Assessing the Impact of COVID-19 Regulations on Air Quality in Asian Cities: A Time Series Analysis

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ABSTRACT
Air pollution represents a growing threat to ecosystems and the health of all living organisms, carrying risks of heart and respiratory diseases, as well as a spectrum of other health issues. The outbreak of the COVID-19 pandemic prompted worldwide lockdowns, effectively restricting outdoor activities, and imposing strict controls on vehicular movement. This period of stringent regulations led to discernible changes in air quality. This research leverages various time series analyses on Air Quality Index (AQI) data to assess the influence of COVID-19 on air quality. Our dataset comprises AQI records from nine major cities in Asia, spanning from January 2019 to September 2022. Rigorous data preprocessing procedures were applied to create a comprehensive dataset encompassing AQI readings from diverse urban centers. Through detailed analysis of AQI values and their temporal trends, we unveil the impacts of COVID-19 on air quality.

To model and forecast AQI values, we employed three distinct approaches: ARIMA, Prophet, and LSTM. Model selection was guided by comprehensive performance comparisons. Utilizing the chosen model, we forecasted future AQI values, providing insights into the anticipated air quality trends. Our findings conclusively demonstrate that COVID-19 regulations positively influenced air quality in all analyzed cities. Among the modeling techniques, ARIMA emerged as the standout performer, boasting the highest R-squared score. By generating AQI forecasts using the ARIMA model, we underscore the potential of regulatory interventions during the COVID-19 pandemic to exert a quantifiable impact on air quality. This research endeavors to deliver valuable insights that can inform global strategies for combatting air pollution. Ultimately, we aspire to contribute to the global mission of reducing air pollution, safeguarding the health of our planet, and promoting a sustainable future for generations to come.

Keywords
Time Series Analysis, COVID-19, Lockdown, Air Quality, Air Pollution, Air Quality Index (AQI).

1. INTRODUCTION
Air, an essential element for all living organisms, plays a vital role in sustaining life through respiration for animals and the process of photosynthesis for plants. However, the deteriorating quality of air due to escalating pollutant emissions poses a significant threat to human health, accelerates climate change, contributes to biodiversity loss, and perpetuates pollution and waste. Alarmingly, the World Health Organization estimates that seven million people prematurely lose their lives annually due to inhaling polluted air, affecting 99 percent of the global population [1]. Notably, the Asia-Pacific region, where approximately 92 percent of its four billion inhabitants are exposed to hazardous air pollution levels, accounts for 53 percent of global emissions [2]. Consequently, it is crucial to address the sources and impact of air pollution comprehensively. Based on data from the company's global network, Bangladesh is the country with the worst PM2.5 air pollution, while New Delhi in neighboring India ranks at the bottom of the list of capital cities for bad air. Chad, Pakistan, Tajikistan, and India round out the five worst nations for air quality [3]. Air pollution arises from a multitude of sources, both natural and anthropogenic, and can travel across regions, causing haze and having adverse biological effects. The identification of the most significant pollution sources depends on location and time of year. To assess air quality, eight key pollutants—particulate matter (PM) 10, PM2.5, ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), lead (Pb), and ammonia (NH_3)—are considered. These pollutants are subject to short-term national ambient standards, and their levels are quantified using the Air Quality Index (AQI), which informs the public about air cleanliness, pollution levels, and associated health risks. AQI values range from 0 to 500, with higher values indicating increased pollution and health risks [4]. Figure 1 lists the different sources of pollution.

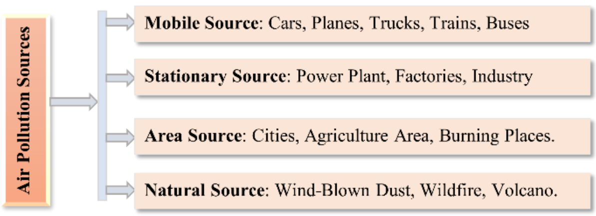


Fig 1: Different sources of air pollution.

As per CPCB's (Central Pollution Control Board) air quality standards, AQI is categorized into six parts [4], which are shown in Figure 2.

AIR QUALITY INDEX (AQI)	CATEGORY
0-50	Good
51-100	Satisfactory
101-200	Moderate
201-300	Poor
301-400	Very Poor
401-500	Severe

Fig 2: different air quality levels.

Life quality is lowered by poor air quality. Pollutants in the air can irritate people. Some have unpleasant odors. Some air contaminants led people to cancer and respiratory illnesses. People's capacity for physical activity may be restricted by poor air quality. People who already have diseases like asthma, emphysema, or COPD are more likely affected by the effects of poor air quality. The biggest health risk is posed by PM2.5, which is defined as particulate matter having a diameter of 2.5 micrometers or less. PM2.5 is frequently used as a metric in regulatory air quality requirements. Using Air Quality Index (AQI), we can get the information about environment condition and what will be the impact of polluted air according to AQI value on people day to day life [5]. Table 1 shows the health impact based on AQI value.

Table 1. Health impact according to AQI value

AQI Value	Health Impact
0-50	Minimal Impact
51-100	Sensitive people might experience minor breathing discomfort
101-200	Lung disease patients may have discomfort in breathing, and heart disease, children and older adults might experience discomfort.
201-300	Breathing discomfort on prolonged exposure, and discomfort to heart disease patients
301-400	Prolonged exposure might lead to respiratory illness. Severely affects people with lung and heart diseases
401-500	While healthy people may experience respiratory problems, lung or heart disease patients can have severe health impacts. Even during light physical activity, people may experience health impacts

The COVID-19 pandemic prompted lockdowns worldwide, restricting outdoor activities, travel, and industrial operations. Consequently, AQI values witnessed substantial reductions due to reduced emissions from industrial and vehicular sources. Analysis suggests that adopting cleaner technologies and better combustion practices in urban areas could mitigate ambient air pollution levels by up to 30%. During the lockdown, PM and NO2 concentrations decreased by more than 60% in many global cities, resulting in an average AQI reduction of 30-50% [6]. This study aims to analyze daily air quality indexes using time series analysis to assess the impact of COVID-19 lockdown measures on air quality. Key objectives include data collection, time series analysis of AQI data, evaluation of lockdown effects, statistical assessment of air quality changes, development of robust analysis methods, comparison of forecasting models, and proposing strategies to mitigate air pollution based on the research findings. The outcomes of this research will contribute to a better understanding of the influence of lockdown measures on air quality and inform future efforts to enhance air quality and reduce pollution levels.

2. RELATED WORKS

In recent years, there has been a growing interest in the application of deep learning techniques for time series forecasting in the context of air quality prediction.

Zaini et al. [8] conducted a comprehensive review of a system employing deep-learning neural networks for time series forecasting, outlining future development directions in this field. Espinosa et al. [9] proposed a multi-criteria methodology for air quality prediction, leveraging deep learning techniques such as GRU, LSTM, random forest, Lasso regression, and Support Vector Machine. Their model demonstrated reliable predictions of air pollutant concentrations, with a particular focus on nitrogen oxide, a known contributor to respiratory problems. Wang et al. [15] introduced an early warning system based on fuzzy time series, offering robust and accurate forecasts for major air pollutants. Their hybrid model combined fuzzy time series techniques with data reprocessing, providing a valuable tool for monitoring and analyzing air pollution. Jephcote et al. [16] conducted a national comparison of air quality changes during lockdown periods, highlighting the modest contribution of traffic to air quality and suggesting sustainable improvements across various sectors. Dey et al. [17] implemented counterfactual time series analysis to assess the impact of state-level emergency declarations on air pollution reduction, focusing on regional elements. This study provides a benchmark for estimating achievable air pollution reductions. Gao et al. [19] analyzed the spillover effect of COVID-19 lockdown policies on PM2.5 concentrations in Wuhan city, emphasizing the need for stringent lockdown measures to reduce emissions. Du et al. [20] introduced the Deep Air Quality Forecasting Framework (DAQFF), a hybrid deep learning model addressing dynamic, spatial-temporal, and nonlinear properties of air quality time series data. The DAQFF model exhibited strong generalization and forecasting capabilities. Tiwari et al. [21] employed deep learning methods, including LSTM and encoder-decoder LSTM, to predict air quality in Delhi over various prediction horizons, considering the effects of seasons and the COVID-19 pandemic. Lin et al. [22] developed a deep learning model, GC-DCRNN, for short-term PM2.5 concentration prediction, considering both spatial and temporal dependencies in air quality data. Freeman et al. [23] applied deep learning techniques to predict air pollution time series, enabling long-range forecasting while prioritizing critical characteristics. Al-qaness et al. [24] proposed an adaptive neuro-fuzzy inference system (ANFIS) for air quality prediction in Wuhan, achieving superior performance compared to other algorithms and highlighting significant decreases in pollutant concentrations. Liu et al. [25] discussed fundamental forecasting algorithms, including shallow and deep learning predictors, exploring data processing techniques and hybrid approaches to improve forecasting capacity. Benhaddi and Oarzazi [26] introduced a model based on stacked residual causal dilated convolutions, demonstrating its superiority in urban air quality prediction compared to LSTM and GRU models. Kolehmainen et al. [27] compared different neural network methods for air quality forecasting and found that applying an MLP network directly to the original data yielded the best forecast estimations.Cameletti [28] assessed the effectiveness of lockdown measures on air quality improvement using interrupted time series modeling, revealing significant improvements in air quality post-lockdown. Samal et al. [29] emphasized the value of analytics models for pollution estimation, showcasing the efficacy of SARIMA and Prophet model for air pollution forecasting in Bhubaneswar City. These studies collectively highlight the diverse range of deep learning and data-driven approaches employed in air quality forecasting, providing valuable insights for further research and development in this critical domain.

3. METHODOLOGIES

As the world is getting developed every day and the population is increasing with the time ahead, we therefore, need to emphasize air pollution and take steps and necessary measures to control air pollution. Monitoring air quality is important because polluted air can be bad for our health—and the health of the environment. As air pollution cannot be stopped in one day, we need to move forward to control it and focus on remedy measures to reduce air pollution. Monitoring air quality index it gives us a way of showing changes in air quality and indicates the amount of pollution.

In this research as we mainly focus on air quality index data for air pollution, the AQI dataset is time series data that captured air quality index during time-to-time intervals. Time series data can be processed and used for forecasting and taking necessary measures in the future. The methodology drives by collecting time series data of AQI, processing it, and use for forecasting. Figure 3 illustrates the overview of the process.

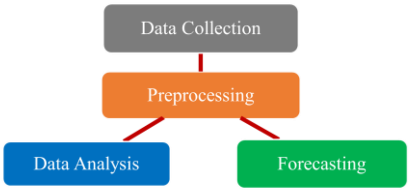


Fig 3: The process overview of air quality analysis.

If the process is expanded, it can be shown as a combination of different processes and methods as time series datasets are difficult to process. As the dataset is changes with time, it needs proper analysis and processing. Figure 4 shows the detailed process of time series analysis.

3.1 Experimental Environment

In this research, we use Google Colab [31] as our notebook environment and Python [32] as our programming language to implement the code. We use the python library Pandas [33] as our data handler, Matplotlib [34] as the graphical interface, Statsmodels [35] to analyze the time-series data as well as implement the ARIMA model [18], Prophet [36] to implement prophet model [30] and Tensorflow [37] to implement LSTM method [11]. We also use Sklearn [38] to show and compare the performance matrices.

3.2 Dataset Creation

The Air Quality Index dataset is collected from airnow.gov [39] and focuses on the polluted cities of the Asia region. The range of the dataset is from January 2019 to September 2022. As the dataset is time series it contains data on AQI with time interval of 1 hour. The dataset covered data of nine polluted cities in the Asia region. They are Dhaka, Hyderabad, Kolkata, Mumbai, Bishkek, Karachi, Lahore, Shanghai, and Colombo. We made the dataset of AQI by combining the AQI dataset of four years starting from 2019 to 2022.

3.3 Data Preprocessing

Data preprocessing is a phase in the data mining and data analysis process that converts raw data into a format that computers and machine learning algorithms can understand and evaluate. As huge amounts of data are collected in time series because timing is so important, so these records might be lacking or the incidents might be infrequent. Unordered timestamps, missing values (or timestamps), outliers, and data noise are the most frequent issues with time series. It is challenging to manage missing data in time series since conventional mathematical methods cannot be used to address them. We use several preprocessing methods such as duplicity removal, missing value filling, resampling to make our dataset ready for futher analysis and forecasting.

3.3.1 Removing Duplicates

To correctly apply statistical operation, the dataset must only have unique entry every day. Duplicate removal operation ensures that for a single date, there is only one AQI value in the dataset. If the duplicates are not be removed, the time series dataset of AQI will fail to give correct forecasting and value trends. So, we use duplicate removal to ensure the quality of the dataset for the subsequent analysis.

3.3.2 Fill Missing

Fill missing is the process of adding missing data and correcting the values in the dataset. Fill missing will correct all of the inconsistency of time series data and fill the missing data in the dataset with data from previous day.

3.3.3 Dataset Resampling

Data from time series need to resample into suitable intervals. It functions with the objects that have a DateTime index. Data resampling can be considered a data reduction process that not only makes the analysis easier but also more accurate while cutting down on data storage requirement.

The original data in our dataset is in hourly interval. We found by inspecting our AQI dataset that the plot of hourly data is chaotic and it's difficult to find any meaningful insight. So, we use resample() function with the 'D', 'W' and 'MS' argument accordingly for daily, monthly and yearly resampling. The values in day and week interval are very hard to find any meaning. The value in the month is a lot smoother and easier to understand. So, we resample the data to monthly to use the dataset for further analysis. Resampling data is done using the sum, average, or median of air quality data. In this research, we choose average as resample method for our monthly resample

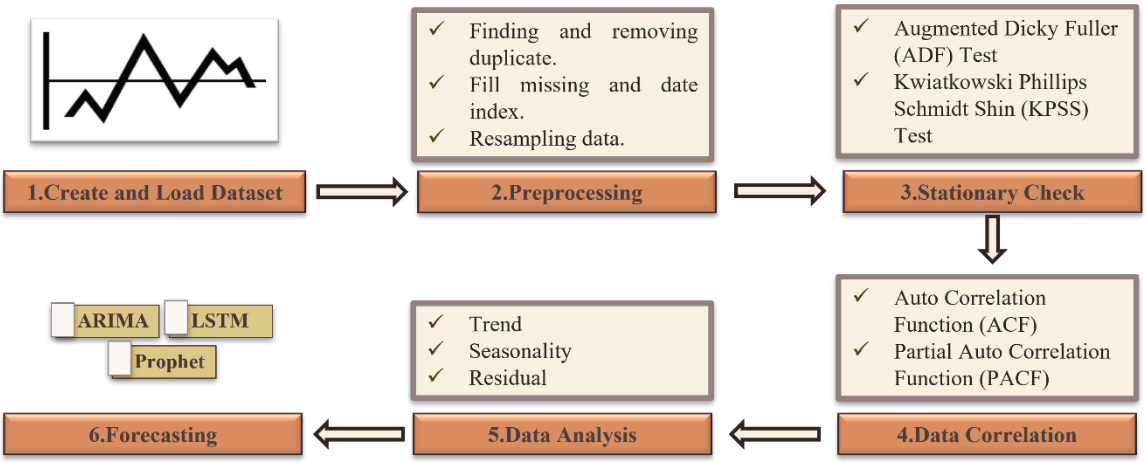
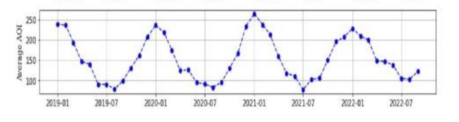
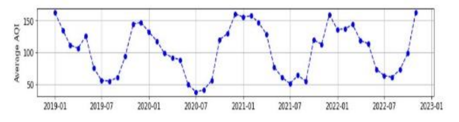
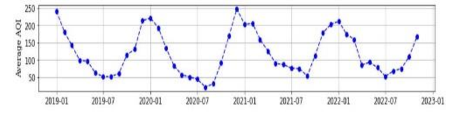
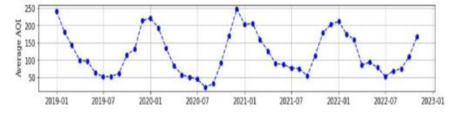
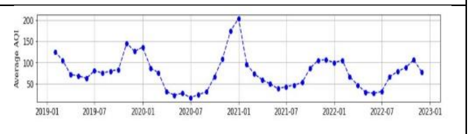
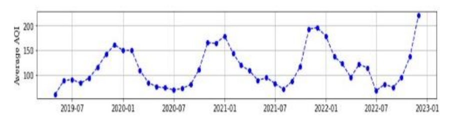
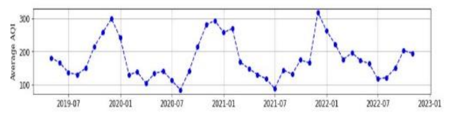
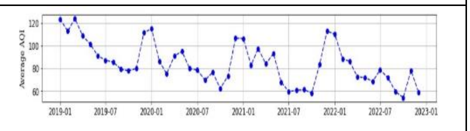
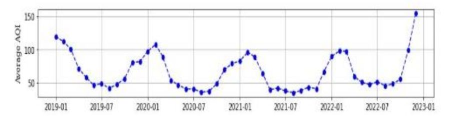


Fig 4: The detailed process of air quality analysis

data. Table 2 shows the plot of our dataset for monthly resample.

Table 2. Plot of resampled AQI datasets.

City	Plot of Resampled AQI Values
Dhaka	
Hyderabad	
Kolkata	
Mumbai	
Bishkek	
Karachi	
Lahore	
Shanghai	
Colombo	

3.4 Dataset Characteristics Analysis

3.4.1 Seasonality Analysis

Seasonality is the repetition of a cycle or repeating pattern that can give a strong signal while forecasting a time series dataset. For this, analysis and forecasting of air quality data will lead to errors if it contains a repeated cycle. We mainly focus on two types of tests for seasonality checks. They are:

- **Augmented Dickey-Fuller Test (ADF Test):** It is a common statistical test used to test whether a given Time series is stationary or not. It is one of the most commonly used statistical tests when it comes to analyzing the stationary of a series.
- **KPSS Test:** It is considered as a unit root test that finds out the stationarity around a deterministic trend.

3.4.2 Data Correlation Analysis

Correlation is a statistical measure (expressed as a number) that describes the size and direction of a relationship between two or more variables. There are two types of correlation used in this air quality dataset:

- **Data Correlation**: The mathematical representation of the degree that indicates the similarity of the time series data with a lagged version of itself over one or more time periods.
- **Partial Correlation**: The mathematical representation of the strength of the relationship between variables with the controlling effect of other variables.

Our developed dataset is non-linear time series data. The variables of the dataset are loosely correlated.

3.5 Data Analysis

3.5.1 Yearly Average AQI Analysis

As the dataset that we developed covered AQI data of four years ranging from January, 2019 to September, 2022, we can calculate yearly average AQI of every four years. By calculating yearly average AQI, we can analysis the AQI of that city on that year and evaluated the air quality. We also found that lockdown had a noticeable impact on air quality of all city

3.5.2 Time Series Decomposition

This step includes the seasonal decomposition of a time series dataset that deconstructs a time series into several components, each representing one of the underlying categories of the pattern including:

- **Trend**: Indicate the persistent increasing or decreasing direction of data.
- **Seasonality**: Reflect the fact of influencing dataset by seasonal factors.
- **Residuality**: Describe random, irregular influence on time series dataset.

Figure 5 shows the process of decomposition of time series dataset.

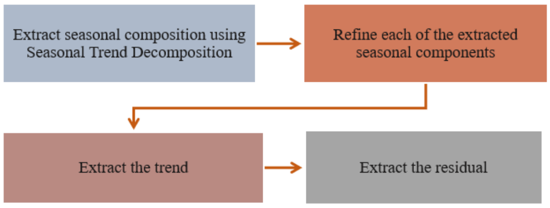


Fig 5: The process of seasonal decomposition

Seasonal decomposition is performed in the following ways:

- **Additive Decomposition**: It is the sum of time series data and its component. It is estimated by subtracting the trend from the time series dataset.
- **Multiplicative Decomposition**: It is the product of time series data with its components. It is collected by dividing the time series data by trend.
- **STL Decomposition**: It models complex seasonality with multiple periods of the season. It can tackle the time series data with multiple patterns.

3.6 Time Series Forecasting

3.6.1 Time Series Forecasting Methods

Time series forecasting is the technique that uses data to predict future value over a period of time. By analyzing the dataset, we can predict the future value that helps us to make informed decisions and understand future trends. We can use AQI forecasting to make people aware of air pollutant levels so that they can make judgments about their daily activities.

We have used three methods for predicting and forecasting AQI values. These methods are:

- **ARIMA**: Auto Regressive Integrated Moving Average method (ARIMA) [18] is the statistical analysis model that uses the time series dataset for better analysis and to predict future value. ARIMA is considered as a classical time series model that considers three values: P(lags), Q (Moving Average) and D(integration). In this research,
  - We used ARIMA to frame the sequence as the supervised problem.
  - 70% of the data is considered as training and the rest 30% to test model.
  - The P, Q, and D values are set to 6, 1, and 1.
  - The training and test data are scaled to [-1, 1].
- **Prophet**: Prophet [30] is the additive model that considers non-linear trends fitted with yearly, weekly, or daily seasonality for forecasting future value. It works best for time series with several seasonal effects of historical data. In this research,
  - The AQI dataset is converted to prophet data format where the date is considered as a column.
  - The dataset is split into 70% as training and 30% as test.
  - Prediction made based on data frame with ds column
- **LSTM**: Long Short-Term Memory (LSTM) [11] is one kind of recurrent neural network used in the deep learning field for learning long-term dependency in prediction. In this research,
  - The state of the model between training epochs is cleared.
  - The batch size is specified as 1 and neurons as 1.
  - The stateful is set as true and shuffle as false.
  - The epoch is 100.

3.6.2 Evaluation Parameters

The performance of the three methods in this research is evaluated by using four evolution measures. They are:

- **Mean Absolute Error (MAE):** MAE is the absolute value of the difference between the actual and predicted value. MAE ranges from 0 to infinity but the lower the value, the more accurate the model is.
- **Root Mean Squared Error (RMSE):** RMSE is a good measure for calculating the response that the model predicts. RMSE ranges from 0 to infinity but the lower the value, the better the model is.
- **Mean Squared Error (MSE):** MSE is the mean of errors squared from data. MSE ranges from 0 to infinity but if the value is lower, the method will show better performance.
- **R-Squared Score:** R-squared score indicate the variation analyzed by the method. The R-squared score ranges from 0 to 1. The higher the score, the method shows better performance, and is easy to explain the performance of any method using the R-squared score.

3.7 Forecasted Data Analysis

We take the best-fitted model and generate forecasts up to December 2023 to analyze the future trend of AQI and the further effect of COVID-19. We take two training datasets, one up to COVID time, and another up to recent times. We train our best model on those two datasets. The dataset up to COVID time represents the future AQIs if the lockdown regulations are properly used. The other dataset represents how the air quality changes if the normal regulations are still continued to be implemented. We compare the trends of AQI values. Comparing those two datasets, we determine which regulations will be more effective if implemented. Also, this defines the long-term effect the COVID-19 lockdown can have on the air quality.

4. RESULTS AND DISCUSSION

In this research, we have analyzed the AQI values in the dataset using time series analysis as well as forecasted the trend of air quality based on the analysis. The analysis of AQI values has shown a positive impact of COVID-19 and the lockdown on air quality. It has also given us an impression of what should be done to control the air pollution in polluted cities.

4.1 COVID-19 Impact Analysis

4.1.1 Average AQI Analysis

The average AQI of the cites gives us the overview of the air quality over the year. From this, we can also deduce about suitability of living of that place as well as the associated risks of respiratory problems of the citizens living there. The average AQI of the last 4years of different cities of Asia region is shown in Table 3.

Table 3. Average AQI of different cities

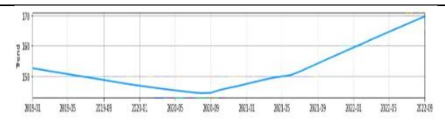
City	Average AQI of 2019	Average AQI of 2020	Average AQI of 2021	Average AQI of 2022
Dhaka	150.8887	147.5183	161.6041	155.3319
Hyderabad	106.0697	93.5966	107.1667	107.3357
Kolkata	120.6056	112.3118	130.8322	115.8048
Mumbai	100.1093	97.5321	101.9149	95.0604
Bishkek	92.8128	66.4818	79.7415	68.2982
Karachi	104.2375	108.6347	123.1184	120.2162
Lahore	191.6725	167.5351	175.7395	179.4114
Shanghai	98.4133	84.0329	80.5529	74.8137
Colombo	71.9728	62.1227	56.2129	74.6463

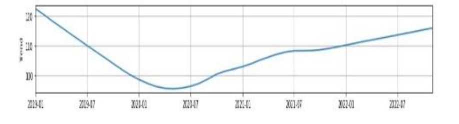
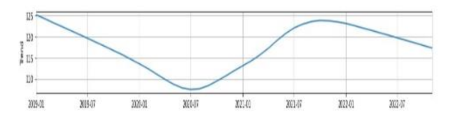
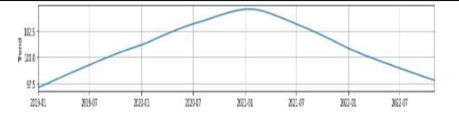
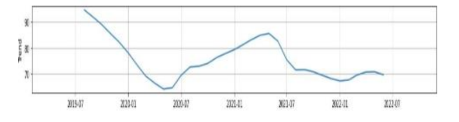
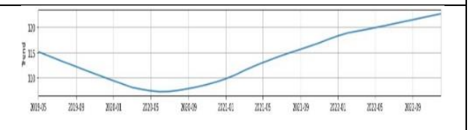
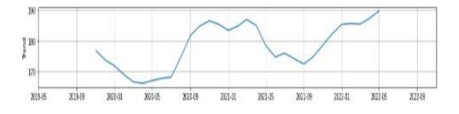
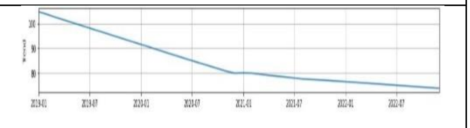
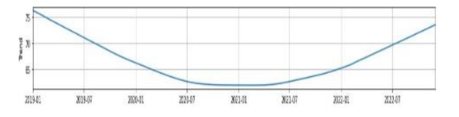
From the table, we can see that the air quality of the Asia region is not satisfactory at all. In 2020 and 2021 when governments of different countries implied lockdowns then air quality showed a substantial decrease in all most all cities. Then again, when the lockdown was lifted and the life started to become normal again the AQI started to rise in 2022. This shows that, the lockdown imposed for COVID-19 had a positive impact on AQI

4.1.2 Yearly Trend Analysis

The yearly trend from the time series can show the impact of COVID-19 lockdown in better details. The trend shows how the AQI of the location had changed throughout the year during COVID-19. Table 4 shows the yearly trend of AQI during lockdown.

Table 4. Yearly trend of cities

City	Plot of Resampled AQI Values
Dhaka	

City	Plot of Resampled AQI Values
Hyderabad	
Kolkata	
Mumbai	
Bishkek	
Karachi	
Lahore	
Shanghai	
Colombo	

We can visualize the impact of the lockdown on the air quality index dataset by using STD decomposition. The trend is analyzed by six months intervals and it exposes that air quality starts going downward trend when the lockdown is imposed because of COVID in 2020 and 2021.

It indicates that air quality become improving and air pollution has substantial change from industrial activities and vehicular emissions, and relatively clean transport of air masses from the upwind region. The improvement of the air holds until June of 2021. But when the lockdown imposed started to lift off, the air quality started to worsen and AQI trend rose again. We can also see that, even in monthly averages, the air quality improves when there are lower transport and running industries.

4.2 Time Series Forecasting

4.2.1 ARIMA

Performance of the ARIMA model trained on the AQI dataset of different cities is summarized in Table 5.

Table 5. Performance of ARIMA model

City	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Ensemble Value of MAE & RMSE
Dhaka	13.573	16.894	15.234
Hyderabad	19.692	26.760	23.226
Kolkata	22.398	25.687	24.043
Mumbai	11.999	15.031	13.515
Bishkek	13.331	15.763	14.547
Karachi	27.416	34.785	31.101
Lahore	34.831	52.391	43.611
Shanghai	12.298	14.131	13.215
Colombo	15.199	21.634	18.417

4.2.2 Prophet

Performance of the Prophet model trained on the AQI dataset of different cities is summarized in Table 6.

Table 6. Performance of Prophet model

City	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Ensemble Value of MAE & RMSE
Dhaka	15.226	18.787	17.007
Hyderabad	11.174	12.380	11.777
Kolkata	50.247	53.135	51.691
Mumbai	12.299	14.460	13.379
Bishkek	26.565	34.924	30.745
Karachi	22.076	27.136	24.606
Lahore	40.324	47.128	43.726
Shanghai	11.320	15.257	13.289
Colombo	15.427	24.540	19.985

4.2.3 LSTM

Performance of the LSTM model trained on the AQI dataset of different cities is summarized in Table 7.

Table 7. Performance of LSTM model

City	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Ensemble Value of MAE & RMSE
Dhaka	22.945	27.384	25.165
Hyderabad	25.948	32.554	29.251
Kolkata	31.125	38.252	34.689
Mumbai	23.760	30.278	27.019
Bishkek	14.857	19.106	16.982
Karachi	28.862	33.290	31.076
Lahore	38.171	53.539	45.855
Shanghai	11.320	15.257	13.289
Colombo	16.090	22.060	19.075

4.2.4 Performance Evaluation

From previous sections, we conclude that ARIMA has smaller values of MAE and RMSE than Prophet and LSTM. Since, MAE and RMSE gives a better fit on smaller values of error, ARIMA shows better and more consistent behavior compared with the other two methods. Figure 6 shows the comparison between MSE values for different methods on the cities.

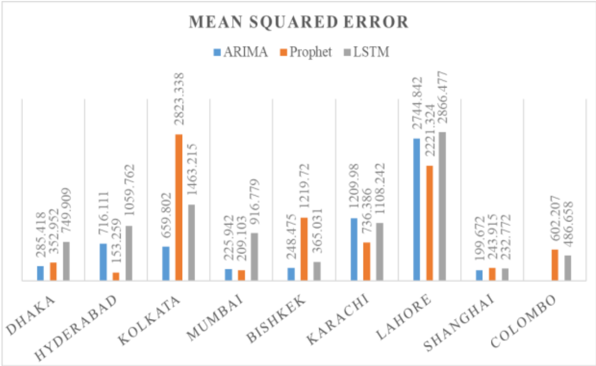


Fig 6: Mean Squared Error of evaluated methods

We can see that the lower value, the better fit for mean squared error but the higher value, the better fit for the r-squared score. We can analyze from the figure 7 that ARIMA has better performance and increased accuracy in predicting values than Prophet and LSTM. It indicates that ARIMA fits the AQI dataset better than the other two methods and it has consistent performance.

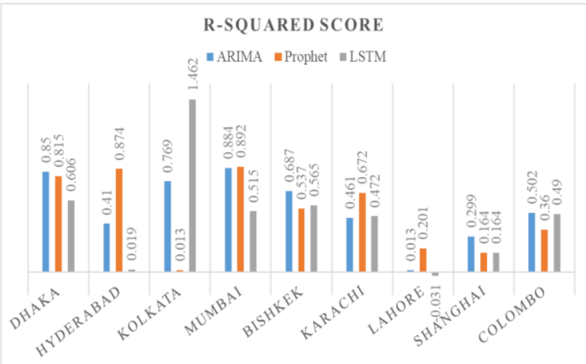
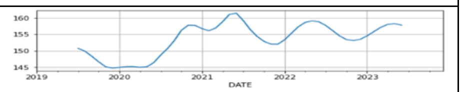
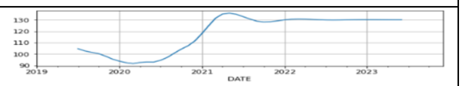
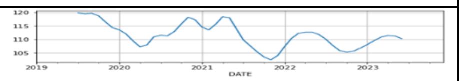


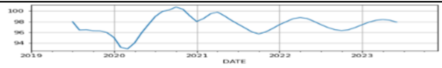
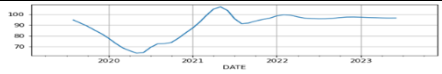
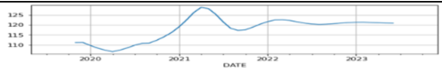
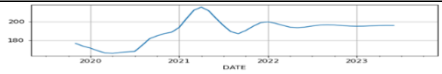
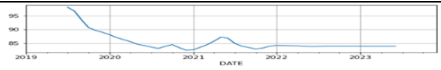
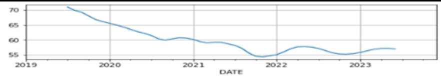
Fig 7: R-Squared score of evaluated methods

4.3 Analysis of Forecasted AQI

We can see from the analysis of AQI dataset that lockdown has a positive impact on value of AQI. As a result, AQI value turned into downward trend while lockdown was imposed in cities because of COVID. As ARIMA method shows better performance comparing with other two methods, we can use ARIMA model for forecasting future AQI value. The forecasted value using the AQI values of COVID time is showed in Table 8.

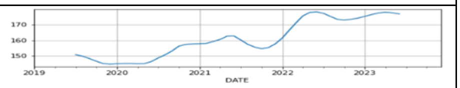
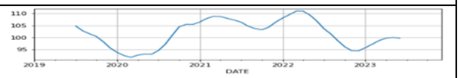
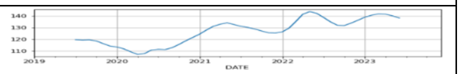
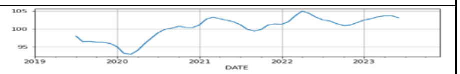
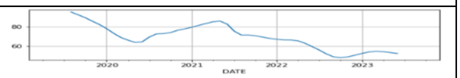
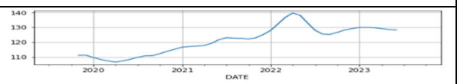
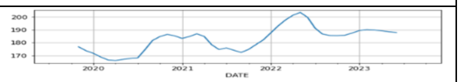
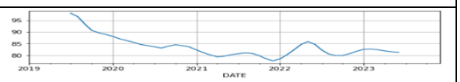
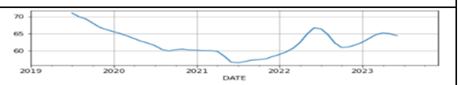
Table 8. Trend plot of the forecasted values using values of AQI during COVID time.

City	Trend Plot of AQI Values
Dhaka	
Hyderabad	
Kolkata	

City	Trend Plot of AQI Values
Mumbai	
Bishkek	
Karachi	
Lahore	
Shanghai	
Colombo	

The forecasted values using the AQI values of time after COVID is showed in Table 9.

Table 9. Trend plot of the forecasted values using values of AQI after COVID time.

City	Trend Plot of AQI Values
Dhaka	
Hyderabad	
Kolkata	
Mumbai	
Bishkek	
Karachi	
Lahore	
Shanghai	
Colombo	

From the table, we found that how lockdown impacts the air quality during COVID. If people followed all rules till now like COVID, then it can positively impact the future AQI value. But as everything became normal, future AQI value follows the normal increasing trend as before COVID. In Dhaka city, if forecasting AQI value is done by training data during COVID, then the forecasted peak AQI value can be 157 in 2023 but it will be 178 if forecasting AQI is done by training data after

COVID. The same change in forecasting is noticed while forecasted AQI values of other cities in Asia region.

4.4 Future Directives

The COVID-19 pandemic and the subsequent implementation of lockdown measures yielded a remarkable and sustainable impact on Air Quality Index (AQI) values. As elevated AQI values serve as a stark indicator of air pollution, it is imperative that we take deliberate steps to control and mitigate these values. The unique opportunity presented by the pandemic allows us to explore diverse strategies for achieving this goal, based on the analysis of the COVID-19 era. In Figure 8, we present an illustrative depiction of the air quality management cycle aimed at enhancing air quality.

Fig 8: Air Quality Index management cycle.

Initial steps that we can recommend by analyzing the impact of lockdown on air quality are: 1) Sustainable industrialization to use less fuel and energy. 2) Reducing traffic in cities using prior planning. 3)Restrict avoidable outdoor gathering. 4) Use renewable fuel in vehicle and industries. 5) Normalize working from home where applicable. 6) Use bicycle and walking for moving from place to place. 7) Planting more trees and increasing consciousness among people. 8) Use more "work from home" model where applicable.

5. CONCLUSION AND FUTURE WORKS

In conclusion, this research underscores the critical relationship between air quality and public health, emphasizing the global significance of addressing air pollution. The COVID-19 pandemic and the ensuing regulatory measures provided a unique opportunity to assess the impact of reduced human activities on air quality. Through a meticulous analysis of time series data, we demonstrated that the pandemic-induced lockdowns had a positive effect on air quality in nine polluted cities across the Asian region.

Our findings, supported by robust statistical modeling, revealed that the ARIMA method outperformed other forecasting techniques, showcasing its effectiveness in capturing the trends in AQI values. Moreover, we used this model to forecast AQI values for the post-COVID-19 era, confirming a sustained positive impact of the lockdown regulations on air quality.

As we look ahead, this research not only serves as a catalyst for further investigations into air quality across diverse cities and regions but also encourages the evaluation of multiple parameters to comprehensively understand the influence of regulations on air quality. We hope that these findings will guide policymakers and authorities in implementing measures to improve air quality and foster a healthier environment for all. This study marks a crucial step toward a more in-depth analysis of the intricate relationship between human activities and our environment, particularly in terms of air quality.

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