a maximum of ten ground truth points for model evaluation. The second validation is applied on two datasets (August and September) based on the availability of historical data.

Figure 6 represents linear and polynomial model performance validation from August-November 2020. **Figure 7** represents the linear and polynomial model evaluation validation of August-September in 2020.

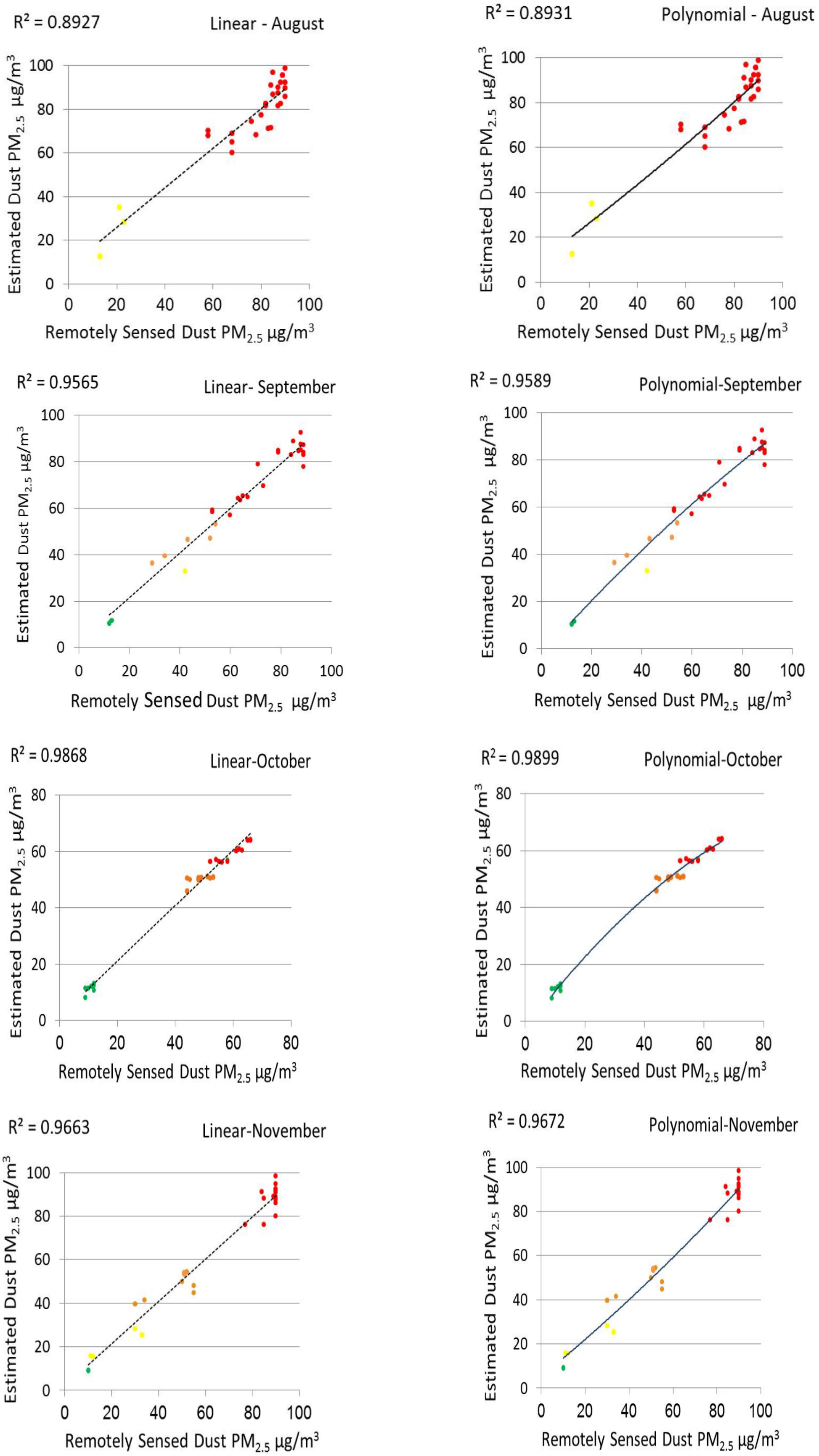

Figure 6. Linear and polynomial model performance validation of August-November.

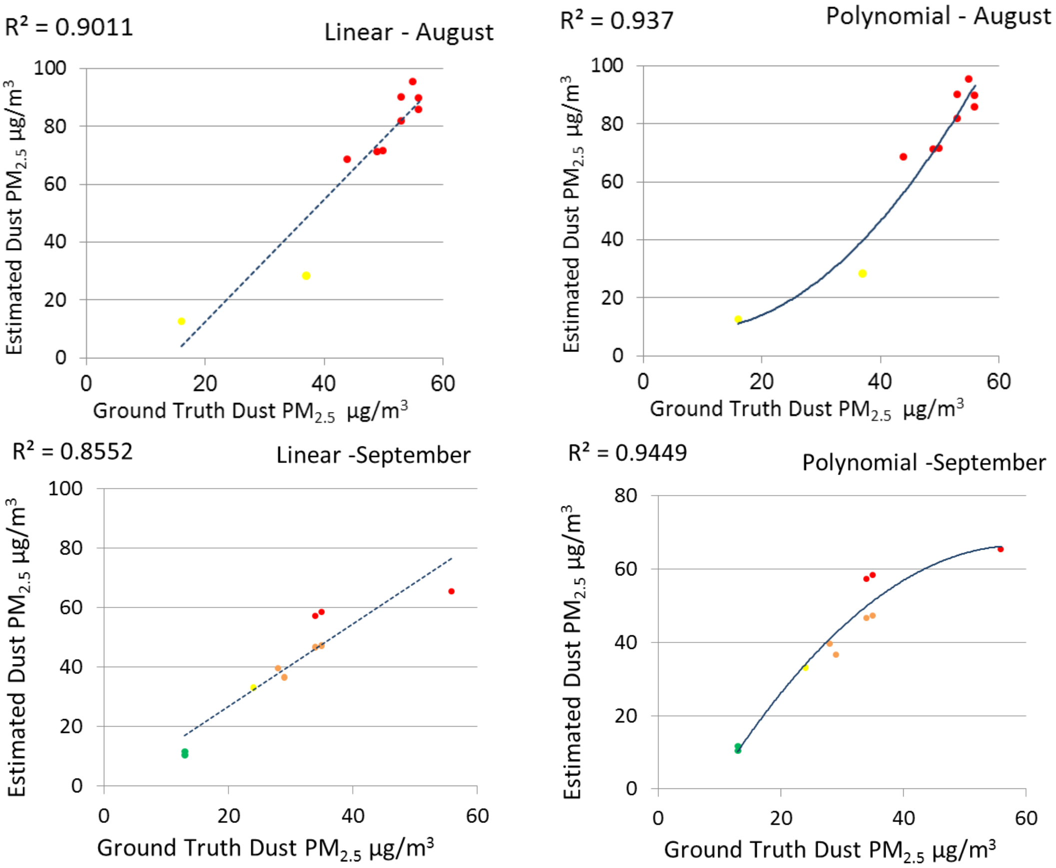

Figure 7. Linear and polynomial model evaluation validation of August-September.

3. Discussion

As shown in **Figure 3** specifically, the concentrations of dust $PM_{2.5}$ were high, exactly in the southern parts of the study area. Based on **Table 3** EPA standards, the air quality is unhealthy covering large parts of the region. Central parts of Iraq revealed moderate air category in terms of dust PM2.5. North-East parts showed good air quality which is represented with slight coverage in the study area.

In **Figure 4** the distributed remotely sensed gaseous pollutants reported a good state of air quality. According to [6,26] the EPA standard (**Table 3**) and national ambient air quality criteria for NO_2, O_3, and $SO_{2,}$ our results report low levels of these pollutants. No health effects fall in these levels inside the study area. Based on **Figure 5**, in August, the predicted $PM_{2.5}$ was about (12.62–98.66) $\mu g/m^3$. According to Hamed [22] the health effects in this range are (moderate, and unhealthy air quality). In September the dust $PM_{2.5}$ concentration was about (10.98–92.4) $\mu g/m^3$. While in October was (7.96–64.21) $\mu g/m^3$ and in November ranged from (9.15–98.45) $\mu g/m^3$. Based on $PM_{2.5}$ standards reported by Hamed [22] the air category is described as (Good, moderate, unhealthy for sensitive groups, and unhealthy).

Based on **Table 2**, the independent factors (climatic data) demonstrated high relationships with dust $PM_{2.5}$. The correlation is significant with dust $PM_{2.5}$. Besides, a high R^2 was acquired from regression analysis, which refers to the strength of the model. Furthermore, the study analysis achieved the purpose of finding the relationship between climatic factors that affect the linear correlation.

Based on **Figures 6** and **7**, the validation is to test the power of the model's equations. Where the estimated dust $PM_{2.5}$ levels fit alongside the remotely sensed dust $PM_{2.5}$ levels for model performance. The models shown a positive pattern referring that when all independent variables are increased, the estimated $PM_{2.5}$ values also increase, this also reported by Mahmood and Jumaah [27] using artificial intelligence and air quality modeling. The model evaluation also had positive trends. Furthermore, Jumaah [6] conducted an air pollution investigation in 2020 in Iraq and reported the same bad air quality. Climatic effects studied [28] using regression technique integrated with Artificial Neural Network ANN concluded climatic effect on pollutant levels. The formulation and implementation of practical ideas and techniques for air pollution reduction calls for a strong basis for the determination of the concentration of the pollutants. Concerning the effects of pollution on the lives of individuals of all ages, the need to act against pollution is very essential [29].

4. Conclusions

This study discussed the influence of climate factors like relative humidity and air temperature on dust daily $PM_{2.5}$ (particulate matter) levels. This investigation used the OLS (ordinary least squares) and polynomial modeling to predict the $PM_{2.5}$ levels from measured data from August to November 2020. The discovery emphasizes the possible climate effects patterns in the area directly on the model's representative indication. Moreover, the pattern of the models was performance assessed through validation methods of techniques. This study displayed the findings in which the obtained accuracy has been very high, with R^2 values of 0.89, 0.95, 0.98, and 0.96 for each given month from August to November 2020. The models, after review, exhibited a positive pattern such that when the climatic variables were greater, the $PM_{2.5}$ values estimated using the dust model also increased. At the same time, the study revealed the large role maintained by meteorological information in predicting the amount of $PM_{2.5}$ in dust $PM_{2.5}$ levels. The results shed light on the role played by air pollution in inter-acting with climatic factors in the research region. The next step in the research is to develop more complex models and study the connections beyond the hypothesized ones to better the prediction and intervention.

Furthermore, this research also looked into the risks posed to human health by particulate matter ($PM_{2.5}$), where the cases are distributed across the study area will also be taken into account. Such a survey demonstrated various air pollution types, with the categories of good to unhealthy being indicators of health risks concerning high levels of $PM_{2.5}$. Moreover, it stressed the usefulness of remote sensing information and statistical analysis in air quality research. The use of satellite imagery appeared to be the exact analog of precise and quantitative $PM_{2.5}$ level forecasting, thus broadening comprehension of air quality. It turned out that more specific attention should be paid to industrial activities as a source of air pollution.

The study suggested the enforcement of monitoring and regulation policies aiming at keeping the amounts of particles and pollutants in the factories at a minimum. Such a case underlines the necessity to decrease industrial emissions in such places with the help of targeted interventions and strictly regulating air quality to improve health. Noteworthy, the investigation brought some knowledgeable insights pertaining to $PM_{2.5}$ levels as well as spatial distribution and their impact on human health. They illustrated the value of geographical information system (GIS) analysis as well as the remote sensing data for the same purpose.

Hence, for successful reduction in air pollution, there remains a need for additional research and teamwork to develop efficient measures and influence air quality positively in a lasting way.

The obtained result highlights the paramount role of climatic parameters in air pollution in Iraq. Through the synergy of remote sensing information and historic climatic data, a polynomial model is constructed, which provides us with complex climate-air quality bond patterns. The outcome of this work gives a basis for responsible management, enhances the air quality development plans, and provides an approach to diminish the factors of climate impact on air quality in Iraq. Future research can focus on long-term trends and the impact of climate change on air quality in Iraq.

Author Contributions

H. J. Jumaah gathered study data and applied the analysis; M.A. Dawood; wrote the introduction, Sh. Mahmood; discussed the results; H. J. Jumaah edited and updated the paper.

Conflict of Interest

The authors confirm that there are no competing financial interests or personal relationships that would have a potential influence on the work reported in this paper.

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Data Availability Statement

Data that support the findings of this study are available on request from the corresponding author Huda Jamal Jumaah.

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