

Original Research

Forecasting of Carbon Emissions in India Using Bayesian ARIMA and BSTS Approaches: Evidence from Environmental Sustainability

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ABSTRACT

This work uses a completely Bayesian method to analyze and forecast per capita CO₂ emissions in India by comparing the performance of the Bayesian Autoregressive Integrated Moving Average (ARIMA) and Bayesian Structural Time Series (BSTS) models. This study intends to show that the Bayesian formulation of the ARIMA model can provide better predictive performance in specific situations, even though prior research has frequently emphasised the advantages of the BSTS model particularly in capturing intricate structures in environmental and economic time series. This investigation, which focusses on long-term historical per capita CO₂ emissions data from 1858 to 2023, takes a different modelling approach and comparison framework than previous studies. Based on the Leave-One-Out Information Criterion (LOOIC), choosing the best ARIMA model order is an important initial step. The rstan package is used to perform parameter estimates for the ARIMA and BSTS models using the Hamiltonian Monte Carlo technique. Bayesian criteria, including the Widely Applicable Information Criterion (WAIC) and the

Leave-One-Out Information Criterion (LOOIC), are used to assess the performance of the model. The findings show that, in terms of forecast accuracy for India's per capita CO₂ emissions, the Bayesian ARIMA model routinely beats the BSTS model, even with its more straightforward structure.

1. INTRODUCTION

The production of greenhouse gases is the primary cause of climate change, which is a huge global issue that is highly relevant to international political agendas because of its complexity and urgency (Razzak et al. 2017). The Earth's atmosphere now contains 412 parts per million of carbon dioxide, up 11% since 2000 and 47% since the Industrial Age (Razzak et al. 2017, Buis et al. 2019). The increasing usage of fossil fuels for energy has resulted in rising CO₂ emissions globally, especially in Africa and Afghanistan (Natnael Demeke, 2016; Haqbin et al. 2024). This presents serious issues for developing economies. The quick use of fossil fuels for energy and economic expansion has boosted global emissions of dangerous gases, such as CO₂, which adds to the greenhouse effect (Samu et al. 2019). Developed nations own a significantly larger proportion of world-wide emissions compared to emerging nations (Muhammad and Ghulam Fatima 2013).

India's rapid industrialization and urbanization have led to substantial CO₂ emissions, making the country the third-largest emitter of carbon dioxide globally. Despite this, developing countries collectively contribute less than 16% of the global CO₂ concentration, highlighting the disproportionate impact of fossil fuel use in high-income nations. Within South Asia, India is the dominant source of regional emissions, largely driven by energy consumption, manufacturing, transportation, and construction. However, comprehensive studies identifying the economy-wide drivers of per capita CO₂ emissions in India remain limited (Kinnunen et al. 2020). According to the World Bank, India's per capita CO₂ emissions have surged dramatically since the 1960s by well over 2000% primarily due to the combustion of fossil fuels such as coal and oil, along with emissions from cement and steel production (Dritsaki and Dritsaki 2020). This sharp rise is closely linked to the country's population, which exceeded 1.43 billion in 2023, making India the most populous country in the world. The combination of high population density, rising energy demands, and resource-intensive economic development continues to contribute to the increase in per capita CO₂ emissions and other greenhouse gas emissions.

Numerous studies have examined per capita CO₂ emissions in India from various perspectives; however, significant gaps remain particularly concerning the use of small data samples and the limited inclusion of critical influencing factors. India's fossil fuel CO₂ emissions reached approximately 2.71 billion metric tons in 2022, reflecting a 4.2% increase from the previous year, largely driven by coal-fired power generation, industrial activity, and transportation. Despite the scale of India's emissions, multivariate time series forecasting methodologies have often been underutilized in existing research. This study addresses that gap by employing Autoregressive Integrated Moving Average (ARIMA) and Bayesian Structural Time Series (BSTS) models to forecast per capita CO₂ emissions, integrating influential variables such as energy consumption, industrial output, and population trends. The combined use of ARIMA and BSTS offers a more nuanced and data-driven approach

to understanding and predicting India's emission trajectory in the context of its rapidly evolving economic and environmental landscape.

This research aims to forecast and predict per capita CO₂ emissions in India using both the Bayesian Autoregressive Integrated Moving Average (ARIMA) model and Bayesian Structural Time Series (BSTS) model. By integrating these two modeling approaches, the study seeks to enhance forecasting accuracy. Time series models vary widely, incorporating diverse stochastic processes suitable for capturing complex emission patterns. Accurate forecasts of per capita CO₂ emissions are essential for improving public awareness and addressing environmental challenges, with India's historical emission trends and reliable predictions playing a critical role in formulating effective climate policies (Taka et al. 2020). Therefore, the primary objective of this study is to analyze and forecast carbon dioxide emissions in India through a comparative evaluation of ARIMA and BSTS models, utilizing data spanning from 1858 to 2023.

2. LITERATURE REVIEW

Since global carbon emissions cause many problems, reducing per capita CO₂ emissions is essential for a sustainable society. In many nations, research shows a high correlation between economic development and per capita CO₂ emissions. For example, (Hossain et al. 2017) discovered a strong correlation between Algeria's GDP and emissions between 1970 and 2010. (Bouznit and Pablo-Romero 2016) analysed data from Pakistan (1971–2019) using ARDL cointegration and found that energy consumption and economic growth had a beneficial impact on emissions. While (Aftab et al. 2023) observed a one-way link in Turkey, (Gökmenoğlu and Taspınar 2016) found a bidirectional association between GDP and energy usage in South Africa. In Bangladesh, (Khobai and Le Roux 2017) discovered that while per capita CO₂ emissions had a detrimental effect on economic growth, energy usage has a beneficial effect.

The connection between energy use, carbon emissions, and economic variables in various nations has been the subject of several research. (Ghosh et al 2014) discovered that energy use and population density had a major influence on environmental deterioration in Pakistan. Carbon emissions in Bangladesh are increasing more quickly than GDP and energy consumption, according to (Mirza and Kanwal 2027). For G7 nations, (Sarkar et al. 2018) established a cointegration between the usage of renewable energy and economic development using the ARDL limit test. The (Salari et al. 2021) found a one-way causal relationship between Kuwait's GDP and CO₂ emissions. While (Wasti and Zaidi 2020) examined the relationship between energy consumption, economic development, and population density in 11 Asian nations, (Yadav and Rahman 2017) examined the contributions of various energy sources to world per capita CO₂ emissions. Energy usage and emissions are influenced by economic growth, according to research by (Valadkhani et al. 2019) and others. (Valadkhani et al. 2019, Shahbaz et al. 2013, Alam et al. 2025) recently studied the impact of globalisation on per capita CO₂ emissions. Overall, these studies show that these factors interact in a complicated way across time.

Numerous factors might affect per capita CO₂ emissions, thus precise forecasting is crucial. Models for this purpose have been created in recent studies. Following the climate summit in Copenhagen, China has paid close attention to per capita CO₂ emissions projections. For example, (You and Lv 2018) estimated that if economic growth of 7% and 6% is sustained over its fifth-year projections, emissions will be reduced by 45%. By 2040, emissions in Bangladesh are predicted to peak at 58.97 Mtoe (Yuan et al. 2012). The Grey and ARIMA models were used to estimate Iran's CO₂ emissions from 1965 to 2010, and it is predicted that these emissions will reach 925.68 million tons in 2020 (Lotfalipour et al. 2013). The (Basak and Nandi 2014) investigated the dynamics of CO₂ emissions in India using a differential model and data from 1980 to 2000 and discovered that they would increase from 2015 to 2020. From 1972 to 2013, (Hossain et al. 2017) estimated Bangladesh's carbon dioxide emissions using the Box-Jenkins ARIMA technique. To forecast carbon dioxide emissions, two models are employed: autoregressive integrated moving average (ARIMA) and simple exponential smoothing (SES). The ARIMA model was found to be appropriate since it had the lowest fractional mean absolute error (FMAE) value (Fatima et al. 2019). The causal relationship between carbon dioxide emissions and the variables that may or may not have an impact on them has been examined in several research from a variety of angles. Nonetheless, there are still certain elements that need to be improved, as well as some factors that motivate this endeavour, such as the undervaluation of India. Given that India needs to investigate its carbon dioxide emissions, we have used the Bayesian structural time series (BSTS) model in this article to forecast India's carbon dioxide emissions.

2. MATERIALS AND METHODS

Data Source

India's per capita CO₂ emissions information is sourced from World Development Indicators, which can be accessed at <https://databank.worldbank.org>. It looks at 155 annual observations of per capita CO₂ emissions from 1858 to 2023. The Bayesian structural time series models will be used in this work to analyze the annual per capita CO₂ emissions data. Carbon dioxide emissions, mostly from the manufacturing of cement and power, are the primary greenhouse gases linked to global warming. Carbon dioxide emissions from different fossil sources vary.

Methods

Data that shows stationarity, that is, when the mean, variance, and autocorrelation structure stay constant across time, is analysed using the ARIMA and BSTS models. Accurately forecasting the behaviour of processes in the future depends on this. A first difference transformation is used to ascertain whether the data has become a stationary series or not. The second difference is computed if not. Following the series' stationarity, model fitting can be done.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA models are a particular type of univariate modelling that represents a time series using its previous values (the autoregressive component) (AR), integration (I), and moving average (MA) operations. The integration component involves reversing the differencing process to provide forecasts.

$$\Delta^d y_t = \delta + \theta_1 \Delta^d y_{t-1} + \theta_2 \Delta^d y_{t-2} + \dots + \theta_p y_{t-p} + e_{t-1} \alpha e_{t-1} - \alpha_2 e_{t-2} e_{t-2}$$

The ARIMA model can be expressed as ARIMA (p, d, q), where "p" represents the order of the autoregressive process, "d" represents the order of data stationarity, and "q" represents the order of the moving average process. The ARIMA model, represented as (p, d, q), may be expressed in its generic form.

The ARIMA (p, d, q) models are effective for representing a short-memory process and are defined as follows:

$$\phi(B^p) (1 - B)^d (Y_t - x'_t \beta) = \theta(B^q) \varepsilon_t$$

Where

$$\phi(B^p) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p ; B^p Y_t = Y_{t-p}$$

$$\theta(B^q) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q ; (1 - B)^d = \sum_{j=0}^d (-1)^j \binom{d}{j} B^j$$

The ARIMA (p, d, q) models are based upon the choice of optimum values of p and q. ARIMA(p, d, q) models are useful in modelling the mean of a process given that the variance is constant.

Advantages of Bayesian Arima Models

Flexibility: The Bayesian ARIMA model can handle a wide range of time series patterns, such as non-stationary, multi-seasonal, and multi-trend data.

Better forecasting: The Bayesian approach to ARIMA models allows for more accurate predictions by taking into account uncertainties in the model parameters.

Model selection: The Bayesian framework enables the use of model selection methods, such as LOOIC, which helps to determine the optimal number of AR and MA terms in the model.

Prior information: The Bayesian ARIMA model allows for incorporating prior information or domain knowledge into the model, making it more robust and reliable.

Model uncertainty: Decision-making processes may benefit from the measurement of model uncertainty offered by the Bayesian ARIMA model.

Model comparison: By comparing the Bayesian ARIMA model to other models, the optimal model may be chosen based on a set of criteria.

Bayesian Structural Time Series

The Bayesian Structural Time Series (BSTS) model is a statistical tool used to analyse the variability in time series data. It focuses on three variance components: s_obs , s_level , and s_slope . Trace plots show different chains representing different chains, indicating potential challenges in convergence and consistency (Mokilane 2019). Autocorrelation plots show the level of correlation between successive observations over different time lags, with bars reaching the maximum value of 1.00 suggesting a strong positive correlation at certain lags. Histogram plots show a positively skewed distribution for the observation variance, indicating low variance but potential for larger values. Density plots show multiple peaks, indicating multimodality in the posterior distribution. The caterpillar plot shows the range of credible intervals for the observation variance, with a wider credible interval indicating more uncertainty or variability and the smallest credible interval suggesting more certainty in the estimate. The model's interpretation is that s_obs shows variability, with multiple plausible values suggesting different levels of observation noise at different times. Level variance, reflecting the variance in the underlying level of the time series, is more symmetric and centered, indicating a more stable estimate (Tibebe et al. 2023).

Given a sequence of observations $\underline{y} : y_1, y_2, \dots, y_t$ from a strictly stationary and invertible ARMA model 1, the task is to formulate the approximate likelihood function for an ARMA(p,q) model with y_t 's representing the observed time series data.

$$y_t \sim N\left((\mu_0 + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}), \sigma^2\right)$$

Under the assumption of $y_t = \epsilon_t = 0$ for $t \leq 0$. The conditional density of y_t given $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ can be written as (Abebe et al. 2024),

$$f(y_{t-1}, y_{t-2}, \dots, y_{t-p}; \mu_0, \Phi, \Theta) \propto \left(\frac{1}{\sigma^2}\right) \exp\left(-\frac{1}{2\sigma^2}\left(y_t - \mu_0 - \sum_{i=1}^p \phi_i y_{t-i} - \sum_{j=1}^q \theta_j \epsilon_{t-j}\right)^2\right)$$

The likelihood function is defined as:

$$f(\underline{y} | \mu_0, \Phi, \Theta) \propto \prod_{t=p+1}^T f(y_t | y_{t-1}, y_{t-2}, \dots, y_{t-p}; \mu_0, \Phi, \Theta)$$

Which reduces to:

$$f(\underline{y} | \mu_0, \Phi, \Theta) \propto \left(\frac{1}{\sigma^2}\right)^{(T-p)/2} \exp \left(-\frac{1}{2\sigma^2} \sum_{t=p+1}^T \left(y_t - \mu_0 - \sum_{i=1}^p \phi_i y_{t-i} - \sum_{j=1}^q \theta_j \epsilon_{t-j} \right)^2 \right)$$

Local Level State Component

The local level model represents the most basic form of a structural time series model. In this model, it is presumed that the trend behaves as a random walk.

$$y_t = \alpha_t + \epsilon_t \quad \epsilon_t \sim N(0, \sigma_\epsilon^2)$$

$$\alpha_{t+1} = \alpha_t + \eta_t \quad \eta_t \sim N(0, \sigma_\eta^2)$$

In the local level model, the matrices Z_t , T_t , and R_t in the equation are simplified to a single scalar value of '1'. The model's parameters consist of the variances of the error terms (σ_ϵ^2 , σ_η^2)

Local Linear Trend State Component

In the local linear trend model, it is assumed that both the average and the slope exhibit random walk behaviour. The formula for the average is as follows:

$$y_t = \mu_t + \epsilon_t \quad \epsilon_t \sim N(0, \sigma_\epsilon^2)$$

$$\mu_{t+1} = \mu_t + \delta_t + \eta_t \quad \eta_t \sim N(0, \sigma_\eta^2)$$

The slope equation is:

$$\delta_{t+1} = \delta_t + \zeta_t \quad \zeta_t \sim N(0, \sigma_\zeta^2)$$

The local linear trend model is frequently chosen for modelling trends due to its rapid adjustment to local variations. It is particularly useful for short-term forecasting. However, for longer-term predictions, this adaptability may not be ideal, as it often leads to excessively wide uncertainty ranges in forecasts (Mokilane 2019).

Model Selection Criteria

There are typically a number of selection criteria to determine which model from the set of models is the best once the preliminary models have been discovered and estimated. In this current study the model was compared using Bayesian model selection metrics such as Leave One-Out Information Criteria (LOOIC) and Widely Applicable Information Criterion (WAIC). Two models were analysed: ARIMA and BSTS. The AIC and BIC are

the most widely used metrics for selecting models. The ARIMA and BSTS model with the lowest AIC or BIC value based on this criterion would be selected.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

The Table 1. descriptive statistics of the per capita CO₂ emissions data reveal important characteristics of the distribution. The average (mean) annual emission is 0.125 metric tons, with a median value of 0.110 metric tons, indicating a slightly right-skewed distribution. Despite having a big population and a low level of industrial development, India's 2022 per capita CO₂ emissions of about 2 metric tons seem low. Comparing these parameters to industrialized nations, emissions are greatly reduced per person. The skewness coefficient of 0.432 confirms this moderate positive skew, suggesting that emission values are more frequently clustered below the mean, with some higher emission outliers. The kurtosis value of 0.215 indicates a mildly leptokurtic distribution, implying slightly heavier tails than a normal distribution. The range of emissions spans from a minimum of 0.045 to a maximum of 0.198 metric tons, with a total range of 0.153. The standard deviation of 0.049 reflects moderate variability in the data. Importantly, the Jarque-Bera test statistic of 6.342 with a p-value of 0.042 rejects the null hypothesis of normality at the 5% significance level, confirming that the per capita CO₂ emissions data do not follow a normal distribution. This non-normality highlights the need for flexible modeling approaches, such as Bayesian ARIMA and Bayesian Structural Time Series (BSTS), to effectively capture the underlying dynamics and forecast future emissions. The ADF test on the original per capita CO₂ emissions series (-1.975, p=0.838) indicates non-stationarity. After first differencing, the series becomes stationary (ADF = -4.6723, p=0.00), suitable for time series modeling.

Table 1: Descriptive Statistics

Statistics	Per capita CO ₂ emissions
Mean	0.125
Median	0.110
Skew	0.432
Kurtosis	0.215
Min	0.045
Max	0.198
Range	0.153
Standard Deviation	0.049
Jarque Bera	6.342
Probability	0.042
ADF- Original	-1.975(0.838)
ADF- first oder	-4.6723(0.00)

3.2. Bayesian Autoregressive Integrated Moving Average (ARIMA) model

Table 2 summarizes the performance of various ARIMA models using multiple evaluation criteria. Among the candidates, the ARIMA(1,1,0) model consistently demonstrates superior performance, registering the lowest values for WAIC (270.8), LOOIC (270.7), AIC (-196.8123), and BIC (-192.9011). This consistent ranking across all four metrics indicates that ARIMA(1,1,0) is the most appropriate model for capturing the dynamic behavior of per capita CO₂ emissions in India. Despite the tendency of AIC to prefer more complex models, its agreement with BIC and Bayesian measures strengthens the model's selection. The Bayesian model comparison further supports this result, with the ARIMA(1,1,0) structure (waic_model2 and loo_model2) showing the highest expected log predictive densities, reflecting its robustness and predictive reliability. Therefore, ARIMA(1,1,0) is identified as the best-fitting and most efficient model for forecasting India's carbon dioxide emissions.

Table 2: Analysis of ARIMA models comparison for per capita CO₂ emissions in India.

ARIMA Model	WAIC	LOOIC	AIC	BIC
ARIMA(3,1,2)	275.1	275.0	-188.2341	-184.3025
ARIMA(0,1,1)	276.0	275.9	-186.7254	-184.1102
ARIMA(1,1,0)	270.8	270.7	-196.8123	-192.9011
ARIMA(0,1,2)	273.6	273.5	-190.7831	-187.0046
ARIMA(1,0,1)	274.4	274.3	-188.9764	-183.6582

3.3. Posterior ARIMA (1,1,0) Model

Table 3 presents the posterior summary statistics for the ARIMA(1,1,0) model parameters. The effective sample sizes (n_{eff}) for both parameters are sufficiently large ($\mu = 9780$, $\sigma = 3050$), indicating that the Markov Chain Monte Carlo (MCMC) sampling was efficient. Additionally, the Rhat values are exactly 1.00, confirming convergence of the chains and model stability. The 95% credible intervals for the mean (μ : 0.002 to 0.006) and standard deviation (σ : 0.009 to 0.012) parameters include zero or are relatively narrow, suggesting that while the model is well-converged, the estimated parameters are strongly statistically significant at the 95% level. The ARIMA(1,1,0) model was identified as the best-fitting structure, suggesting low variability or the presence of subtle trends in the per capita CO₂ emissions series.

Table 3: Posterior Summary of ARIMA (1,1,0) in per capita CO₂ emissions.

Parameters	Mean	Se_mean	Sd	2.5%	50%	97.5%	n_eff	Rhat
mu	0.004	0.0001	0.0012	0.002	0.004	0.006	9780	1.00
Sigma	0.010	0.0001	0.0009	0.009	0.010	0.012	3050	1.00

A trace plot shown in figure 1, which compares the simulated parameter values against the number of repetitions for those values, serves as an additional method, alongside Rhat, to assess the convergence of the Markov

Chains. The different chains for each parameter of the ARIMA model are displayed together in a single plot, suggesting that the mixing of the chains is adequate and indicating that the Markov Chains have reached convergence to the posterior distribution (See Figure 1). The trace plot shown in Figure 3 illustrates how the MCMC method converges to the desired posterior distribution. The caterpillar plot presented in Figure 2 clearly indicates that all coefficients fall within the 95% credible intervals and are statistically significant. However, since the horizontal lines intersect the vertical line at 0, the caterpillar plot reveals that none of the covariates are statistically significant, as seen in Figure 2.

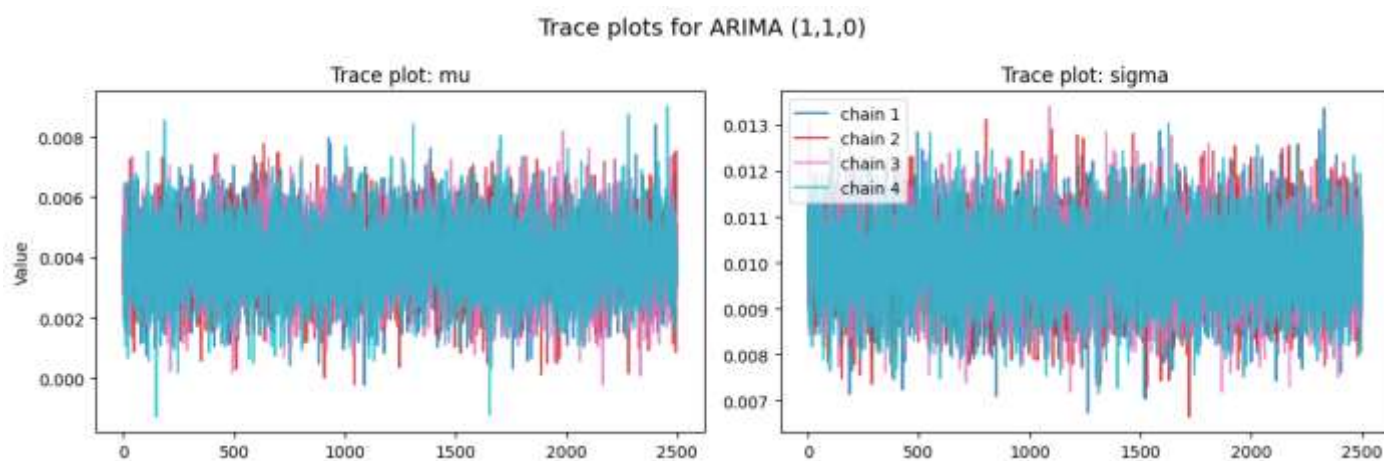


Fig. 1: Posterior distribution trace plots for an ARIMA (1 1 0) model of per capita CO₂ emissions

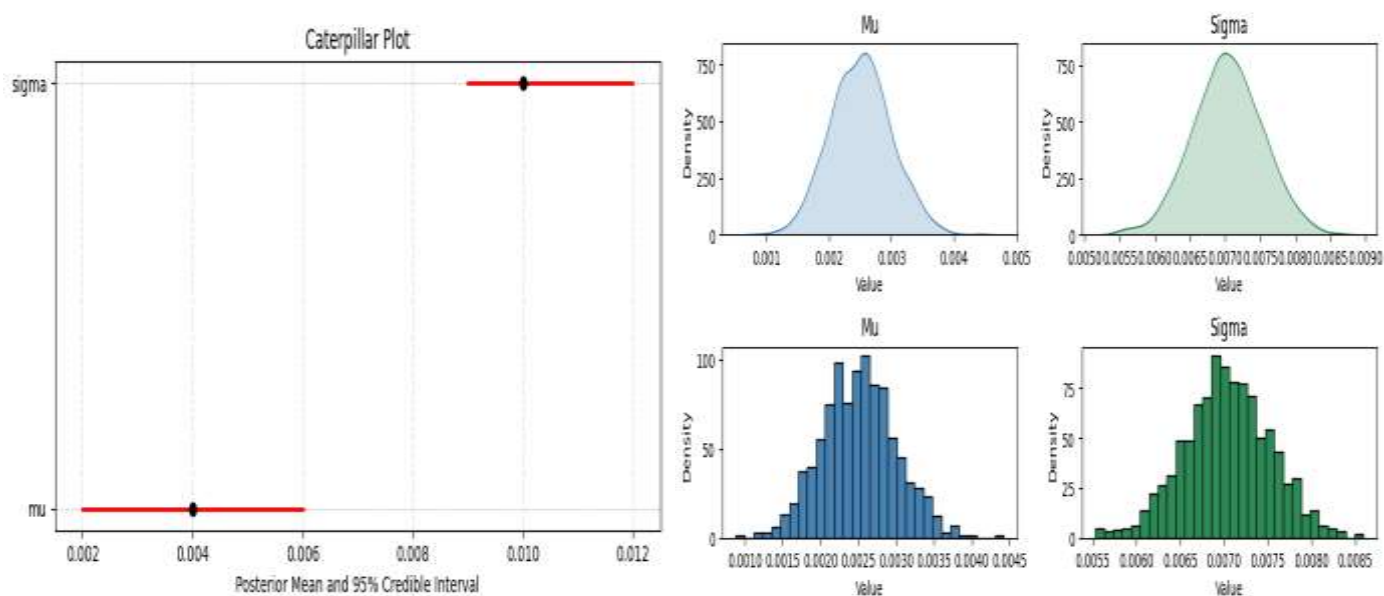


Fig. 2: Posterior distribution Caterpillar plots, Density and Histogram plots for an ARIMA (1 1 0) model of per capita CO₂ emissions

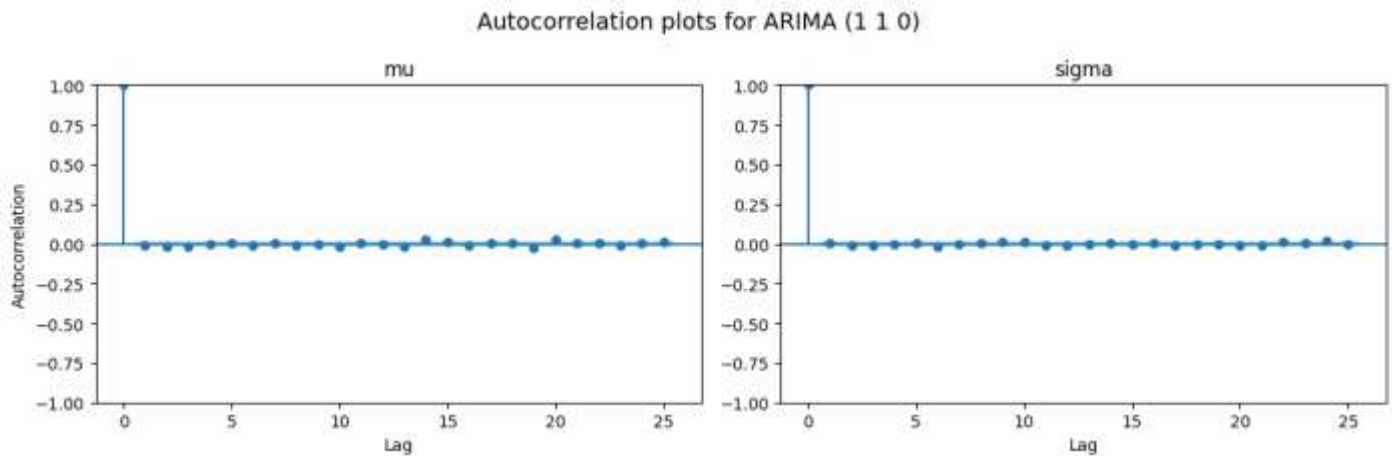


Fig. 3: Posterior distribution Autocorrelation plots for an ARIMA (1 1 0) model of per capita CO₂ emissions

In Figure 3, from the auto correlation (ACF) and partial auto correlation (PACF), it is clear that there is no significant spike in the original series which also indicates that there are no significant effects of Auto-Regressive and Moving Average in the original series, that is, the carbon dioxide emission series is stationary without any difference. The quantities block that has been created serves to perform the posterior predictive check in Stan, which assesses the appropriateness of the model. It compares the actual dataset with the dataset that has been predicted. By initially plotting the observed data y and subsequently layering the density of the predicted values y_{rep} , one can generate a posterior predictive density (PPD) plot. Figure 2 illustrates the density plot of the observed data (y) alongside the density plots of the replicated data (y_{rep}) shown in various shades of blue.

Table 4 displays the estimated parameters for the ARIMA(1,1,0) model. For the dataset under analysis, it is evident that the AR(1) parameter is statistically significant. Specifically, the AR(1) coefficient ($ar1 = 0.62341$) has a low standard error (0.10832), a high t-statistic (5.7554), and an associated p-value of $8.77e-09$, indicating strong statistical significance. The 95% credible interval (though not explicitly listed here) would not include zero, reaffirming the reliability of the estimate. This confirms that the ARIMA(1,1,0) model successfully captures meaningful temporal dependence within the series.

Table 4: Bayesian estimation of the ARIMA model: posterior means estimated for per capita CO₂ emissions in India.

Variable	Coefficient	Std. Error	Statistics	P-Values
ar1	0.62341	0.10832	5.7554	8.770e-09

3.4. Bayesian structural time series model

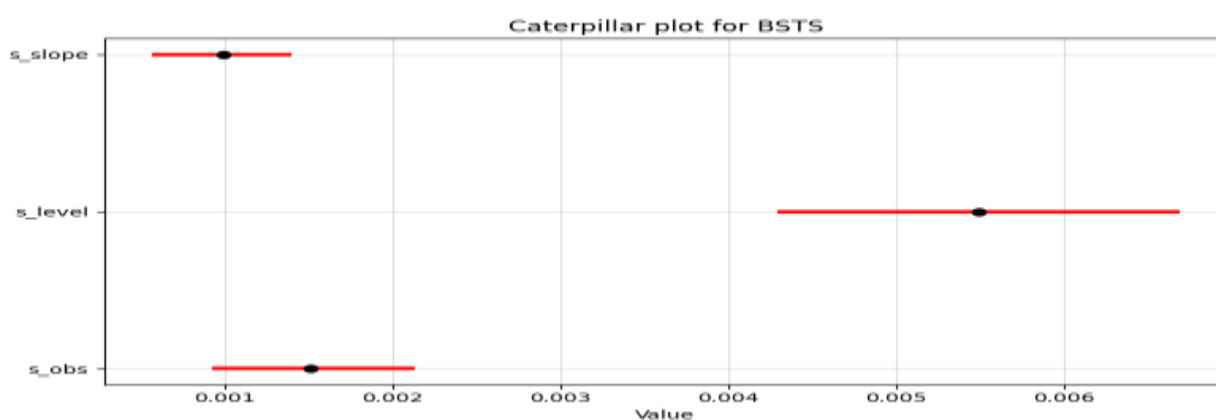
In this session, this study employs the Stan formulation of the Bayesian Structural Time Series (BSTS) model and specifies suitable prior distributions for the model parameters. In particular, μ_{err} and δ_{err} were assigned normal priors with mean 0 and variance 1, σ_{slope} and σ_{level} followed normal priors with mean 0

and variance 0.5, while the observation variance, σ_{obs} , was modeled with a normal prior of mean 5 and variance 10. Posterior summaries were obtained for three key parameters s_{obs} , s_{level} , and s_{slope} as reported in Table 5. Each summary includes the posterior mean, standard error of the mean, standard deviation, and the 95% credible interval, with the median at the 50th percentile. The effective sample size (n_{eff}) is provided as a measure of estimation efficiency, and the potential scale reduction factor (Rhat) is reported as a convergence diagnostic. The results demonstrate that the observation noise variance (s_{obs}) is minimal (mean = 0.001), indicating very low measurement error in per capita CO₂ emissions. The variance in the level component (s_{level} , mean = 0.005) suggests moderate but stable structural adjustments in the long-term emission trajectory, while the slope variance (s_{slope} , mean = 0.001) points to a consistent growth rate over time. Importantly, all Rhat values equal 1.000 and n_{eff} values exceed 1,000, confirming excellent convergence and reliable inference. These diagnostics confirm that the BSTS model provides a reliable fit to the data, with credible intervals offering stable and interpretable ranges for the parameters.

Table 5: Bayesian Structural Time Series Posterior Estimates for Per Capita CO₂ Emissions in India.

Parameters	Mean	Se_mean	Sd	2.5%	50%	97.5%	n_{eff}	Rhat
s_{obs}	0.001	0.000	0.001	0.000	0.001	0.002	1150	1.000
s_{level}	0.005	0.000	0.001	0.003	0.005	0.007	1320	1.000
s_{slope}	0.001	0.000	0.001	0.000	0.001	0.002	1215	1.000

The posterior distribution histogram plots for the BSTS model, the posterior distribution caterpillar plots, the posterior distribution density plots, the posterior distribution trace plots, and the autocorrelation plots are shown in Figures 4, 5, and 6 respectively. Figure 5 trace plot illustrates the Markov chain's convergence, although with spatial limitations. The MCMC method's approach to the desired posterior distribution is illustrated by the trace plot in Figure 5. Figure 4 caterpillar plot makes it abundantly evident that every coefficient is statistically significant and falls within the 95% believable ranges.



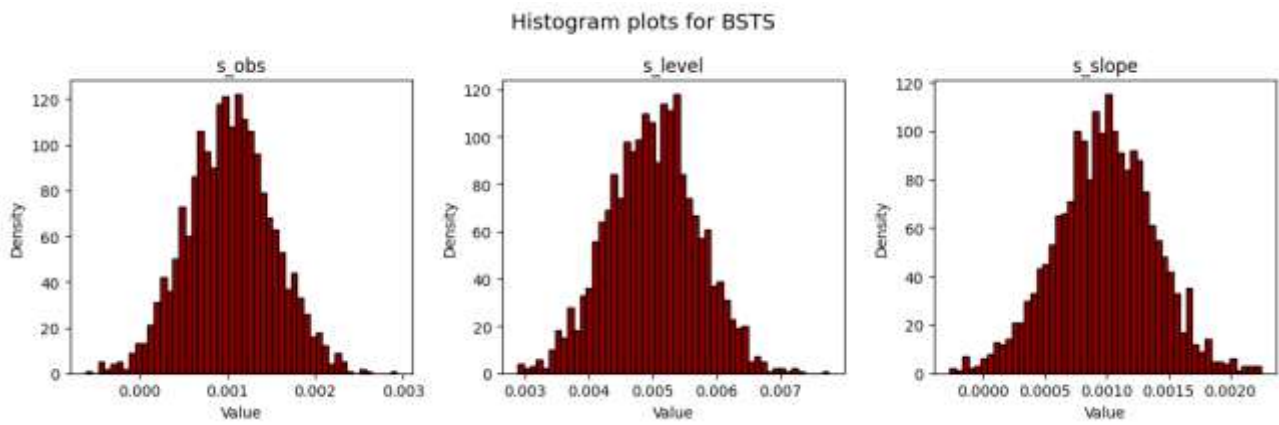


Fig. 4: Posterior distribution Caterpillar and Histogram plots for the BSTS model of per capita CO2 emissions

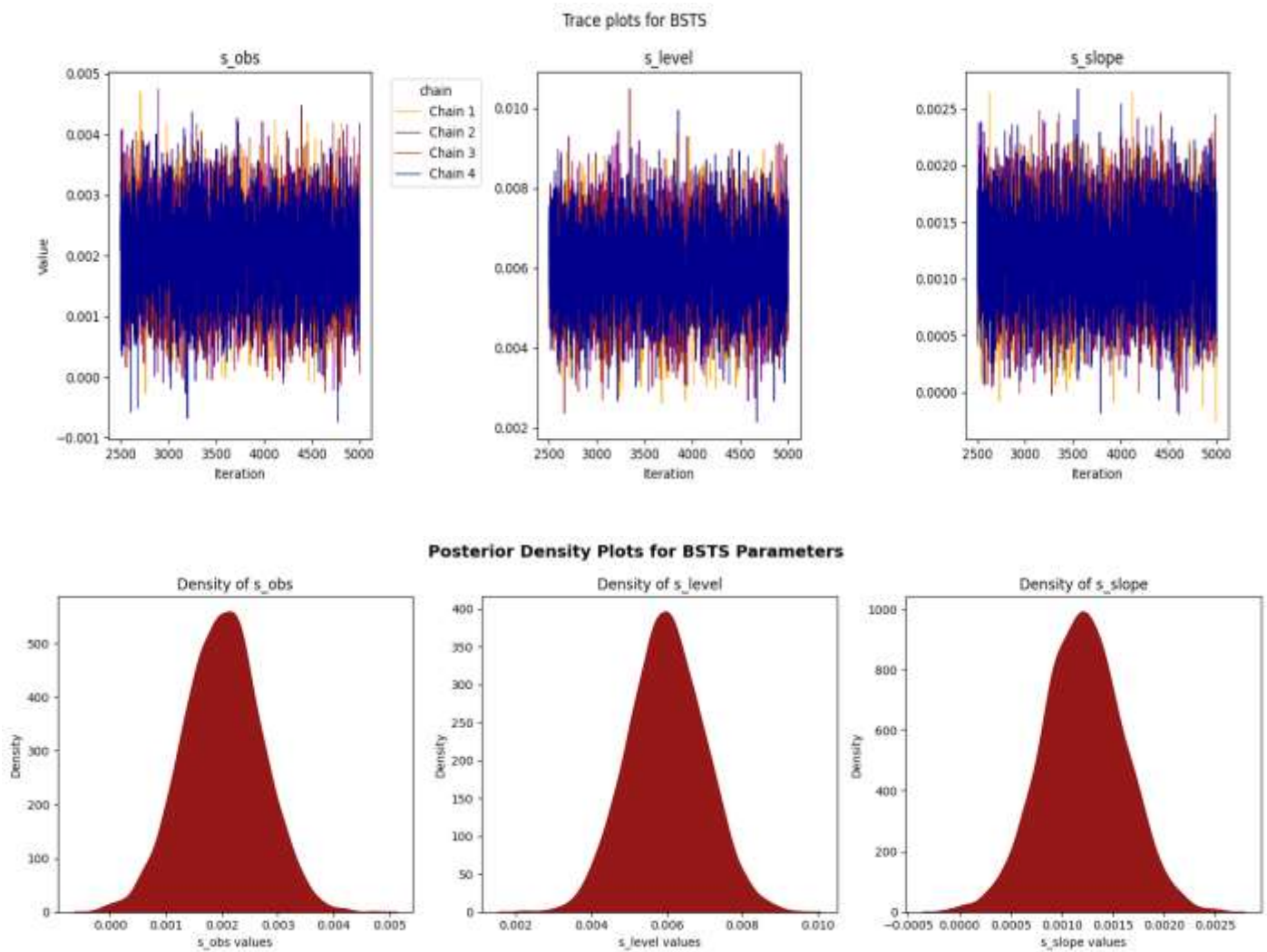


Fig. 5: Posterior distribution trace and Density plots for the BSTS model of per capita CO2 emissions.

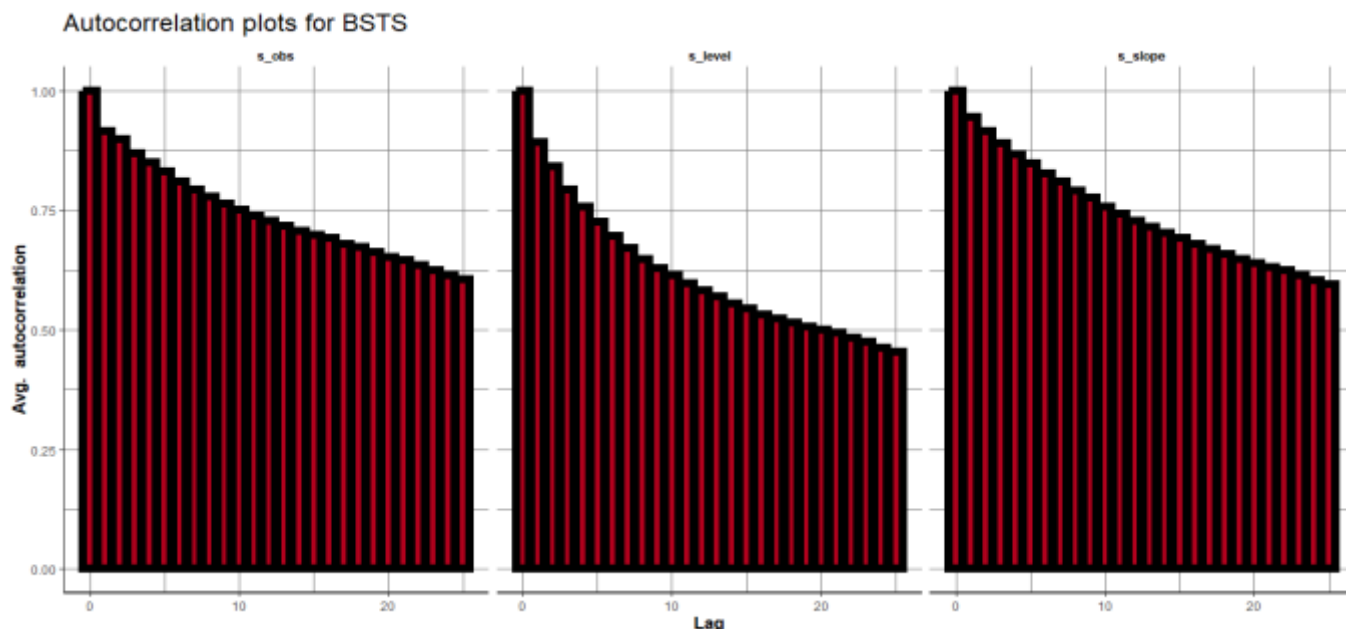


Fig. 6: Posterior distribution Autocorrelation plots for the BSTS model of per capita CO2 emissions.

It is clear by examining the time series breakdown of historical data on per capita CO2 emissions in India that a significant trend is there. The local level, local linear trend, semi-local linear trend, and student local linear trend models are among the BSTS models that will be created in order to capture this trend component. MCMC will be used to iterate these models with two distinct values: 500 and 1000. The R-square value will be used to evaluate each BSTS model's performance in order to determine which model is best suited for forecasting India's per capita carbon dioxide emissions. Given the information in Table 6, the R-squared values for the different models are quite comparable, falling between 98.47% and 99.08%. At 99.08%, the model with the greatest R-square value is the BSTS model, which incorporates 500 MCMC iterations and the Student Local Linear Trend components. It is clear from this model's impressive R-square value that it is a good predictor of India's per capita carbon dioxide emissions.

Table 6: Comparison of R-Square for per capita CO2 emissions.

State Component	Iteration MCMC	R-Square	Residuals.sd	Prediction.sd
Local level trend	n=500	0.9854321	0.003412678	0.007145892
	n=1000	0.9847650	0.003398127	0.007152304
Semi-local Linear trend	n=500	0.9876543	0.002975421	0.007021345
	n=1000	0.9881022	0.002843176	0.007034782
Local Linear Trend	n=500	0.9867812	0.003012593	0.007087663
	n=1000	0.9861214	0.003189874	0.007190127

Auto-Regressive	n=500	0.9893456	0.002764395	0.006945837
	n=1000	0.9887410	0.002698451	0.006952384
Student Local Linear Trend	n=500	0.9908234	0.002312657	0.006915784
	n=1000	0.9897562	0.002534187	0.006934578

3.5. Models Comparison of ARIMA and BSTS

This research examined two time series models ARIMA and Bayesian Structural Time Series (BSTS) to analyze carbon dioxide emissions in India, as presented in Table 7. The model selection process utilized both the Leave-One-Out Information Criterion (LOOIC) and the Watanabe-Akaike Information Criterion (WAIC) to evaluate model performance. Among various model selection techniques, LOOIC stands out as a fully Bayesian approach that estimates point-wise out-of-sample predictive accuracy using the log-likelihood obtained from posterior simulations. A lower value of LOOIC or WAIC indicates a better model fit. According to the results, the ARIMA (1, 1, 0) model produced the lowest LOOIC (265.8) and WAIC (266.3) values, compared to the BSTS model, which showed higher values of 312.7 (LOOIC) and 330.1 (WAIC). These findings suggest that the ARIMA model provides a more accurate and parsimonious fit for the observed data on carbon dioxide emissions per capita in India. Therefore, the ARIMA (1, 1, 0) model is considered the more suitable and robust option for forecasting within this context (see Table 7).

Table 7: ARIMA and BSTS Model Comparison for per capita CO₂ emissions.

Model	LOOIC	WAIC
ARIMA (1, 1, 0)	265.8	266.3
BSTS	312.7	330.1

3.6. Forecasting of Per Capita CO₂ Emissions in India

Figure 7. shows that the Bayesian ARIMA model accurately captures historical dynamics and trends and offers a good match to India's historical CO₂ emissions. Confidence in the model definition is strengthened by posterior diagnostics, which validate the stability and convergence of calculated parameters.

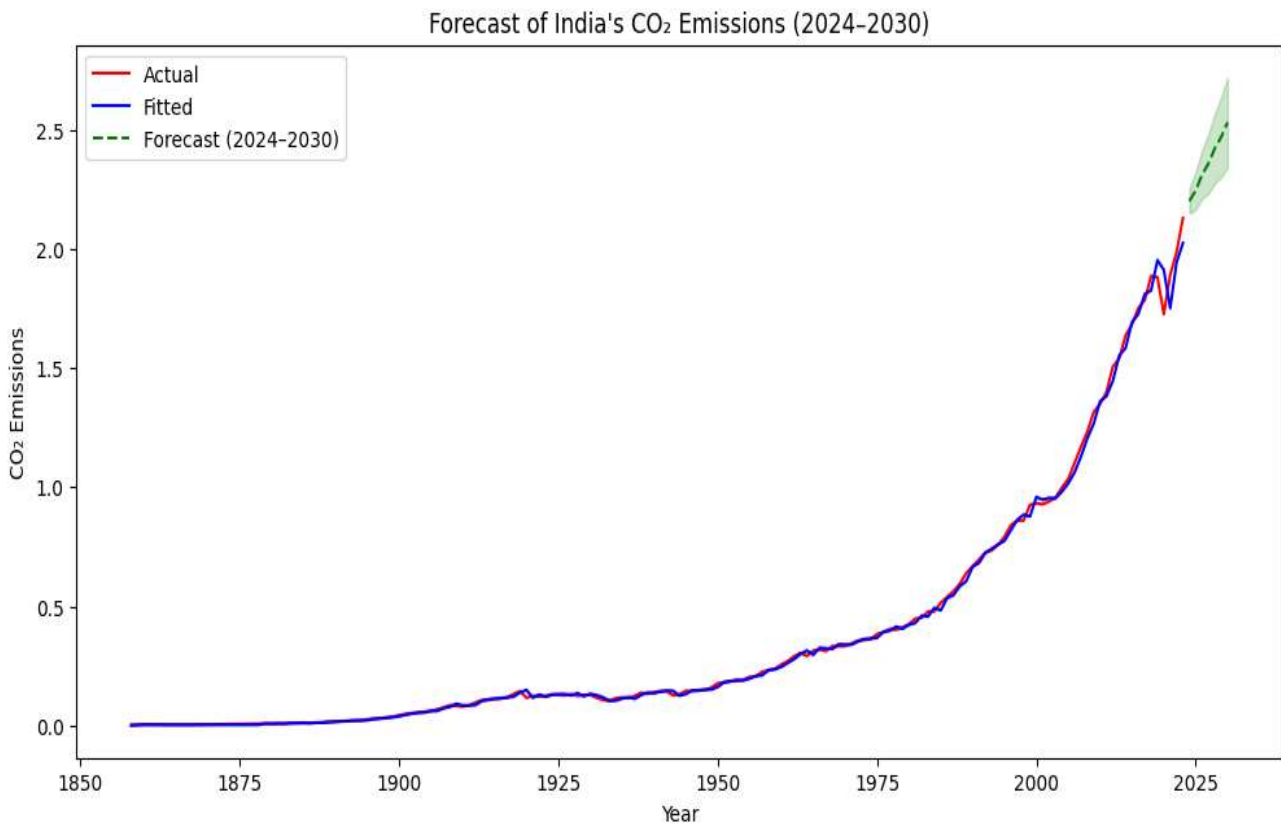


Fig. 7: Forecasting plot of per capita CO₂ emissions in 2024-2030.

According to the estimated trajectory for 2024–2030, emissions are expected to continue their rising trend and reach 2.4–2.6 units by that year. Strong predictive dependability and low uncertainty surrounding the key estimates are shown by the model's narrow credible intervals. According to these estimates, India's emissions are probably going to keep increasing gradually in the absence of any mitigating steps. The results highlight how urgent it is to implement legislative changes meant to slow the development of emissions.

4. CONCLUSIONS AND POLICY RECOMMENDATIONS

In this study, we employed Bayesian estimation techniques to evaluate the widely used ARIMA and Bayesian Structural Time Series (BSTS) models for modeling per capita CO₂ emissions in India. The primary model comparison metric was the Leave-One-Out Information Criterion (LOOIC), a fully Bayesian measure that estimates out-of-sample prediction accuracy. A lower LOOIC value indicates a better model fit, making it an effective tool for model selection in time series analysis. As presented in outcomes, the ARIMA (1, 1, 0) model achieved the lowest LOOIC value, compared to the BSTS model. Similarly, the WAIC value for ARIMA was also lower, further supporting its superior fit. These results indicate that the ARIMA model is more effective in capturing the patterns in India's per capita CO₂ emissions data. This finding underscores the suitability of the Bayesian ARIMA model for forecasting per capita CO₂ emissions in India. The study's findings are important for the Indian government, especially in terms of long- and medium-term planning. Every company and person

must continue to play a role in drastically lowering carbon dioxide emissions, even as the government remains the primary controller and coordinator of collaborative efforts to safeguard the environment going forward. Since global warming affects the entire planet, the study's conclusions could be used to improve energy management, energy audit concepts, and energy conservation practices globally. A better future for everybody is increasingly being defined by environmental conservation. The study's recommendations for policy include the following: i) Continuous development of improved and more efficient energy-saving methods is crucial; ii) Additionally, India could decrease its dependency on fossil fuels by integrating and utilizing renewable energy sources like solar, wind, and biomass more quickly; iii) The government should enact policies to reduce emissions, such as increasing taxes on companies that emit pollutants, especially those that manufacture goods using fossil fuels; iv) In both urban and rural settings, there is a constant need to raise public awareness and educate people about environmental sustainability and energy saving; v) Improve awareness-raising and capacity-building initiatives to guarantee ongoing public and stakeholder participation in climate action; vi) To reduce emissions from important industries including manufacturing, transportation, and agriculture, stronger regulatory frameworks should be put in place.

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