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(Dedicated to Honor Dr. R. C. Singh Chandel on His 75th Birth Anniversary Celebrations)

STATISTICAL AND TIME SERIES ANALYSIS OF BLACK CARBON IN THE MAJOR COAL MINES OF INDIA

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Abstract

Time series analysis has been widely used by the researchers in the field of mathematical forecasting; it has been mainly used to obtain the forecast of time series dealing with pollutants, groundwater level, and stock exchange so as to study their future behavior of such time series. The present research work deals with the black carbon concentrations in three major coal mines of India namely, Bokaro, Jharia and Raniganj. In this study, a time series data last 38 years (from 1980 to 2018) obtained from a reliable source (*NASA*) have been considered by statistical analysis tools like mean, median, mode, standard deviation, skewness, kurtosis, coefficient of variation and time series (*ARIMA* (Autoregressive Integrated Moving Average)) model at 95% confidence limits have been applied.The validation of the model is tested using *R*-square, stationary *R*-square, root mean square error *(RMSE)*, normalized Bayesian information criterion *(BIC)*. It is observed that the model fitted very well, based on these past observations, *ARIMA* model is applied to obtain the prediction of the amount of black carbon emission for next 7 years 5 months (from Jun 2018 to Oct 2025). These results will help to develop new policies and preventive measures in future by the government agencies, NGOs in these areas and take a note of the seriousness and impact of such huge concentration of black carbon emission in these areas.
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1 Introduction

Black carbon (*BC*) has emerged as an alarming area of interest among the researchers, in recent times due to its share in global warming and severe health impacts. Black carbon is black sooty material produced as substantial particle of the carbonaceous aerosol released due incomplete combustion of biofuels, fossil fuels and biomass in coal-fired power plants, steel plants, petroleum industries and oil refineries. In indoor conditions it mainly released due to cooking and burning of fuels like wood, coal, animal manure, residues of crops [3, 38]. In Asia, the contribution of open biomass burning from fossil fuels is nearly 40%, and that from burning of biofuels is 20% in the overall *BC* emission [29]. It is a global problem as it has negative impact on human health such as Inhalation of *BC* leads to problems related to respiratory such as chronic bronchitis and asthma, lung disease, damage to eye sights, cardio vascular disease, cancer and even leads to birth defects. It gets mixed with air, water and soil thus entering the food chain and enters the human body. Carbonaceous aerosols have received a great attention of the researchers recently due to its severe impact on human health [14, 17, 21, 26, 37], agriculture [7] and the quality of air [10, 13, 39].

Black carbon is the major absorber of solar heat radiation in the atmosphere, *BC* leads to the heating of the Earths atmosphere as it results into the reduction in incoming short-wave solar radiation at the Earths surface [8, 11, 12], and thus leading to the change in the temperature of the troposphere, which affects the microphysical properties of the clouds and thus affecting the rainfall mechanisms [20]. *BC* aerosol affects the rainfall pattern by influencing the cloud formation and precipitation process [28]. India is the worlds second largest producer of coal in the world and various mining activities performed in the coal mining regions are leading to the spontaneous emission of black carbon along with various other harmful gases in these regions [35].

Time series modeling has been largely used [9, 24, 30] to study the fluctuations and making good modeling forecasts, it is very beneficial in decision-making of climatic conditions and estimation of future data. The Auto regressive integrated moving average (*ARIMA*) models have been used in various studies of time series modeling of air pollution [1, 2, 4, 6, 7, 16, 27] and water pollution [22, 24, 25, 36, 40].Time series modeling methods have also been used to study the emission of black carbon [1, 5, 15, 31, 32, 33, 34].

Thus due to the above discussed severe impact of black carbon on human life and environment both nationally and globally, the future study of black carbon is very important for framing national and international policies for prediction of the level of black carbon emission in the future. Coal mines region being one of the major sources for *BC* emission, the aim of this study is to calculate the amount of *BC* mass concentrations in the major coal fields of India viz. coal field area of Raniganj, Jharia and Bokaro and making future forecast for these regions using statistical and time series analysis.

2 Research methodology

2.1 Statistical analysis

Statistical analysis consists of mean, median, mode, standard deviation, kurtosis, skewness and coefficient of variation, the spreadness or variability of the data in the sample is explained by standard deviation, to determine the nature of the distribution curve it is classified as platykurtic, mesokurtic and leptokurtic which depends on the peakedness or flatness of the curve we use kurtosis, skewness refers to the symmetry of the sample, the relative measure of the series is termed as coefficient of variation (CV) [22, 23] and is defined as:

(2.1) $$CV\% = \frac{\sigma}{\mu} \times 100\%,$$

where, σ is the standard deviation and μ is the mean of the series. It is used to find the total variation in the *BC* concentration.

2.2 Time series

A time series is a sequential set of data points measured over successive time intervals arranged in a proper chronological order. It is one of the most widely used mathematical technique developed by researchers in the field of mathematical modeling for studying fluctuations, extracting meaningful statistics and making good forecasts of the time series. It is very beneficial in decision-making of climatic conditions and estimation of future values [18, 19].

2.2.1 Autoregressive Moving Average *ARMA* (p, q) Model

The Autoregressive (*AR*) and the Moving average (*MA*) are effectively combined together to form the Autoregressive Moving average (*ARMA*) model. Mathematically it is represented as,

(2.2) $$y_t = c + \epsilon_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}.$$

2.2.2 *ARIMA* Model

The most widely used time series model is the Box Jenkins based *ARIMA* (Autoregressive Integrated Moving) model. In recent years the *ARIMA* model has been widely used in the fields of medicine, engineering, stock markets, weather forecasting, economics, business, finance etc. In *ARIMA* model a non-stationary time series can be converted to stationary by using the finite differencing technique. Mathematically the *ARIMA* (p, d, q) model is expressed,

(2.3) $$\phi(L) = (1 - L)^d y_t = \theta(L)\epsilon_t,$$

i.e.,

(2.4) $$\Big(1 - \sum_{i=1}^{p} \phi_i L^i\Big)(1 - L)^d y_t = \Big(1 + \sum_{j=1}^{q} \theta_j L^j\Big)\epsilon_t.$$

Here p, d and q are the order of the autoregressive, integrated and moving average parts and these are non-negative integers greater than or equal to zero. If any of these values become zero than it becomes the basic *AR*, *MA* or the *ARMA* model of the time series.

The level of differencing is defined by the parameter d and it keeps a check on the level of differencing. The value of $d = 1$ in most of the cases and if $d = 0$ then the model gets reduced to the *ARMA* (p, q) model.

If $d = q = 0$, then $ARIMA(p, 0, 0)$ reduces to the $AR(p)$ model and if $p = d = 0$, then $ARIMA(0, 0, q)$ reduces to the $MA(q)$ model.

If $p = q = 0$ and $d = 1$, then *ARIMA* $(0, 1, 0)$ becomes $y_t = y_{t-1} + \epsilon_t$ which is known as the Random walk model.

2.3 Root Mean Square error *(RMSE)*

It is the coefficient of error representing the standard deviation of the difference of actual values of the data from the values predicted by the time series model also termed as the residual values, it is used to determine amount of spreadness of the values from the line of best fit for a model and to determine the accuracy of the forecasted values. Mathematically it is given by,

(2.5) $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$,

where n denotes the time period and e_i denotes the error of forecasting.

2.4 *R*-squared and stationary *R*-squared values

These values are used as a measures for goodness of fit for a time series model; they are used as a coefficient of determination of a model. The value of R square ranges from 0 to 1 while that of stationary R-squared ranges from $-\infty$ to 1, higher values indicate that the model considered is better than the baseline model.

3 Results and discussion

3.1 Sample sites

Raniganj ($23^o\,40'\,N\,87^o\,05'\,E$) in West Bengal, Jharia ($23^o\,50'\,N 86^o\,33'\,E$) and Bokaro ($23^o\,46'\,N\,85^o\,55'\,E$) in Jharkhand as shown in ***Fig.* 3.1** are main focused sites for our current study, these are among the major coal mines of India.The data of *BC* is obtained by *NASA* and processing the data is done via Giovanni website (http://nasa.gov/). Using statistical and time series analysis the concentration of black carbon at these three sites have been discussed. The results are based on long term trend analysis of the concentration of black carbon expressed in volume(magnitude) as $e^{-11}\,kgm^{-3}$ units over the past 38 year, 05 months data from Jan 1980 to May 2018. *IBMSPSS* Statistics software has been used for testing and training the data for choosing an appropriate time series model. Further the statistical and time series results have been obtained using the same.

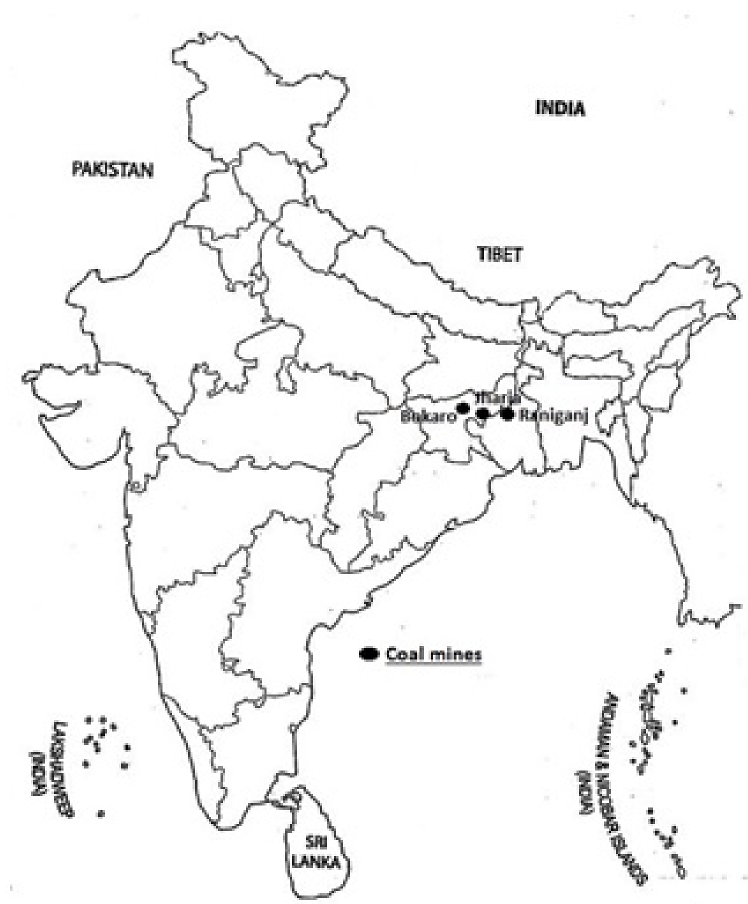

***Figure* 3.1:** Map of India showing coal mines of Raniganj, Jharia and Bokaro.

3.2 Statistical Analysis of Black carbon

Statistical parameters such as mean, mode, median, standard deviation, variance, skewness, kurtosis, range, coefficient of variation have been used to study the behavior of our parameter i.e. *BC* concentration. The results of statistical analysis have been shown in ***Table* 3.1** and bar chart depiction of the observed results has been shown in ***Fig.* 3.2**.

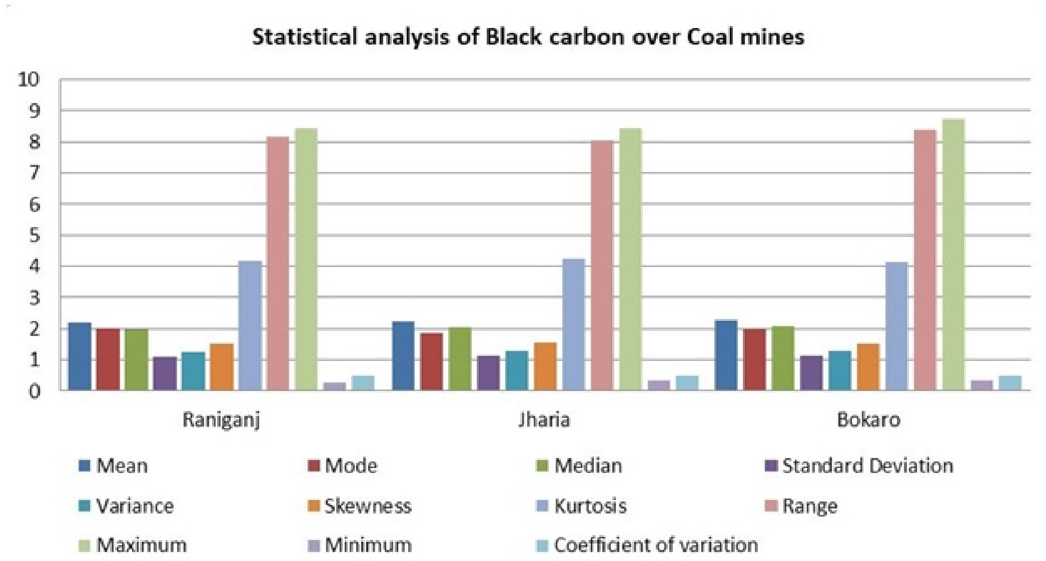

***Figure* 3.2:** Statistical analysis of black carbon at Raniganj, Jharia and Bokaro.

3.2.1 Raniganj (23^o 40′ N 87^o 05′ E)

The mean, mode and median value of *BC* concentration are at 2.192875807, 2.002202643 and 1.983193277, these values are close to 2 depicting that the data distribution curve is symmetrical and follows a normal distribution. The value of standard deviation and skewness are at 1.113654555 and 1.507609253 indicating that the data points are distributed close to each other along the mean and the distribution curve is moderately skewed to the right. The curve is leptokurtic as indicated by the value 4.192888602 in the ***Table* 3.1**.

***Table* 3.1:** Time series and *ARIMA* forecast of Jharia

	Raniganj	Jharia	Bokaro
Mean	2.192875807	2.232444485	2.269679113
Mode	2.002202643	1.846846847	1.962719298
Median	1.983193277	2.059907834	2.078581871
Standard Deviation	1.113654555	1.130771534	1.142111571
Variance	1.240226469	1.278644263	1.30441884
Skewness	1.507609253	1.560077228	1.529151854
Kurtosis	4.192888602	4.245785802	4.152665796
Range	8.145594714	8.065878378	8.391812865
Maximum	8.423127753	8.414977477	8.742690058
Minimum	0.27753304	0.349099099	0.350877193
Coeff. of variation	0.507851175	0.506517202	0.503203983

3.2.2 Jharia ($23^o\,50'\,N 86^o\,33'\,E$)

As shown in ***Table* 3.1** the mean, mode and median value of BC concentration stand at 2.232444485, 1.846846847 and 2.059907834 all near to 2 as shown in the ***Table* 3.1** indicating that the data exhibit normal distribution and the distribution curve is symmetrical. Standard deviation is 1.130771534 and skewness as 1.560077228 indicating moderately positive skewness of the data with data value near to each other. The curve is leptokurtic as the value of kurtosis is 4.245785802.

3.2.3 Bokaro ($23^o\,46'\,N\,85^o\,55'\,E$)

The value of mean, mode and median value of BC concentration are 2.269679113, 1.962719298 and 2.078581871 all near to 2 as shown in ***Table* 3.1** indicating that the data curve exhibit normal distribution and is symmetrical. Small value of standard deviation along with skewness at 1.142111571 and 1.529151854 respectively indicate that the data values are closely distributed with the mean and the data is positively skewed moderately towards the right. The curve is leptokurtic as the value of kurtosis is greater than 3.

3.3 Time series prediction of Black carbon

For all the sample sites, it is observed that time series *ARIMA* (1,0,1) (0,1,1) model fitted very well to the data at 95% confidence limits with 460 degree of freedom. As shown in ***Table* 3.2**, the values of stationary R^2 and R-squared which are the measures for goodness of fit, are both close to 1 depicting that the applied model fitted very well to the data.

***Table* 3.2:** Time series and *ARIMA* forecast of Bokaro

Fit Statistic	Raniganj	Jharia	Bokaro
Stationary R²	0.703	0.678	0.663
R-squared	0.63	0.624	0.619
RMSE	0.64	0.662	0.677
Normalized BIC	-0.851	-0.783	-0.739
DF	460	460	460
ARIMA Model	(1,0,1)(0,1,1)	(1,0,1)(0,1,1)	(1,0,1)(0,1,1)
Predicted value	2.33769715	2.369926804	2.426624731
LCL	1.247798074	1.271560365	1.272485047
UCL	3.761368167	3.82001922	3.945160031
Residual	0.004329502	0.004394215	0.004352878

Small value of RMSE show that the actual time series is very near to the model predicted, it can also be seen from the ***Fig.* 3.3** , ***Fig.* 3.4** and ***Fig.* 3.5** that the actual time series of the data and the predicted time series obtained using *ARIMA* (1,0,1) (0,1,1) model are nearly coinciding with each other, along with the LCL (lower confidence limit) and UCL (upper confidence limit) values presented in the figures. The figures also represent the forecasting for next 7 years and 5 months starting from Jun 2018 to Oct 2025 obtained using this model.The numerical values of normalized BIC, mean predicted, lower confidence limit (LCL), upper confidence limit (UCL) and residual values for each of the sample sites is discussed below.

3.3.1 Raniganj ($23^o\,40'\,N\,87^0\,05'\,E$)

The value of normalized BIC is -0.851. The mean predicted, lower confidence limit (LCL), upper confidence limit (UCL) and residual values are observed to be 2.33769715, 1.247798074, 3.761368167 and 0.004329502.

3.3.2 Jharia ($23^o\,50'\,N\,86^o\,33'\,E$)

Normalized BIC value is at -0.783. The mean predicted, lower confidence limit (LCL), upper confidence limit (UCL) and residual values are observed to be as 2.369926804, 1.271560365, 3.82001922 and 0.004394215.

3.3.3 Bokaro ($23^o\, 46'\, N\; 85^o\, 55'\, E$)

For normalized BIC the value is -0.739. The mean predicted, lower confidence limit (LCL), upper confidence limit (UCL) and residual values are observed to be 2.426624731, 1.272485047, 3.945160031and 0.004352878.

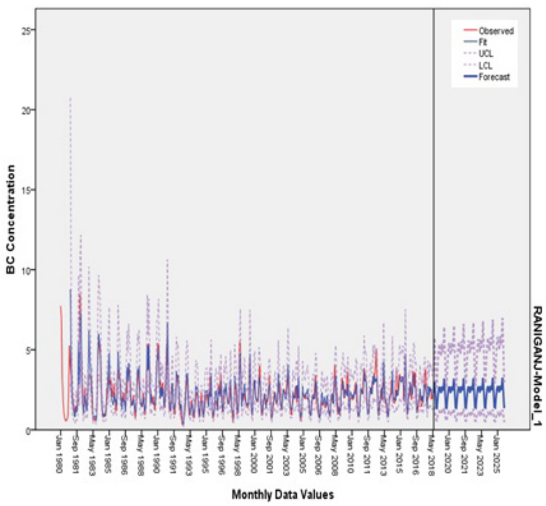

***Figure* 3.3:** Statistical analysis of black carbon

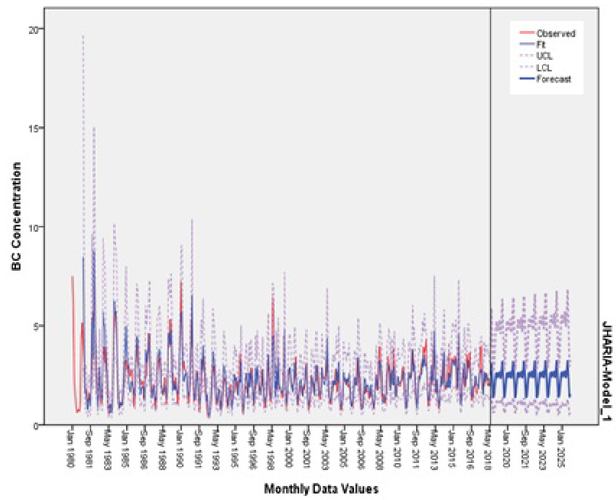

***Figure* 3.4:** Time series analysis of black carbon

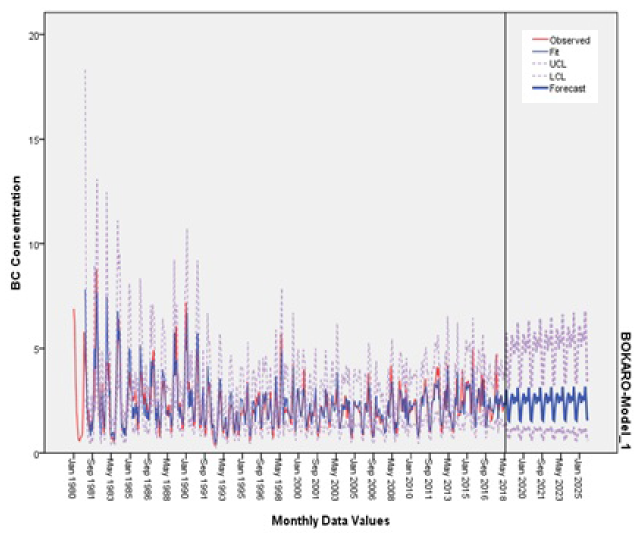

***Figure* 3.5:** Time series and *ARIMA* forecast of Raniganj

4 Conclusion

Considering a long term data for black carbon concentration of 38 years, 05 months from Jan 1980 to May 2018for coal mine regions of Raniganj, Jharia and Bokaro,time series *ARIMA*(1,0,1) (0,1,1) model is used to obtain a prediction of next 7 years and 5 months starting from Jun 2018 to Oct 2025. The shape of the distribution curve is leptokurtic at all the three sites. Small value of $RMSE$ in all the three cases indicates that the values of the original time series and the predicted model are very close to each other. It can been seen from ***Fig.* 3.3** , ***Fig.* 3.4** and ***Fig.* 3.5** that *ARIMA*(1,0,1) (0,1,1) model fitted quite well to the data over the three sample sites, the curves representing the observed and predicted values of black carbon concentration coincide with each other depicting that the difference between the values is very small. The figure also represents the future prediction made from Jun 2018 to Oct. 2025. Thus the model applied gave quite reliable results and it can be used as a future forecasting tool over the coal mines to measure the BC concentration over these regions and help in framing policies necessary for controlling air pollution and its adverse effect due to black carbon in the coal mine regions of India.

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