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

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ABSTRACT

This study uses a completely Bayesian method to analyze and forecast per-capita CO_2 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 emphasized the advantages of the BSTS model, particularly in capturing intricate structures in environmental and economic time series. This investigation, which focuses on long-term historical per-capita CO_2 emissions data from 1858 to 2023, takes a different modelling approach and comparison framework than previous studies. Choosing the best ARIMA model order is an important initial step based on the Leave-One-Out Information Criterion (LOOIC). The rstan package was 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 Leave-One-Out Information Criterion (LOOIC), were used to assess the model performance. The findings show that, in terms of forecast accuracy for India's per-capita CO_2 emissions, the Bayesian ARIMA model routinely outperforms the BSTS model, even with its more straightforward structure.

INTRODUCTION

The production of greenhouse gases is the primary cause of climate change, which is a significant 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, an increase of 11% since 2000 and 47% since the Industrial Revolution (Razzak et al. 2017, Buis et al. 2019). The increasing use of fossil fuels for energy has resulted in rising CO_2 emissions globally, especially in Africa and Afghanistan (Natnael Demeke 2016, Haqbin & Khan 2024). This presents serious issues for developing economies, such as Indonesia. Developed nations own a significantly larger proportion of worldwide emissions than emerging nations (Muhammad & Ghulam Fatima 2013).

India's rapid industrialization and urbanization have led to substantial CO_2 emissions, making it the third-largest emitter of carbon dioxide globally. Despite this, developing countries collectively contribute less than 16% of the global CO_2 concentration, highlighting the disproportionate impact of fossil fuel use in high-income countries. Within South Asia, India is the dominant source of regional emissions, which are largely driven by energy consumption, manufacturing, transportation, and construction. However, comprehensive studies identifying the economy-wide drivers of per-capita CO_2 emissions in India remain limited (Kinnunen et al. 2020). According to the World Bank, India's per capita CO_2 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 & 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 worldwide. The combination of high population density, rising energy demands, and resource-intensive economic development continues to contribute to the increase in per-capita CO_2 emissions and other greenhouse gas emissions.

Numerous studies have examined per-capita CO_2 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 CO_2 emissions reached approximately 2.71 billion metric tons in 2022, reflecting a 4.2% increase from the previous year, which was 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 this gap by employing Autoregressive Integrated Moving Average (ARIMA) and Bayesian Structural Time Series (BSTS) models to forecast per-capita CO_2 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 landscapes.

This study aims to forecast and predict per-capita CO_2 emissions in India using both the Bayesian Autoregressive Integrated Moving Average (ARIMA) and Bayesian Structural Time Series (BSTS) models. By integrating these two modeling approaches, this study seeks to enhance forecasting accuracy. Time-series models vary widely and incorporate diverse stochastic processes suitable for capturing complex emission patterns. Accurate forecasts of per-capita CO_2 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 the ARIMA and BSTS models, utilizing data from 1858 to 2023.

BACKGROUND RESEARCH

As global carbon emissions cause many problems, reducing per capita CO_2 emissions is essential for a sustainable society. Research in many nations shows a high correlation between economic development and per-capita CO_2 emissions. For example, Hossain et al. (2017) discovered a strong correlation between Algeria's GDP and emissions from 1970 to 2010. Bouznit and Pablo-Romero (2016) analyzed data from Pakistan (1971–2019) using ARDL cointegration and found that energy consumption and economic growth have a beneficial impact on emissions. While Aftab et al. (2023) observed a one-way link in Turkey, Gökmenoğlu & Taspinar (2016) found a bidirectional association between GDP and energy usage in South Africa. In Bangladesh, Khobai & Le Roux (2017) found that while per capita CO_2 emissions had a detrimental effect on economic growth, energy usage had a beneficial effect.

The connection between energy use, carbon emissions, and economic variables in various countries has been the subject of several studies. Ghosh et al. (2014) discovered that energy use and population density had a major influence on environmental deterioration in Pakistan. According to Mirza & Kanwal (2017), carbon emissions in Bangladesh are increasing more quickly than GDP and energy consumption. For the G7 nations, Sarkar et al. (2018) established a cointegration between the usage of renewable energy and economic development using the ARDL limit test. Salari et al. (2021) found a one-way causal relationship between Kuwait's GDP and CO_2 emissions. While Wasti & Zaidi 2020) examined the relationship between energy consumption, economic development, and population density in 11 Asian nations, Yadav & Rahman (2017) examined the contributions of various energy sources to world per capita CO_2 emissions. According to Valadkhani et al. (2019) and others, energy usage and emissions are influenced by economic growth. Valadkhani et al. (2019), Shahbaz et al. (2013), and Alam et al. (2025) studied the impact of globalization on per-capita CO_2 emissions. Overall, these studies show that these factors interact in a complex manner over time.

Numerous factors may affect per-capita CO_2 emissions; thus, precise forecasting is crucial. Models have been created for this purpose in recent studies. Following the climate summit in Copenhagen, China has paid close attention to the per capita CO_2 emissions projections. For example, You & 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 CO_2 emissions from 1965 to 2010, and it was predicted that these emissions would reach 925.68 million tons in 2020 (Lotfalipour et al. 2013). Basak & Nandi (2014) investigated the dynamics of CO_2 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 were employed: autoregressive integrated moving average (ARIMA) and simple exponential smoothing (SES). The ARIMA model was found to be appropriate because it had the lowest fractional mean absolute error (FMAE) value (Fatima et al. 2019). The causal relationship between carbon dioxide emissions and variables that may or may not have an impact on them has been examined in several studies from various perspectives. Nonetheless, certain elements need to be improved, as well as some factors that motivate this endeavor, such as the undervaluation of India. Given that India needs to investigate its carbon dioxide emissions, we used the Bayesian structural time series (BSTS) model in this study to forecast India's carbon dioxide emissions.

MATERIALS AND METHODS

Data Source

India's per capita CO_2 emissions information is sourced from World Development Indicators, which can be accessed at https://databank.worldbank.org. It examines 155 annual observations of per-capita CO_2 emissions from 1858 to 2023. Bayesian structural time series models will be used in this study to analyze the annual per-capita CO_2 emissions data. Carbon dioxide emissions, mostly from cement and power manufacturing, are the primary greenhouse gases linked to global warming. Carbon dioxide emissions from different fossil sources vary.

Methods

Data that show stationarity, that is, when the mean, variance, and autocorrelation structure stay constant across time, are analyzed using the ARIMA and BSTS models. Accurate forecasting of the future behavior of processes depends on this. A first difference transformation is used to ascertain whether the data have become a stationary series. The second difference is computed if the first difference is not. Following the series' stationarity, model fitting can be performed.

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 a forecast.

$$\Delta^{\mathrm{d}}\mathrm{y}_{\mathrm{t}} = \delta + \theta_1\Delta^d y_{t-1} + \theta_2\Delta^d y_{t-2} + \dots$$

$$+ \theta_p y_{t-p} + e_{t-1}\alpha e_{t-1} - \alpha_2 e_{t-2} e_{t-2}$$

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), can 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

$$\phi(B^p) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\,;$$

$$B^p Y_t = Y_{t-p}$$

$$\theta(B^p) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\,;$$

$$(1-B)^d = \sum_{j=0}^{d} (-1)^j \binom{d}{j} B^j$$

The ARIMA (p, d, q) models are based on the choice of optimum values of p and q. ARIMA(p, d, q) models are useful for 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 considering uncertainties in the model parameters.

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

Prior information: The Bayesian ARIMA model allows for the incorporation of 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 using the Bayesian ARIMA model.

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

Bayesian Structural Time Series

The Bayesian Structural Time Series (BSTS) model is a statistical tool used to analyze 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 terms of convergence and consistency (Mokilane, 2019). The autocorrelation plots show the level of correlation between successive observations over different time lags, with bars reaching a maximum value of 1.00, suggesting a strong positive correlation at certain lags. The histogram plots show a positively skewed distribution for the observation variance, indicating a low variance but the potential for larger values. The 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 various times. Level variance, which reflects 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 $\underline{y} : y_1 , y_2 , \quad \cdots , y_t$ 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.

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

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

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

The likelihood function is defined as:

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

Which reduces to:

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

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 like a random walk.

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

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

In the local level model, the matrices Z_t, T_t, and R_L in the equation are simplified to a single scalar value of '1'. The model's parameters consist of the variances of the error terms $\left(\sigma_\epsilon^2,\ \sigma_\eta^2\right)$.

Local Linear Trend State Component

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

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

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

The slope equation is:

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

The local linear trend model is frequently chosen for modelling trends because of its rapid adjustment to local variations. This is particularly useful for short-term forecasting. However, for long-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 several 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 study, the model was compared using Bayesian model selection metrics, such as the Leave-One-Out Information Criterion (LOOIC) and the Widely Applicable Information Criterion (WAIC). Two models were analyzed: ARIMA and BSTS. AIC and BIC are the most widely used metrics for model selection. The ARIMA and BSTS models with the lowest AIC or BIC values based on this criterion were selected.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 presents the descriptive statistics of per-capita CO_2 emissions data, revealing the important characteristics of the distribution. The average (mean) annual emission was 0.125 metric tons, with a median value of 0.110 metric tons, indicating a slightly right-skewed distribution. Despite having a large population and a low level of industrial development, India's per capita CO_2 emissions of approximately 2 metric tons in 2022 seem low. When these parameters are compared to those of 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 outliers of higher emissions. The kurtosis value of 0.215 indicates a mildly leptokurtic distribution, implying slightly heavier tails than those of a normal distribution. The range of emissions spanned 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 the 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 CO_2 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 CO_2 emissions series (-1.975, p=0.838) indicates non-stationarity. After first differencing, the series became stationary (ADF = -4.6723, p=0.00), suitable for time series modeling.

Table 1: Descriptive Statistics.

Statistic	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)

Bayesian Autoregressive Integrated Moving Average (ARIMA) Model

Table 2 summarizes the performances of the various ARIMA models using multiple evaluation criteria. Among the candidates, the ARIMA(1,1,0) model consistently demonstrated 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 CO_2 emissions in India. Despite the tendency of the AIC to prefer more complex models, its agreement with the BIC and Bayesian measures strengthens the model 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) was identified as the best-fitting and most efficient model for forecasting India's carbon dioxide emissions.

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 were sufficiently large ($\mu = 9780$, $\sigma = 3050$), indicating that the Markov Chain Monte Carlo (MCMC) sampling was efficient. Additionally, the Rhat values were exactly 1.00, confirming the convergence of the chains and model stability. The 95% credible intervals

Table 2: Analysis of ARIMA model 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

Table 3: Posterior Summary of ARIMA (1,1,0) for per capita CO_2 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

for the mean (μ: 0.002–0.006) and standard deviation (σ: 0.009–0.012) 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 per-capita CO_2 emissions series.

The trace plot shown in Fig. 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 that the Markov chains have reached convergence to the posterior distribution (see Fig. 1). The trace plot shown in Fig. 3 illustrates how the MCMC method converges to the desired posterior distribution. The caterpillar plot presented in Fig. 2 clearly indicates that all coefficients fall within the 95% credible interval and are statistically significant. However, because

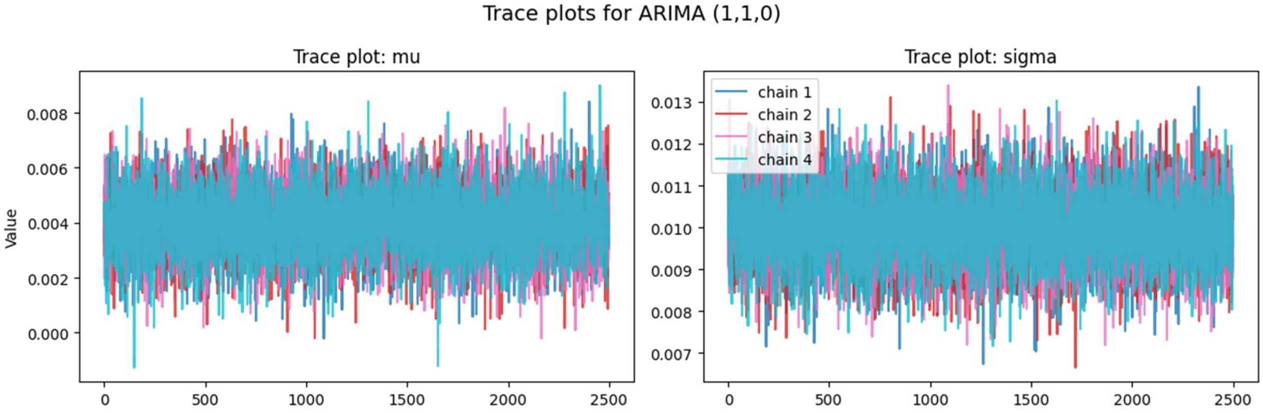

Fig. 1: Posterior distribution trace plots for an ARIMA (1 1 0) model of per capita CO_2 emissions.

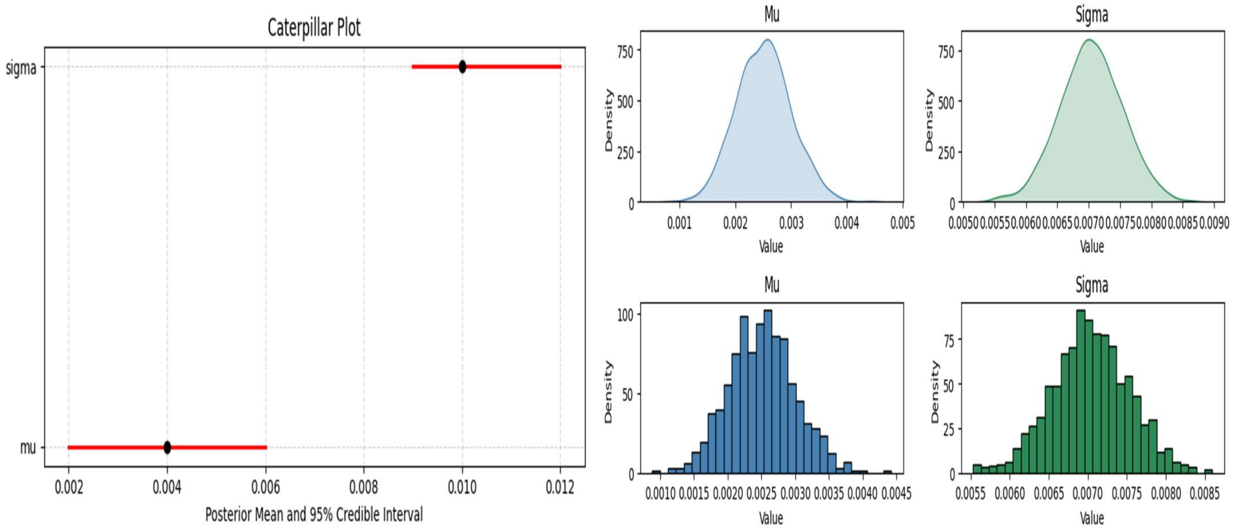

Fig. 2: Posterior distribution Caterpillar plots, density, and histogram plots for an ARIMA (1 1 0) model of per capita CO_2 emissions.

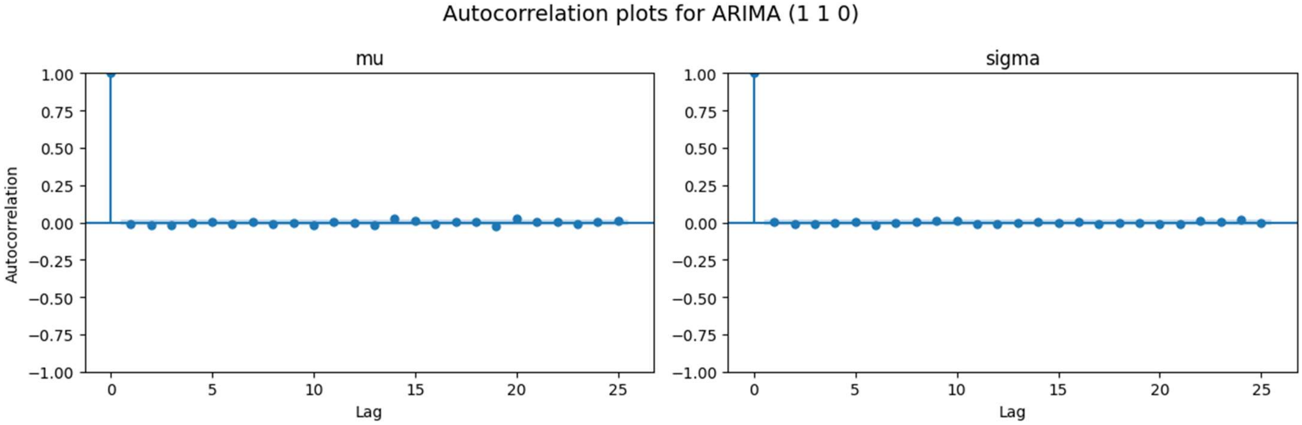

Fig. 3: Posterior distribution autocorrelation plots for an ARIMA (1 1 0) model of per capita CO_2 emissions.

the horizontal lines intersect the vertical line at zero, the caterpillar plot reveals that none of the covariates were statistically significant (Fig. 2).

As shown in Fig. 3, the auto-correlation (ACF) and partial auto-correlation (PACF) indicate no significant spike in the original series, which also indicates that there are no significant effects of auto-regression and moving average in the original series; that is, the carbon dioxide emission series is stationary without any difference. The quantities block 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. Fig. 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 of the ARIMA(1,1,0) model. For the dataset analyzed, it is evident that the AR(1) parameter was 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) does 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 CO_2 emissions in India.

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

Bayesian Structural Time Series Model

In this section, 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 a mean of 0 and variance of 1, σ_slope and σ_level followed normal priors with a mean of 0 and variance of 0.5, while the observation variance, σ_obs, was modeled with a normal prior of a mean of 5 and variance of 10. Posterior summaries were obtained for three key parameters: s_obs, s_level, and s_slope, as reported in Table 5. Each summary included the posterior mean, standard error of the mean, standard deviation, and 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 demonstrated that the observation noise variance (s_obs) was minimal (mean = 0.001), indicating a very low measurement error in per-capita CO_2 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 were equal to 1.000, and n_eff values exceeded 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.

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 Figs. 4, 5, and 6, respectively. The trace plot in Fig. 5

Table 5: Bayesian Structural Time Series posterior estimates for per-capita CO_2 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

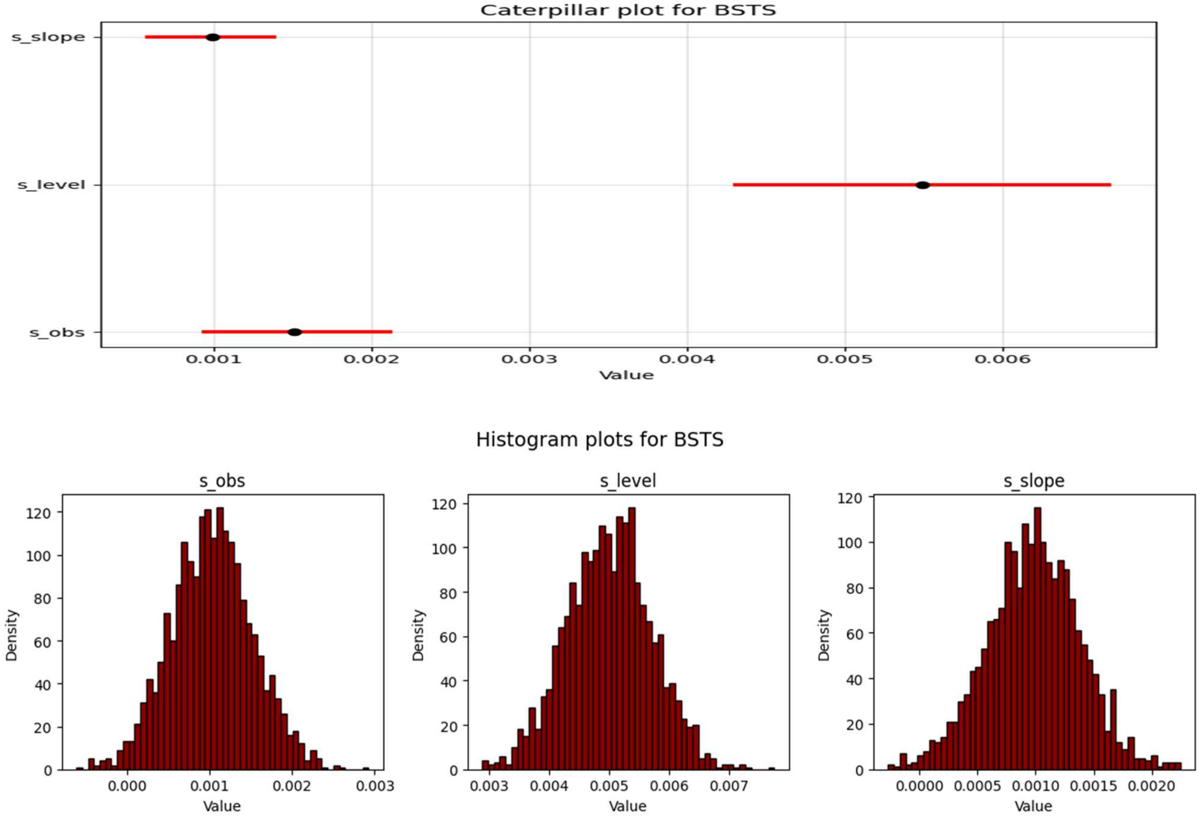

Fig. 4: Posterior distribution Caterpillar, and histogram plots for the BSTS model of per capita CO_2 emissions.

illustrates Markov chain convergence, although with spatial limitations. The approach of the MCMC method to the desired posterior distribution is illustrated by the trace plot in Fig. 5. The caterpillar plot in Fig. 4 shows that every coefficient is statistically significant and falls within the 95% believable range.

It is clear by examining the time-series breakdown of historical data on per-capita CO_2 emissions in India that a significant trend exists. 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 to capture this trend component. MCMC was used to iterate these models with two distinct values: 500 and 1000. The R-square value was used to evaluate each BSTS model's performance 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 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-squared value that it is a good predictor of India's per capita carbon dioxide emissions.

Models Comparison of ARIMA and BSTS

This study 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 the various model selection techniques, LOOIC stands out as a fully Bayesian approach that estimates point-wise out-of-sample predictive accuracy using the

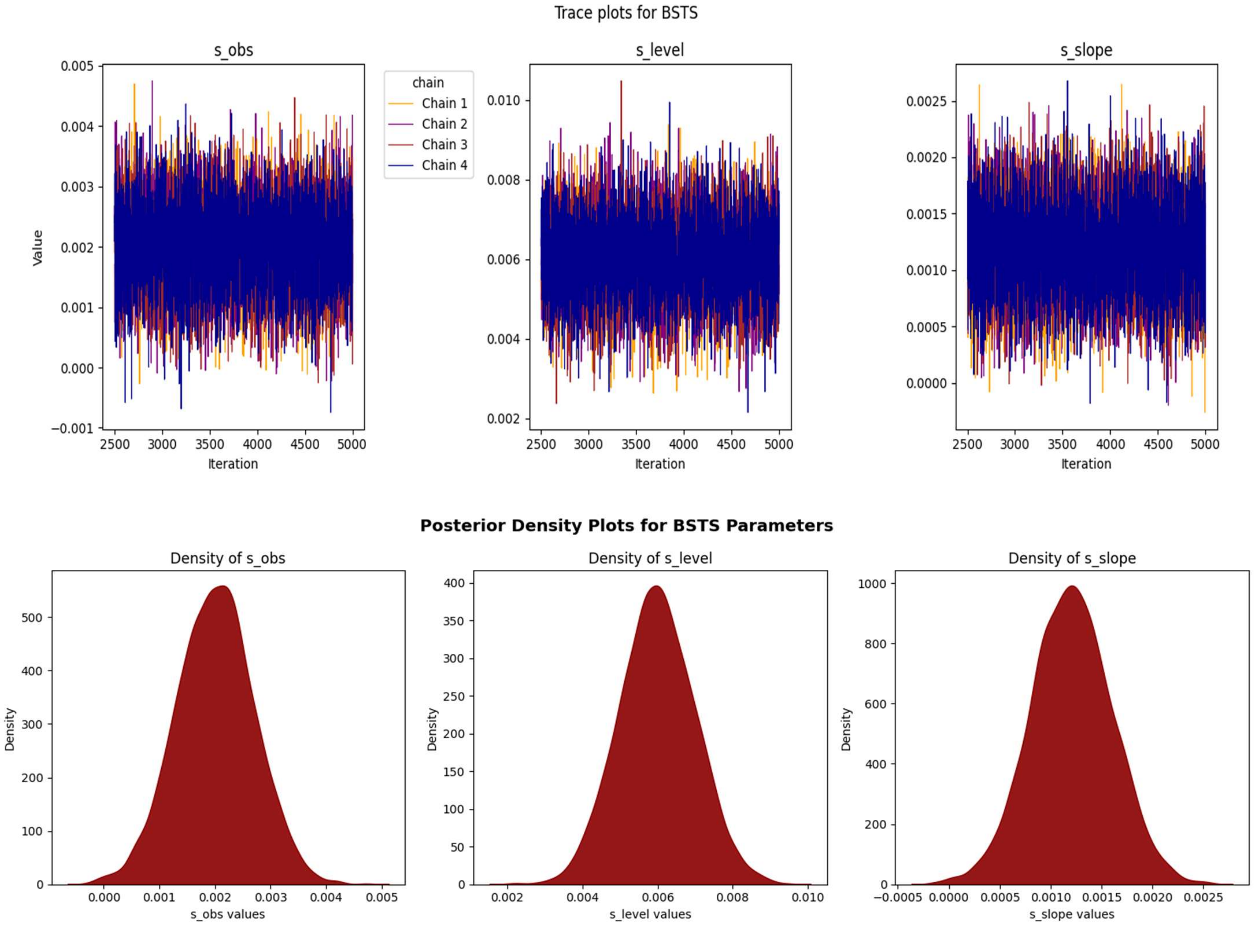

Fig. 5: Posterior distribution trace and density plots for the BSTS model of per-capita CO_2 emissions.

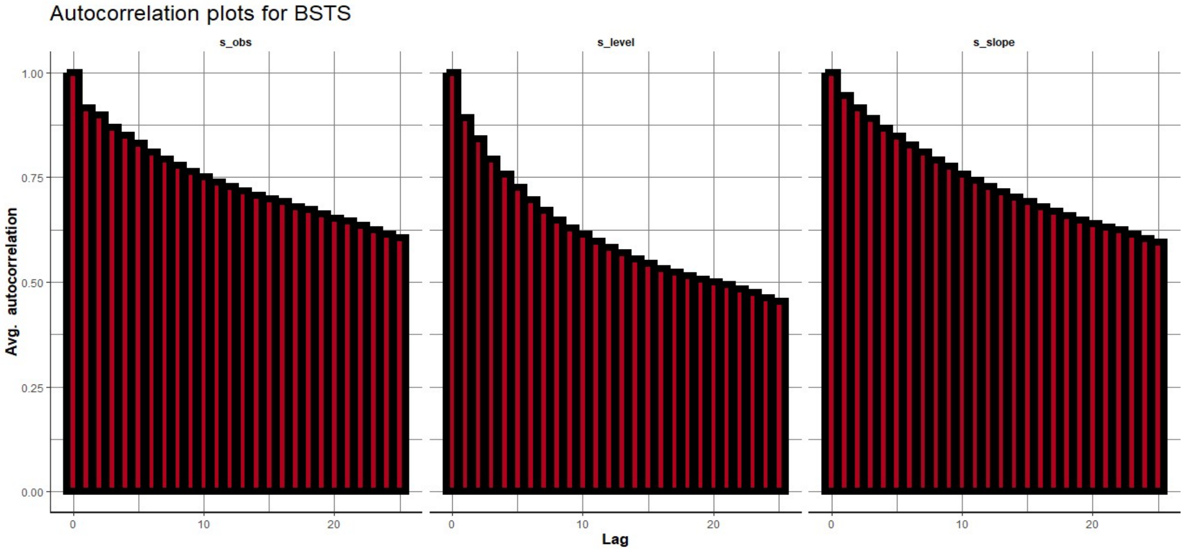

Fig. 6: Posterior distribution autocorrelation plots for the BSTS model of per-capita CO_2 emissions.

Table 6: Comparison of R-squared for per-capita CO_2 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

Table 7: ARIMA and BSTS Model Comparison for Per-Capita CO_2 Emissions.

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

log-likelihood obtained from posterior simulations. A lower LOOIC or WAIC value 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 a more suitable and robust option for forecasting within this context (see Table 7).

Forecasting of Per Capita CO_2 Emissions in India

Fig. 7 shows that the Bayesian ARIMA model accurately captures historical dynamics and trends and offers a good match to India's historical CO_2 emissions. Confidence in the

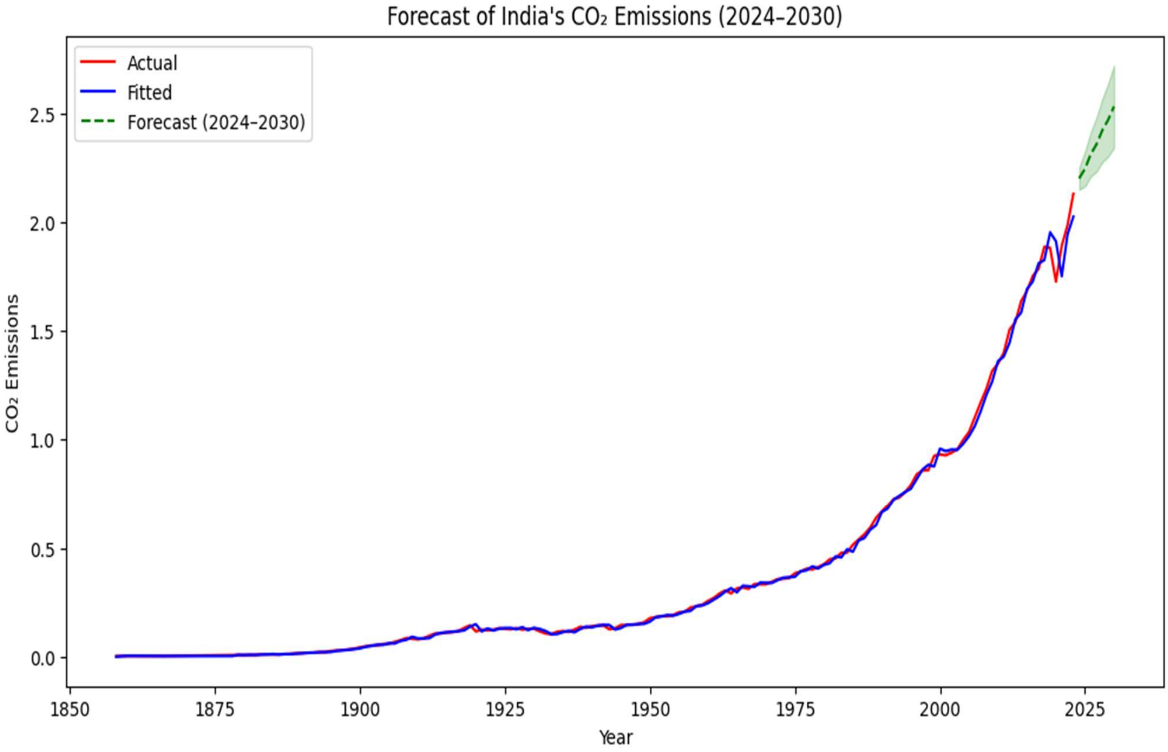

Fig. 7: Forecasting plot of per-capita CO_2 emissions in 2024-2030.

model definition is strengthened by posterior diagnostics, which validate the stability and convergence of the calculated parameters.

According to the estimated trajectory for 2024–2030, emissions are expected to continue to rise and reach 2.4–2.6 units by that year. The model's narrow credible intervals indicate strong predictive dependability and low uncertainty surrounding the key estimates. According to these estimates, India's emissions will likely continue to increase gradually in the absence of any mitigating steps. The results highlight the urgency of implementing legislative changes to slow the development of emissions.

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 CO_2 emissions in India. The primary model comparison metric was the Leave-One-Out Information Criterion (LOOIC), a fully Bayesian measure that estimates the 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 the outcomes, the ARIMA (1, 1, 0) model achieved the lowest LOOIC value compared to the BSTS model. Similarly, the WAIC value for ARIMA was 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 CO_2 emissions data. This finding underscores the suitability of the Bayesian ARIMA model for forecasting India's per-capita CO_2 emissions. The study's findings are important for the Indian government, especially for long- and medium-term planning. Every company and individual 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. Because 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 everyone 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) India could decrease its dependency on fossil fuels by integrating and utilizing renewable energy sources such as 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; and vi) To reduce emissions from important industries including manufacturing, transportation, and agriculture, stronger regulatory frameworks should be put in place.

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