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Prediction of CO_2 Emissions in Sundarban Using Auto-ARIMA: A Comprehensive Analysis

K. Mondal[1*], A. K. Lal[2], U. S. Singh[3]

[1]Department of Mathematics, PRMS Mahavidyalaya, Bankura , West Bengal, India

[2]Department of Mathematics, Simdega College, Simdega, Jharkhand, India

[3]Indian Forest Service (Rtd), Lucknow, Uttar Pradesh, India

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Abstract

Climate change driven by greenhouse gas emissions poses a serious threat to the fragile ecosystem of the Indian Sundarban region. The objective of this study is to analyze the historical pattern of CO_2 emissions in the Indian Sundarbans and to forecast future emission trends using an automated time-series modelling approach. Annual CO_2 emission data for the period 1980–2008 are analyzed using the Auto-ARIMA framework which automatically identifies the optimal model parameters based on information criteria. Prior to model construction, stationarity of the series is examined using both Augmented Dickey–Fuller and KPSS tests. The selected Auto-ARIMA model effectively captures the underlying trend in the emission series and generates reliable short-term forecasts. Auto-ARIMA is used instead of conventional ARIMA to avoid subjective parameter selection and to ensure objective, reproducible model identification through information-criterion-based optimization. The results indicate a persistent increasing trend in CO_2 emissions in the Sundarban region and underscore the growing environmental risk. The findings of this study provide quantitative insight into emission dynamics and may assist policymakers and environmental planners in formulating informed mitigation and adaptation strategies to protect the Sundarban ecosystem.

Keywords: Sundarban Island; Auto ARIMA model; Carbon dioxide; Greenhouse gas; Forecasting; Climate change.

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1. Introduction

Carbon dioxide (CO_2) is a greenhouse gas that significantly contributes to climate change. Human activities, such as burning fossil fuels and deforestation, have raised atmospheric CO_2 levels. Rising temperatures caused by CO_2 emissions are associated with the growing intensity and frequency of tropical storms and cyclones. The Sundarbans frequently experience cyclones that inflict considerable damage on the delicate mangrove ecosystem. The Sundarban region is home to a variety of species, including the Bengal tiger. However,

* *Corresponding author:* kartickmathbhu@gmail.com

climate change, driven by CO_2 emissions, is threatening their natural habitats. Rising water levels, saline water intrusion, and habitat fragmentation are diminishing the living spaces for wildlife, which in turn is leading to a decline in biodiversity. Therefore, accurately forecasting these emissions is essential for creating effective strategies to mitigate their environmental impact.

The papers introduce an automated ARIMA modeling-based data aggregation scheme designed for wireless sensor networks (WSNs), aiming to reduce energy consumption and enhance efficiency. This approach employs time series prediction models to minimise the number of data values transmitted between sensor nodes and aggregators, while ensuring that accuracy remains within a user-defined error threshold [1,2]. The scheme effectively conserves battery energy in wireless sensor nodes and shows a strong correlation between predicted and actual sensed data values [1]. Additionally, Song *et al*. [3] proposes a secure data aggregation solution based on the ARIMA model to bolster network security. This method safeguards private data from potential adversaries while still delivering accurate predictions. When compared to alternative methods, it offers superior security, reduced computation and communication costs, and increased flexibility. Overall, these studies underscore the effectiveness of ARIMA-based data aggregation in enhancing the performance and security of WSNs. The ARIMA model has been extensively used to forecast COVID-19 cases and deaths across various European countries [4]. Research has shown its effectiveness in predicting short-term trends, typically for 5-10 days ahead [4,5]. Where Demongeot *et al.* used the Auto-Regressive Integrated Moving Average (Auto-ARIMA) modeling for analyzing incidence pattern and for generating forecasts (short-term) of cumulative cases being reported in Morocco, Italy, Spain, France and USA, utilizing the data of Worldometer of daily reported cumulative cases. This model has also been employed to assess the impact of non-pharmaceutical interventions on the dynamics of the epidemic [6] and to support healthcare systems in their prevention efforts [7]. Researchers have applied ARIMA to analyse incidence patterns in countries such as Italy, Spain, France, and Turkey, forecasting both case numbers and fatalities [4,5,7]. The model's performance varies at different stages of the epidemic, from initial growth to peak incidence and decline [6]. Additionally, some studies have explored the relationship between ARIMA forecasts and factors such as elevation and average temperature [4].

Lai and Dzombak [8] used Auto ARIMA model to forecast regional precipitation and temperature (near term). The study creates a statistical forecasting model based on ARIMA in order to provide accurate near-term regional temperature and precipitation estimates for civil and environmental engineering applications. Lalon and Jahan [9] and Haque and Ahmed [10] also utilized the model to predict the GDP growth in Bangladesh in 2021 and 2024 respectively. Their study showed that ARIMA (1, 0, 1) is suitable for the prediction. Whereas Rahaman and Hasan [11] studied Carbon Dioxide (CO_2) emission in Bangladesh using Auto ARIMA models and they employed ARIMA (0, 2, 1) to forecast CO_2 emissions. An analysis comparing the ARIMA and VAR models for predicting the price of jute goods in Bangladesh was studied by Parvin and Khanan [12]. The study reveals that ARIMA model is more convenient than VAR model to forecast the price of jute. The model is also applicable for time series studies. A time series analysis was evaluated by Hossain *et al.* [13] regarding onion production in Bangladesh. The article identified that ARIMA (0, 2, 1) is the best forecasting model in this direction. Another time series analysis was done by Hossain and Abdulla [14] for forecasting jute production in Bangladesh and the study suggested that ARIMA (1, 1, 1) model is suitable for prediction. Besides of that, research on inflation [15] in Bangladesh also carried out using ARIMA (2, 1, 0). Some studies were evaluated for analyzing the seasonal variability also utilizing the modeling technique. For example, Masum *et al.* [16] studied on time series prediction on temperature and precipitation trends using ARIMA model. The model applied to forecast and predict temperature and rainfall trends in Chattogram, Bangladesh for the time interval 1953 to 2070. Few studies on CO_2 emissions and its future prediction were conducted by utilizing statistical modeling in some Indian states [17-19]. Dubey *et al.* [20] also worked in this direction and tried to develop a non-linear model to forecast CO_2 emissions in three Indian states. Using ARIMA (0, 1, 1), Pandit *et al.* [21] discussed on temporal analysis of temperature and rainfall of a region of Indian States of Jharkhand. The study analyzed and predicted the temporal trends of rainfall and temperature of that particular region with resulting the increasing rainfall and mixed temperature trends. Mondal *et al*. [22] explored on forecasting CO_2 emissions in Indian Sundarban Island using ARIMA modeling technique. The study reveals that ARIMA (1, 1, 1) is most suitable model which successfully capture the dynamics and trend of the time series and it provides accurate predictions. Sundarban is one of the world's largest biodiversity and spans over India and Bangladesh. Due to climatic threats, the Sundarbans, the biggest mangrove forest in the world confronts several difficulties. Global warming due to climate change is responsible for this crucial situation and CO_2 emissions is one of the most leading factors in this regard. Therefore, studies on CO_2 emissions and greenhouse gases in Sundarbans in a broader range is emergent and it may play a vital role for increasing public consciousness. Present study is an effort to explore the emerging trends of CO_2 emissions in Sundarban so that the policymakers may accept some proper policies to protect the UNESCO world heritage site in advance.

This study investigates the analysis and prediction of CO_2 emissions using Auto-ARIMA, a contemporary time series modeling technique. Understanding historical emission patterns and forecasting future trends are essential given the growing environmental concerns. Accurate forecasting of CO_2 emissions is essential for understanding long-term environmental risks and for supporting evidence-based policy formulation in ecologically sensitive regions such as the Indian Sundarbans. However, CO_2 emission time series typically exhibit non-stationary behaviour, evolving trends and limited historical observations which complicate traditional time-series modelling approaches. Manual ARIMA modelling requires subjective parameter selection and extensive trial-and-error procedures that potentially leads to inconsistent results. The motivation for adopting the Auto-ARIMA framework in this study is to overcome these limitations by providing an automated, data-driven and reproducible approach to model identification and forecasting. By systematically selecting optimal model parameters based on information criteria, Auto-

ARIMA enables reliable short-term prediction of CO_2 emissions while minimising human bias and makes it particularly suitable for environmental impact studies and policy-oriented analyses. Auto-ARIMA is an effective tool for modeling complex time series since it automatically chooses the optimal parameters for the data. The Auto-ARIMA model is applied to anticipate CO_2 emissions in the Sundarbans and to evaluate its effectiveness in capturing future emission patterns. In summary, the study employs the Auto-ARIMA framework to identify an appropriate model and to forecast carbon dioxide emissions in the Indian Sundarbans.

2. Data Description

The dataset used in this analysis comprises historical CO_2 emissions recorded annually. It includes the two columns. One is 'Year' and the other is 'CO_2 Emission'. Where the 'Year' represents the year of the observation and the 'CO_2 Emission' stands for the measured CO_2 emissions for that year. The data spans several decades, providing a comprehensive overview of how emissions have changed over time. The dataset containing yearly CO_2 emissions data from 1980 to 2008 is utilized in this study. The data was loaded from an Excel file, ensuring that the year was correctly formatted to match the time series requirements.

3. Methodology

Auto-ARIMA is an extension of the ARIMA (Autoregressive Integrated Moving Average) model, which is widely used for time series forecasting. Unlike traditional ARIMA, which requires manual selection of the model parameters (p, d, q), Auto-ARIMA automatically identifies the optimal parameters. This automation simplifies the modeling process and enhances accuracy. The mathematical foundation of the Auto-ARIMA model is to transform a non-stationary time series data to a stationary one utilizing differencing (the 'I' part) and then modeling the stationary time series using a combination of autoregressive (AR) and moving average (MA) components. The parameters (p, d, q – orders of AR, differencing, and MA) of the models are selected automatically often by minimizing information criteria like BIC or AIC. Which balance model fit and complexity and then being estimated by using Maximum Likelihood Estimation (MLE). Auto-ARIMA works by automatically testing different combinations of ARIMA parameters. The ARIMA model consists of three main components.:

Auto Regressive (AR) part: This process involves regressing the variable of interest against its lagged values from previous periods. The number of lagged values is specified by the parameter *p*.

$$\mathrm{Y}'_{\mathrm{t}} = \varphi_1 \mathrm{Y}'_{\mathrm{t}-1} + \varphi_2 \mathrm{Y}'_{\mathrm{t}-2} + \varphi_3 \mathrm{Y}'_{\mathrm{t}-3} + \cdots .. + \varphi_{\mathrm{p}} \mathrm{Y}'_{\mathrm{t}-\mathrm{p}} + \epsilon_{\mathrm{t}} \tag{1}$$

where φ_i are AR coefficients

Y'_t is stationary series after differencing and

ϵ_t is white noise term

Integrated (I) part: This process involves differencing the data to achieve stationarity, with the number of differences specified by the parameter d.

$$Y_t' = (1-B)^d Y_t \tag{2}$$

Where B is the backshift operator $BY_t = Y_{t-1}$

Moving Average (MA) part: This entails modelling the error term as a linear combination of error terms that occur both concurrently and at different points in the past. The number of terms is determined by the parameter q.

$$Y_t' = \mu + \epsilon_t + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \theta_3\epsilon_{t-3} + \cdots.. + \theta_q\epsilon_{t-q} \tag{3}$$

Where $\theta_1, \theta_2, \ldots.. \theta_q$ are MA coefficients and μ is constant term

Thus, the full ARIMA (p, d, q) combines:

$$Y_t' = \varphi_1 Y_{t-1}' + \varphi_2 Y_{t-2}' + \cdots.. + \varphi_p Y_{t-p}' + \epsilon_t + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots.. + \theta_q\epsilon_{t-q} \tag{4}$$

Where Y_t' is the *'d'* times differencing the original series Y_t.

For a given time series, the "Auto" portion refers to algorithms that automatically determine the optimal (*p, d, q*) combination. Criteria such as the Bayesian Information Criterion (BIC) or the Akaike Information Criterion (AIC) are commonly employed by these algorithms. In order to successfully balance goodness-of-fit and model parsimony (simplicity), they assess several candidate models and choose the one that minimizes the selected criterion. Mathematical formulation of AIC and BIC is:

$$BIC = -2l + k\ln(T) \text{ and } AIC = -2l + 2k \tag{5}$$

Where $l =$ log-likelihood

$k =$ number of estimated parameters

$T =$ number of observations

After the selection of *p, d* and *q* the coefficients (θ *and* φ) are estimated by utilizing Maximum Likelihood Estimation (MLE). Likelihood function is given by

$$L(\varphi, \theta, \sigma^2) = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\epsilon_t^2}{2\sigma^2}\right) \tag{6}$$

And Maximum log-likelihood

$$l(\varphi, \theta) = -\frac{T}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{T} \epsilon_t^2 \tag{7}$$

Following the selection of the optimal ARIMA model, predictions are produced as follows:

$$\widehat{Y_{T+h}} = E(Y_{T+h} \mid Y_1, Y_2, \ldots\ldots, Y_T) \tag{8}$$

4. Result and Discussion

4.1. *Stationarity*

A time series is deemed stationary if its statistical properties, including mean and variance, remain constant over time. In simpler terms, the data should look similar throughout its length. Stationarity is important because many forecasting models, including ARIMA, work best with stationary data. A stationary data series is more predictable when its mean and variance do not change over time, making it easier to model and forecast. Non-stationary data can produce unreliable and spurious results; hence, differencing or transformation is often applied to achieve stationarity. To ensure accurate prediction of future CO_2 emissions, the stationarity of the time series must be examined. If the data are found to be non-stationary, appropriate transformations are required prior to model development.

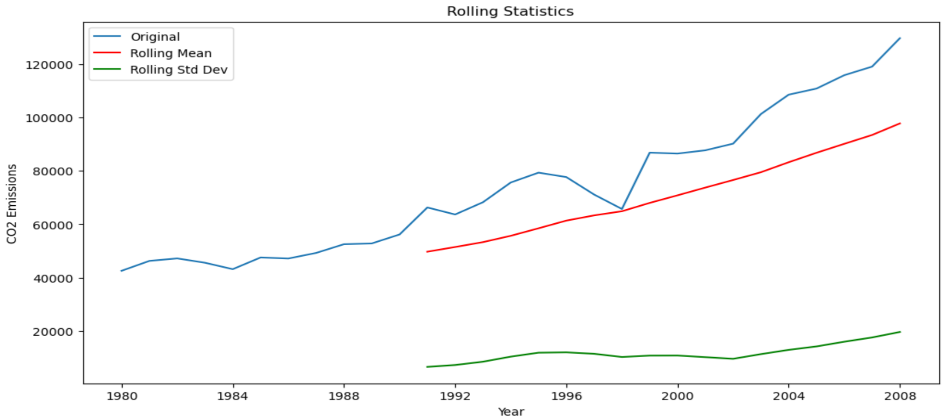

Fig. 1. Graphical display of moving mean and average of CO_2 emissions.

4.2. *Statistical tests for stationarity*

To check if the emissions data is stationary, two statistical tests were used: namely Augmented Dicky-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF test is a widely used method to check for stationarity by testing for the presence of a unit root in the data. A negative ADF Statistic indicates that the time series is stationary and if the p-value is less than 0.05, the data is likely stationary. Critical Values help to determine whether the series is stationary by comparing the ADF statistic to critical values at different confidence levels.

Table 1. Augmented Dicky-Fuller test statistic.

Variable	ADF statistic	P value	Critical Values	Confidence interval (%)	Conclusion
Y	1.0053	0.994	90	-2.63	Not stationary
			95	-2.97	Not Stationary
			99	-3.69	Not Stationary

Based on the analysis, the p-value is larger than 0.05, and the ADF statistic is less negative than the critical values, suggesting that the CO_2 emissions data is non-stationary. The KPSS test checks for stationarity around a deterministic trend. It works in the opposite way of the ADF test.**:** A small value of KPSS Statistic suggests stationarity and if the p-value is less than 0.05, the data is likely non-stationary.

Table 2. KPSS test statistic.

Variable	KPSS statistic	P value	Critical Values	Confidence interval (%)	Conclusion
Y	0.798	0.01	90	0.347	Not stationary
			95	0.463	Not Stationary
			99	0.739	Not Stationary

In this case, the KPSS statistic is greater than the critical values, and the p-value is less than 0.05, indicating that the series is non-stationary. Using both the ADF and KPSS tests helps us confirm the non-stationarity of the CO_2 emissions data. While the ADF test suggests non-stationarity, the KPSS test confirms it, ensuring a more robust conclusion before applying the ARIMA model. By employing both tests, the nature of the data can be confirmed and ensuring that appropriate preprocessing steps such as differencing are applied.

4.2.1. *Detailed analysis of Auto-ARIMA model output*

Auto ARIMA defines a search space in this study for non-seasonal parameters *p, d, q* and it methodically experiments with different combinations of these factors. Auto ARIMA uses an ARIMA/SARIMA model to fit the data for each combination and it calculates the statistical score like AIC/BIC corresponding to every fitted model. These criteria balance the goodness of fit versus model complexity as well. Finally, the model with lowest AIC/BIC is selected as the best model.

Table 3. ARIMA model with different combination of *p, d, q*.

Models	AIC
ARIMA (2,1,2) (0,0,0) [0]	Inf
ARIMA (0,1,0) (0,0,0) [0]	**446.254**
ARIMA (1,1,0) (0,0,0) [0]	448.234
ARIMA (0,1,1) (0,0,0) [0]	448.545
ARIMA (0,1,0) (0,0,0) [0]	447.328,
ARIMA (1,1,1) (0,0,0) [0]	Inf

Therefore, the best model is ARIMA (0,1,0) (0,0,0) [0] with lowest AIC value 446.254 and hence the Auto-ARIMA selected parameters: *p:* 0, *d:* 1, *q:* 0. Now for diagnostic check metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Square Error (RMSE) are utilized for examining the testing performance of the proposed model. These metrics are essential for evaluating model performance.

Table 4. Values of error metrics.

Metrics	MAE	MSE	RMSE
Value	16437.106	298845355.672	17287.144

4.3. *Auto-ARIMA forecasting*

Auto-ARIMA accurately captures the trend in CO_2 emissions data, as seen in the forecast plot (Fig. 2). The predictions of the model align closely with the actual emissions, demonstrating its efficacy in time series forecasting.

Table 5. Future prediction of CO_2 emission.

Year	2009	2010	2011	2012	2013
Emission	132766.67	135877.67	138988.67	142099.68	145210.68

The forecasted values suggest a steady increase in CO_2 emission over the next five years, aligning with historical trends. To facilitate clearer interpretation of the results, a plot illustrating the historical data and the model's forecast is presented below.

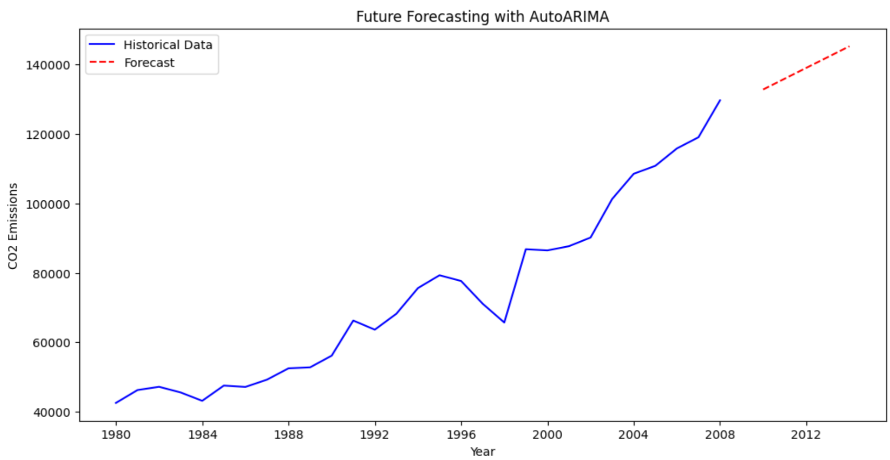

Fig 2. Future forecasting with Auto ARIMA.

In the plot, the solid (blue) line represents historical CO_2 emissions, while the dashed line (red) shows the forecasted emissions. The model captures the increasing trend in CO_2 emissions and provides reasonable future estimates.

4.4. *Comparison with traditional ARIMA*

Compared to a manually configured ARIMA model, Auto-ARIMA offers several advantages:

(i) Efficiency: Automatic parameter selection speeds up the modeling process.

(ii) Accuracy: The model achieves higher forecasting accuracy by exploring a broader range of parameter combinations.

(iii) Simplicity: Auto-ARIMA simplifies the modeling process, making it accessible to non-experts.

5. Conclusion

The primary objective of this study was to analyse the historical behaviour of carbon dioxide (CO_2) emissions in the Indian Sundarban region and to generate reliable short-term forecasts using an automated time-series modelling approach. To achieve this, annual CO_2 emission data from 1980 to 2008 were examined using the Auto-ARIMA framework which enables objective model identification through information-criterion-based optimization. Prior to model implementation, the stationarity of the emission series was rigorously assessed using both Augmented Dickey–Fuller and KPSS tests to confirm the non-stationary nature of the data and the necessity of differencing. The Auto-ARIMA procedure systematically explored alternative model structures and identified an ARIMA (0, 1, 0) specification as the most suitable representation of the underlying emission dynamics. Diagnostic error measures further indicated satisfactory predictive performance of the selected model. The forecasting results reveal a consistent and increasing trend in CO_2 emissions in the Sundarban region over the projected period and highlights the growing environmental pressure on this ecologically sensitive and climate-vulnerable area. These findings emphasize the urgency of proactive policy intervention and long-term emission management strategies. Overall, the study demonstrates that Auto-ARIMA provides a robust, objective, and reproducible framework for analyzing and forecasting CO_2 emissions in data-limited environmental settings. The insights generated from this analysis can support policymakers and environmental planners in developing informed strategies aimed at mitigating climate-related risks and preserving the fragile ecosystem of the Indian Sundarbans.

6. Future Work

This study demonstrated the effectiveness of the Auto-ARIMA model in forecasting yearly CO_2 emissions. However, future research may explore the following:

(i) Incorporating Additional Variables: Future studies could incorporate other greenhouse gases or economic indicators to enhance the model's accuracy.
(ii) Model Enhancements: Explore hybrid models that combine Auto-ARIMA with machine learning techniques for improved predictions.
(iii) Long-Term Forecasting: Extend the forecast horizon to understand long-term trends in CO_2 emissions.

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