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Air Pollution in Agra: ARIMA-Based Forecasting and Its Health Implications

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Abstract: Air pollution is a global concern that has severe effects on the environment and public health. This research seeks to discuss various indoor and outdoor pollutants which are all predicted using the Auto Regressive Integrated Moving Average (ARIMA) model. An ARIMA model can accurately predict pollutant levels thus helping in making interferences aimed at improving air quality by employing historical information from specific sites within Agra City. Various error metrics determine the effectiveness of the ARIMA model in increasing awareness levels and the need for immediate action toward the reduction of harmful substances. The results indicate promising outcomes with Root Mean Square Error (RMSE) values around 1.358 for NO_2, 2.2615 for SO_2, and 1.2501 for PM_{10}, respectively, hence suggesting that the predictions are highly accurate regarding the amount of pollutants present in the air. These findings have a significant effect on employing data-driven approaches to prevent air pollution as well as promoting environmental sustainability.

Keywords: Air pollution, ARIMA, World Health Organization (WHO), Pollutants, health risks

I. INTRODUCTION

Air pollution is a significant challenge for people all over the world because of the numerous adverse effects it has on human health [1-4]. More than 10% of all-cause accidental deaths in 2012 were attributed to ambient air pollution, according to the WHO [5]-[6], which was more than double as compared to the previous estimate. This figure has exceeded more than 20% in 2022. The widespread impact of air pollution, climate change, and global warming on ecosystems and human health has made it a serious concern on a worldwide scale. Aside from endangering human life, air pollution has triggered a climatic change and biodiversity loss. The primary cause is the rise in atmospheric pollution from the release of harmful gases and particles. Both natural and man-made processes, including cooking in homes, driving, manufacturing, building, and cutting down trees, etc., release gases and particulate matter (PM) into the air [7]-[8]. Approximately ½ of the metropolitan inhabitants that are being considered are subjected to air pollution that is at least 2.5 times higher than the levels that are recommended by the WHO for air quality requirements.

According to recommendations for air quality, the six ambient air pollutants that have the most severe impacts on people all over the globe are PM, O_3, NO_2, SO_2, Pb and CO.

The potential impacts of air pollution on human health are a contemporary issue in both industrialized and developing nations [9]. On a global scale, fine particulate matter (PM) is known to be a leading cause of outdoor air pollution and a significant contributor to health risks [10]-[11]. In contrast, NO2 is the major source of indoor pollution among pollutants. In contrast to outdoor levels, primarily caused by vehicular traffic, indoor levels were much higher when NO2 sources, such as gas appliances, were present [12]. Studies have shown that NO_2 levels inside are much greater than outside levels in both Italy and the United States [13]. It was found that gas stove usage, ventilation and outside NO_2 levels were the top three causes of interior NO_2 concentrations [14]. Infants and the elderly spend an even larger proportion of their time inside than the general population, making them more vulnerable to this risk [15]-[16]. A wide range of health issues and symptoms, such as breathlessness, cold and cough, chest pain, and breathing disorders, are related to increased indoor NO_2 concentrations in children who suffer from asthma [17].

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Cities in India are classified as extremely polluted by the CPCB (Central Pollution Control Board) if the levels of criterion pollutants are more than 1.5 times the defined standards. New Delhi, Beijing, Agra, Shanghai, and Mumbai are identified as the cities with the highest levels of pollution in the world [18]-[19]. As the concentration of pollutants in the air continues to rise, it leads to severe health problems [20]. It has a direct impact on a population of millions of people who are experiencing symptoms ranging from shortness of breath and eye irritation to chronic respiratory illnesses, pneumonia, acute asthma, and other similar conditions [21]-[22]. Therefore, it is essential to conduct an analysis of the current state of urban pollution and to determine the extent to which it affects human health to carry out comprehensive environmental planning for the city. Rapid Urbanization and population explosion have resulted in increased pollution levels in Agra. There has been a danger to the lives of persons as well as their well-being from dust, smoke and other poisonous gasses. Therefore, keeping this in view in mind this study has made an effort to examine the current state of environmental quality in Agra city.

II. LITERATURE REVIEW

This section provides context and insight into the study of air quality by determining the findings of various previous studies. The analysis focuses on the distribution of pollutants and evaluates the influence of these pollutants on human health.

The ARMA/ARIMA modelling approach was described by **Imran Nadeem et al. (2020) [23]** as a means of forecasting NO2, SO2, RSPM, and concentrations for the three most polluted sites in Chennai. Nine univariate linear stochastic models were created to forecast each pollutant's concentration at these three locations. An index of contract values and R2 values were used to assess the data from the created ARMA/ARIMA model, which significantly aids in the achievement of real-time pollution forecasting.

This study suggested that the ARMA (1, (1,3)) + model prediction could provide scientific support for TB prevention and control in Urumqi, China. **Zheng Y (2020)** [24] established the ARMA (1, (1, 3)) + model by the time series ARMA model method, cross-correlation analysis, and the principal component regression method, and its forecast performance was better than in this study. The investigation revealed that the incidence of tuberculosis increased with ozone concentration.

In Varanasi, India, seasonal data on air pollutants from 2013 to 2106 were examined by A. **Jaiswal et al. (2018)** [25]. Using historical pollution data from Varanasi's AQI station, this study offers a statistical trend analysis of various air pollutants using Mann-Kendall and Sen's slope estimator approach. The ARIMA model has also been used to forecast future air pollutant level values. The ARIMA model (1,1,1) was shown to be the most appropriate for the predictive modelling of different contaminants in Varanasi after several ARIMA model approaches for predictive analysis were tested using goodness of fit statistics.

Considering monthly air quality data from 2012 to 2015 at four sites in Thiruvananthapuram District, **Naveen V et al.(2017)** [26] examined the levels of NO2, SO2, SPM, and RSPM. The data were collected from the KSPCB. When air quality was forecast using the ARIMA and Seasonal ARIMA methods, it was discovered that the ARIMA models produced more accurate results than the SARIMA model. Additionally, the error between the actual and projected AQI has decreased with the use of these optimisation strategies. To get more accurate results, these findings might be integrated with those from other models.

Based on land use regression approaches for particulates with an aerodynamic diameter (PM10) and NO2, **Fischer PH et al. (2015)** [27] assessed national databases (Netherlands) on mortality, individual characteristics, neighborhood characteristics, residence history, and national air pollution maps. In a Dutch sample of 7.1 million people, they employed Cox proportional hazard models to account for potential person and area-specific confounders and discovered that long-term exposure to PM10 and NO2 was linked to non-accidental and cause-specific mortality.

III. MATERIAL AND METHODS

In this study, we collected air pollution data of the annual distribution from the CPCB monitoring stations in Agra District, spanning from 2015 to 2022. We extracted average concentrations of major air pollutants (NO_2, SO_2, and PM_{10}) from all these monitoring stations. This section showcases the suggested model that uses the ARIMA model to predict the levels of air pollution.

3.1 Area of Study

Agra is a metropolitan city situated on the banks of the sacred Yamuna River, which lies about 200 km south of New Delhi in the Indian state of Uttar Pradesh, in the country's north-central region. The overall population of the city is about 4,418,797, with a population density of roughly 1084 persons/km^2 [28]. The geographical map of Agra is shown in Figure 1 given below.

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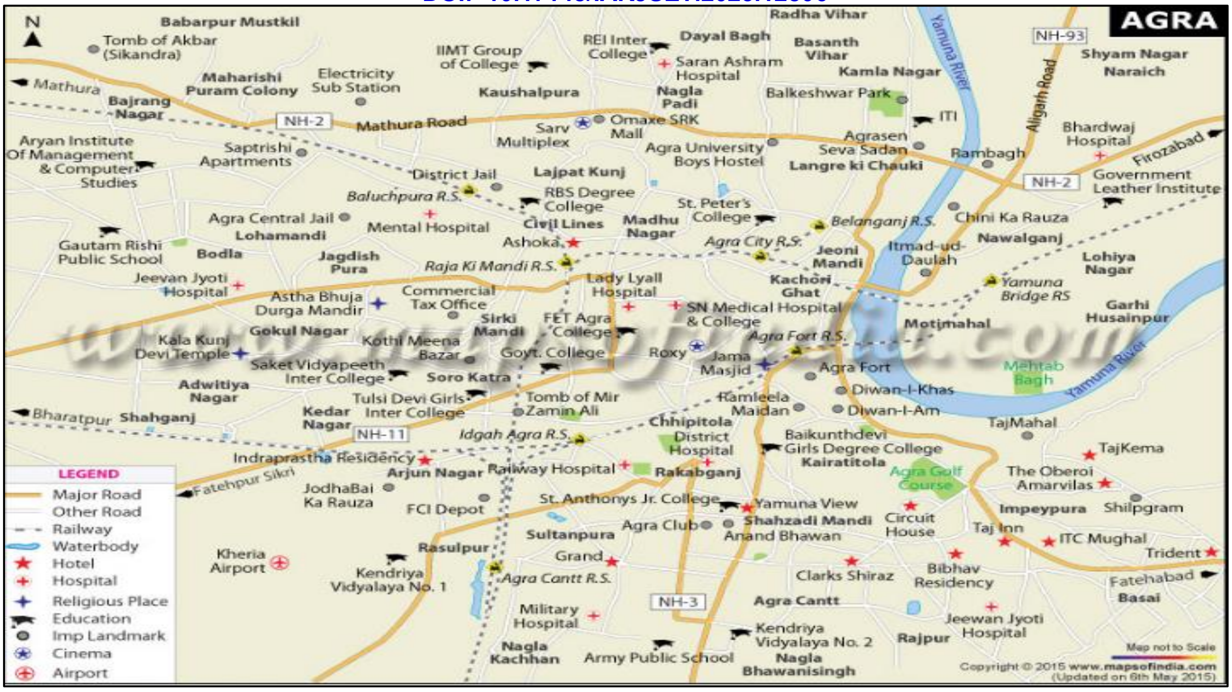

Figure 1. Geographic map of Agra [29]

3.2 Air Quality Index Range and corresponding impact

The AQI range is divided into 6 levels, which represent air quality from the highest to the lowest level, their corresponding air quality levels, categories, representative colours, and impacts on human health, as shown in Table 1 [30].

Table 1. AQI Range and its impact

Air Quality Level	AQI Range	Representative Color	Air Quality Category	Impact on Human Health
Level 1	0-50	Dark Green	Good	Negligible effect
Level 2	51-100	Light Green	Satisfactory	Some persons with sensitive breathing may experience mild pain
Level 3	101-200	Yellow	Moderate	Breathing difficulties in youngsters, older people, and those with preexisting conditions like lung or heart disease
Level 4	201-300	Orange	Poor	Long-term exposure causes individuals to have breathing difficulties.
Level 5	301-400	Red	Very poor	Consequences of long-term exposure on respiratory health
Level 6	>401	Maroon	Severe	Influence on the respiratory system, even in a healthy population

3.3 Enhancing Air Pollution Forecasting using ARIMA Modeling through R Programming

This section describes the development of an ARIMA model through R programming to predict atmospheric pollutants using historical data. Through the integration of R programming and ARIMA modeling, the development of accurate and reliable statistical models becomes instrumental in addressing the challenges posed by air pollution [31-34]. R offers specialized packages such as forecast, tseries, and stats for time series analysis and modeling. The ARIMA model that is used for the purpose of forecasting the future values of a time series by making use of past data. The ARIMA model must be stationary in order for it to be successful in its application. In order for a model to be considered stable, it must possess a mean that is continuous, a variance that is constant, and auto-correlation that is time-independent.

In this study, the Dickey-Fuller Test is utilized to determine if the suggested model exhibits stationarity or not. If the model does not pass the stationarity criteria, then use differencing to create a stationary time series. The first contrasting value is the change from one time interval to another. If the model has not yet become stationary, continue with the second differencing. In order to obtain a stationary model, continue doing this.

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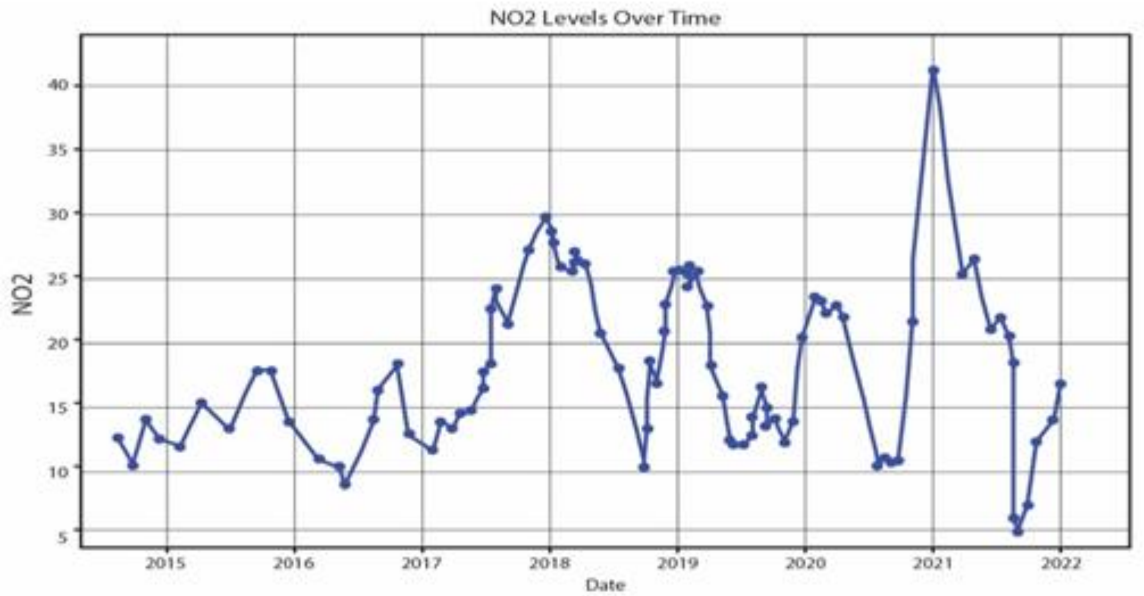
The ARIMA model combines the moving average (MA) and auto-regressive (AR) components, with the difference component serving as the independent variable (I). When two time periods are auto-correlated, it means that there is a relationship between the two. A model is considered auto-regressive if and only if such a relationship exists [35]. The ARIMA model consists of three primary parameters: The variables p, d, and q represent different parameters in the context of autoregressive models. Specifically, p refers to the total number of auto-regressive delays. The value of d is the total amount of differencing operations needed to transform the time-series into a stationary. The q signifies the ordering of the moving average, which refers to the number of past values that are used to anticipate current values by measuring the variations from the mean of the time series [36].

IV. RESULT AND DISCUSSION

This section presents a comprehensive analysis of the results obtained from the experiment:

4.1 Annual distribution of major air pollutants (2015-2022)

The graph in Figure 2 depicts the levels of concentration of NO_2, SO_2, and PM_{10}, respectively in residential areas of Agra over the given duration. The data available here clearly shows how different pollutants vary in terms of their levels as well as the changing trends they have gone through within this period.



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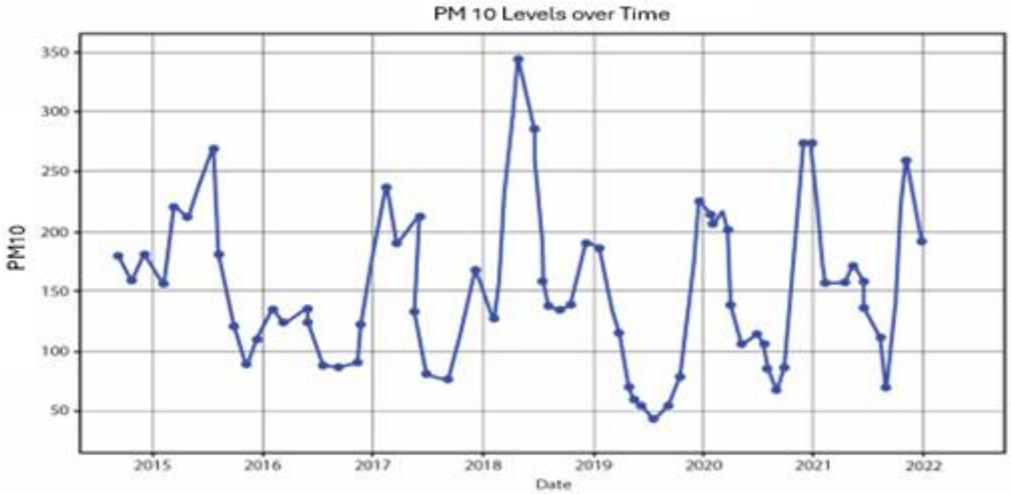

Figure 2. Distribution of (a) NO_2 (b) SO_2 (c) PM_{10} over a specified period

4.2 Dickey-Fuller test

The Dickey-Fuller test has been applied separately for each pollutant: NO_2, SO_2, and PM_{10} to check for the stationarity of the model. The Dickey-Fuller Test determines whether or not the model is stationary. The model is said to be stationary if the computed p-value is very small and the critical values exceed the test statistics. Figure 3 shows the Dickey-Fuller results for each pollutant, thus confirming how stationary these data are and providing a comprehensive analysis to better understand how NO_2, SO_2, and PM_{10} change over time.

```
Dickey-Fuller Test Results for NO2:
Test Statistic: -5.171134858956569
p-value: 1.0066883557264755e-05
Critical Values:
   1%: -3.498198082189098
   5%: -2.891208211860468
   10%: -2.5825959973472097

Dickey-Fuller Test Results for PM10:
Test Statistic: -5.845382667518295
p-value: 3.6940989655175294e-07
Critical Values:
   1%: -3.498198082189098
   5%: -2.891208211860468
   10%: -2.5825959973472097

Dickey-Fuller Test Results for SO2:
Test Statistic: -5.445353673653751
p-value: 2.7182676211269487e-06
Critical Values:
   1%: -3.498198082189098
   5%: -2.891208211860468
   10%: -2.5825959973472097
```

Figure 3. Dickey-Fuller test for each pollutant

4.3 Parameter values

The order of the ARIMA model is established using the Partial Correlation Function (PACF) and Auto Correlation Function (ACF) graphs once the model has become stationary by differencing. Graphs for PACF and ACF for NO_2, SO_2, and PM_{10} are shown in Figure 4. Once the order of the ARIMA model is evaluated, it is assessed using p, d, and q values of (1, 1, 1) correspondingly. The RSS value of the ARIMA model for all pollutants is around 223.1782. The assessed model is considered superior if RSS has a lower value.

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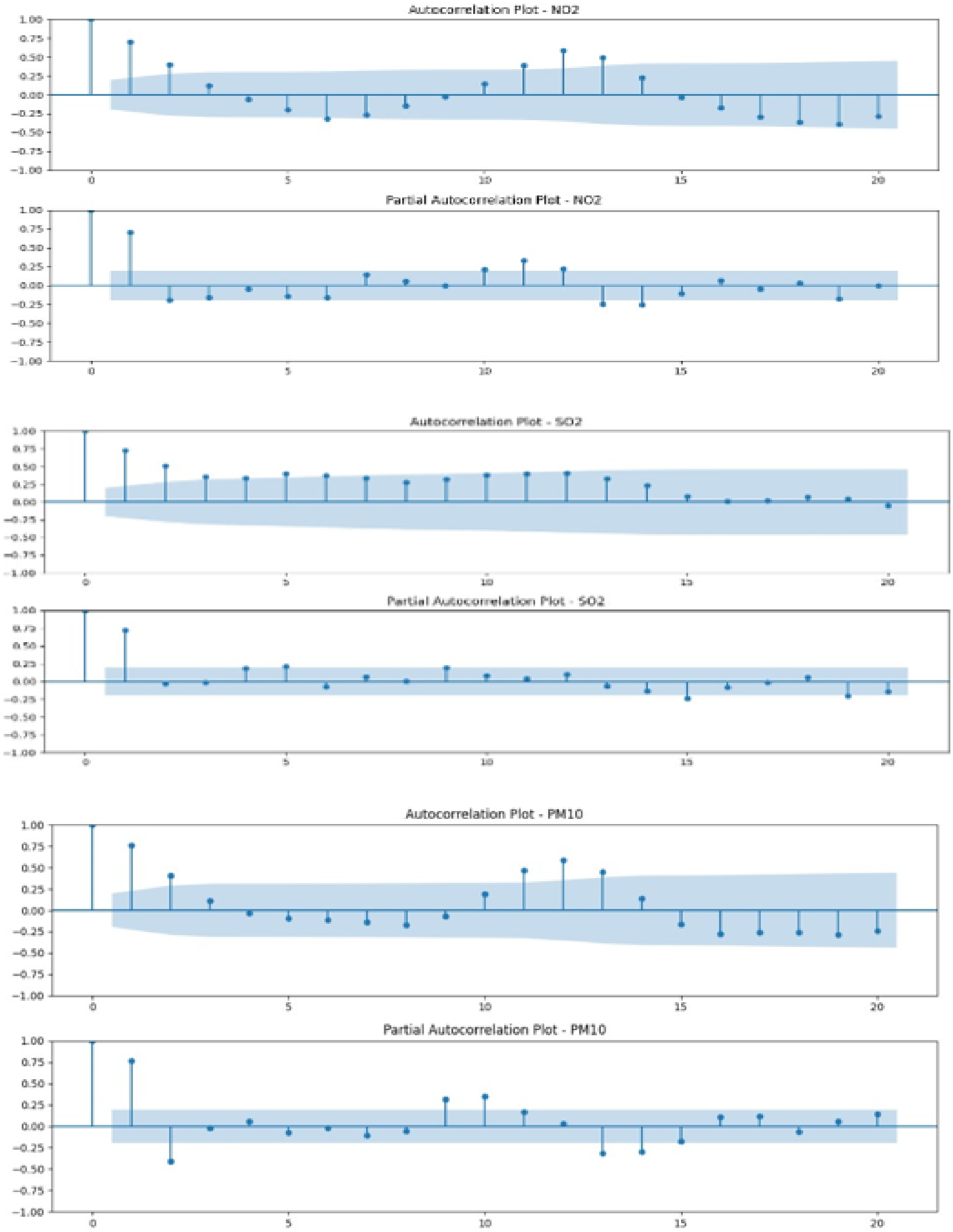

Figure 4. PACF and ACF graphs for NO_2, SO_2, and PM_{10}

4.4 Forecasted value of next 10 years

The following graph employs the ARIMA model to estimate the levels of indoor and outdoor air pollutants such as NO_2, SO_2, and PM_{10} in Agra over the next ten years. Figure 5 demonstrates the predicted values, which are based on a confidence interval of more than 90%.

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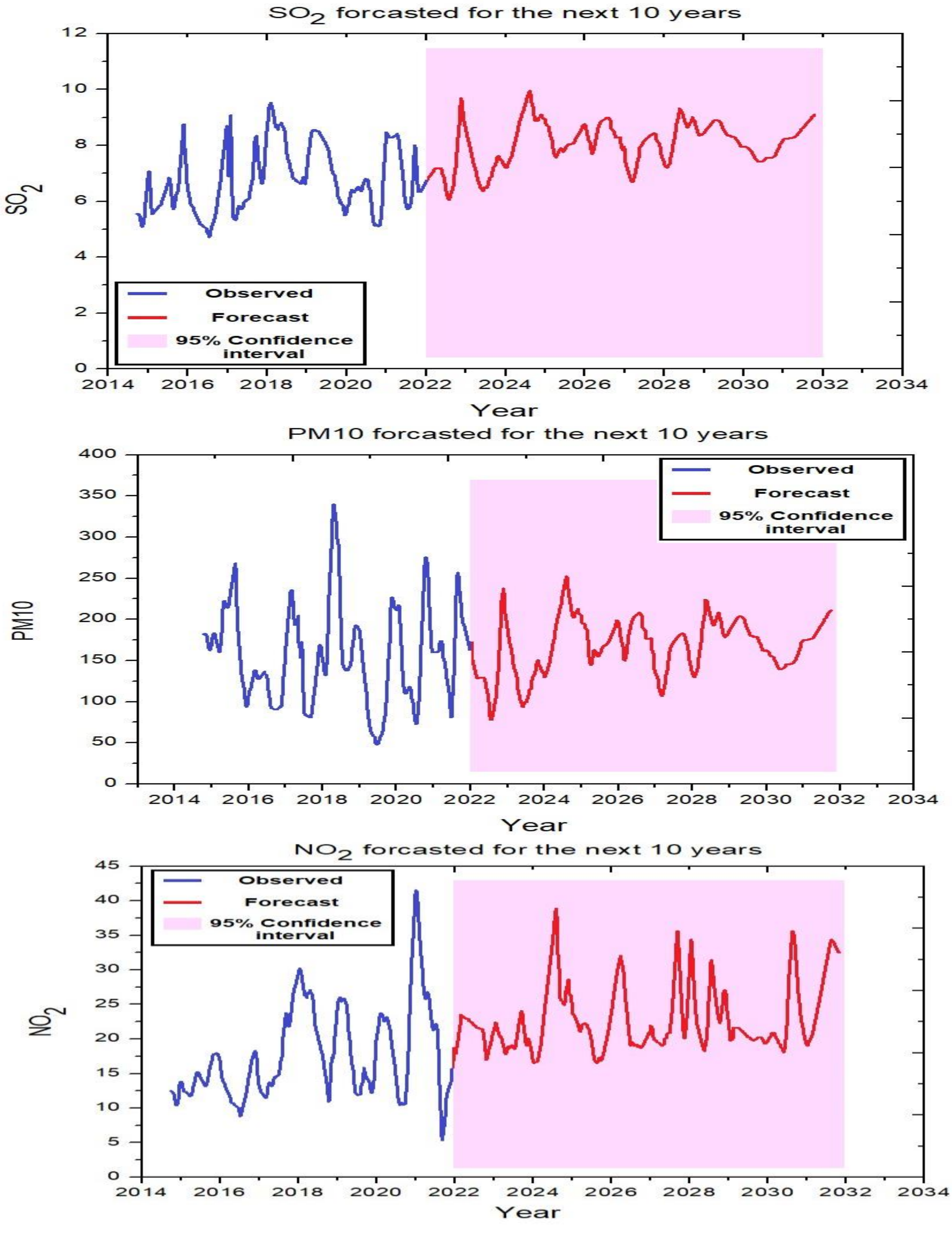

Figure 5. Pollutant forecasting for the next 10 years

4.5 Performance evaluation of ARIMA model

In order to assess the ARIMA model's predictive performance for pollutant levels, various metrics, including Mean Absolute Error (MAE), RMSE, Mean Squared Error (MSE), and Mean Squared Logarithmic Error (MSLE), Mean Absolute Percentage Error (MAPE), Median Absolute Error, R-squared Error (R^2), Explained Variance Score (EV) are calculated. The outcomes illustrated in Table 2 for the ARIMA model reveal that the RMSE value is the smallest among these errors, indicating a higher level of accuracy and reliability in the model's predictions.

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Table 2. Errors calculated for the ARIMA model for each pollutant

Performance metric	Pollutants		
	NO_2	SO_2	PM_{10}
MSE	5.7346896284	5.1147893983	3.0939176424
MAE	1.2744960164	1.9533690503	1.3712075453
RMSE	1.3585876874	2.2615900155	1.2501740587
EV	2.7806754451	0.0002060642	0.5367899792
R^2	2.2083752484	0.3563133460	0.3081334233
MSLE	0.7055495955	0.1104521586	0.3505285163

V. DISCUSSION

The spatial distribution of air pollutants such as NO_2, SO_2, and PM_{10} in the Agra district is crucial for understanding local air quality dynamics. The analysis of this study indicates significant variability in pollutant levels across different parts of the district, as evidenced by the ARIMA model errors. These differences suggest that local emission sources, including industrial activities, vehicular emissions, and geographical factors, contribute to differing pollutant concentrations. This underscores the need for targeted interventions to mitigate air pollution and safeguard public health, particularly in areas with elevated pollutant levels. This supports the hypothesis that industrial activities, vehicular emissions, geographical factors, and other factors would cause air pollutants to have different concentration levels in the Agra District.
Long-term exposure to high levels of air pollutants in the Agra district is associated with increased incidences of respiratory diseases, cardiovascular conditions, and other health issues. The analysis suggests a significant correlation between pollutant concentrations and adverse health outcomes, supporting this hypothesis. Implementing stringent air quality regulations and promoting cleaner technologies are crucial for minimizing the detrimental impact of air pollution on public health. This validates the hypothesis that in the Agra district, chronic exposure to high amounts of air pollutants causes increased instances of respiratory diseases, cardiac conditions, and other health issues among people living there.

VI. CONCLUSION AND FUTURE SCOPE

The study focused on the crucial concern of air pollution globally, emphasizing its harmful effects on the environment and human health. The study employed the ARIMA model for predictive analysis, focusing on air pollutants, namely NO_2, SO_2, and PM_{10}. By using a dataset that had pollutant observations over a certain period in a specific location in Agra city, accurate forecasting of pollutant levels was achieved. This helps in evaluating whether the application of the ARIMA model has met WHO standards, thereby making the public and governments more aware. The study evaluates various error metrics for each pollutant used in performance assessment thus providing an overall understanding of the effectiveness of the ARIMA method in the decision-making process regarding management of environment as well as public health initiatives. It would be beneficial if future investigations covered more pollutants to improve accuracy by incorporating real-time datasets within them into this model. Similarly, deeper insight into pollutant dispersion patterns could be acquired by integrating machine learning algorithms with spatial analysis techniques thus paving a path toward directed strategies for improving air quality.

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