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*Original Article*

# Time-Based Analysis of Annual Forestry Emissions and Forestry Value-Added in Ranchi, Jharkhand for 2001-2050

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***Abstract*** - *The forestry emissions and value-added in the Ranchi region of interest are analyzed from 2001 to 2023, utilizing the Mann-Kendall test, the Sequential Mann-Kendall test, Pearson's Correlation Coefficients, and the Autoregressive Integrated Moving Average model. Trend analysis showed a positive increase in forestry greenhouse gas and carbon emissions at a 5% significance level. In comparison, forestry value-added exhibited a positive increasing trend at a 1% significance level. Based on the result of the correlation analysis, the forestry greenhouse gas and carbon emissions are positively correlated with the forestry value-added, with a correlation coefficient of 0.43 at a 5% significance level. The best accurate model for predicting forestry emissions and value added is ARIMA (1,1,0). The trend analysis of forecasted forestry emissions and value-added indicates a significant positive upward trend in both greenhouse gas and carbon emissions from forestry and the value added from the forestry sector in Ranchi, Jharkhand. This trend is projected from 2024 to 2050 and is significant at a 1% significance level.*

***Keywords*** - *Forestry greenhouse gas emissions, Forestry carbon emissions, Forestry value-added, ARIMA model.*

## 1. Introduction

Forests have a significant capacity to absorb carbon dioxide and play a vital role in the global carbon cycle, which is increasingly recognized. Consequently, they may become essential in mitigating the effects of climate change [1]. India, which is home to around one-sixth of the world's population, has one of the largest economies. Its growth is vital for global development and achieving sustainable goals, but it faces challenges such as climate change. India has a very small impact on global warming, yet the nation is dedicated to tackling climate change by pursuing low-carbon development strategies, targeting net zero by 2070. According to the report (BUR-4) for the year 2020, India's total greenhouse gas emissions, excluding Land Use, Land-Use Change, and Forestry (LULUCF), were 2,959 million tonnes of $CO_2$ equivalent, decreasing to 2,437 million tonnes when LULUCF is included. Carbon emissions comprised 80.53 percent, methane emissions 13.32 percent, nitrous oxide emissions 5.13 percent, and other gases 1.02 percent. In the same year, India's total emissions were reduced by 22% due to its forests and tree cover sequestration of over 522 million tonnes of carbon dioxide. India experienced a decrease of 34 percent in emission intensity per unit of Income between 2005 and 2020, thereby separating revenue growth from greenhouse gas emissions. Between 2005 and 2021, the nation produced an extra carbon sink of 2.29 billion tons of $CO_2$, and its forest and tree cover currently comprises 25.17% of the entire land area.[2]. The total forest cover in Jharkhand was reported at 22,894 km² in 2007 and increased to 23,765.78 km² by 2023. This represents 28.72% of its geographical area in 2007 and 29.81% in 2023. In contrast, the forest cover in Ranchi was 1,904 km² in 2007 but decreased to 1,141 km² in 2023. This accounts for 24.73% of its geographical area in 2007 and 22.38% in 2023. This data indicates that the forest cover in the Ranchi district has decreased by approximately 40% over the past decade [3,4].

Multiple researchers are predicting energy consumption to understand future patterns and variability [5,6]. For instance, in Turkey, the ARIMA model predicts energy use by fuel type, which helps inform policy recommendations [7]. Pao and Tsai utilize the grey prediction model and ARIMA to forecast pollutant emissions, energy consumption, and output for Brazil, recommending energy conservation policies to enhance energy efficiency and reduce energy waste [8]. Ang et al. utilize the ARIMA model to forecast $CO_2$ emissions from gaseous fuel consumption, liquid fuel consumption, solid fuel consumption, electricity production, and transportation in Malaysia, providing recommendations for mitigation measures to reduce these emissions [9]. To predict $CO_2$ emissions associated with energy in the US, Silva also uses ARIMA [10]. Lotfalipour et al. employ the ARIMA model for projecting $CO_2$ emissions in Iran, which can help with policy adoption [11]. Liu et al. utilize the ARIMA model to forecast $CO_2$ emissions from coal-fired thermal power generation, emphasizing the importance of reducing greenhouse gas emissions in China [12]. Greenhouse Gas (GHG) emissions and energy consumption for an Indian company that manufactures pig iron andSen et al. [13] conducted a study to predict Greenhouse Gas (GHG) emissions and energy consumption for an Indian company that manufactures pig iron and to create better environmental policies. Many researchers worldwide prefer using the ARIMA model to forecast greenhouse gas emissions from coal-fired thermal power generation, energy consumption, and various types of fuel consumption, including gaseous, liquid, and solid fuels. They also apply this model to electricity production and transportation. This helps understand future emission patterns and provides recommendations for mitigation strategies to reduce these emissions. However, previous studies have not addressed the projection of forestry emissions and value-added at the district level, highlighting a significant research gap. Therefore, selecting the most appropriate ARIMA model to forecast forestry emissions and value-added at the regional level could be a valuable area for further research.

This paper analyzes forestry emissions and the value added in forestry from 2001 to 2023, focusing on trends and correlations. The ARIMA model forecasts these indicators for 2024 and 2025 to identify patterns. The study provides insights into changing forestry emissions and value added at the regional level, as broader climate studies may be less informative [14,15]. The methodology employed in this study, along with its managerial implications, contributes to its uniqueness. This research can support district-level climate policies by highlighting variations in forest dynamics and encouraging sustainable forest management that aligns with both environmental and economic objectives.

### *1.1. Description of the Study Area*

Ranchi serves as the capital of Jharkhand State. It is located in the northeastern region of the peninsular plateau of India, also referred to as the Chhota Nagpur Plateau. The total geographical area of Ranchi District is 5,097 square kilometres (Figure 1). The average altitude of Ranchi is 600 meters above sea level, featuring undulating landforms. The physiographic characteristics of the district are diverse, including waterfalls, hills, and areas prone to landslides. Lush green forests surround Ranchi. Ranchi district is richly endowed with forests, covering an area of 99,584 hectares, which accounts for 22.024% of the total land area. This percentage is below the national average of 24%. These forests supply essential raw materials to various vital industries, including furniture, matchsticks, paper, rayon production, construction, railway sleepers, and wooden poles [16].

Forest products are classified into two categories:

1. Important Large Products: This includes valuable timbers like Saal, Bamboo, Kusum, and Mahua.
2. Minor/Allied Products: This group features items such as Harra, Behara, Kendu Patta, and Mahua Patta, which have notable medicinal and commercial value.

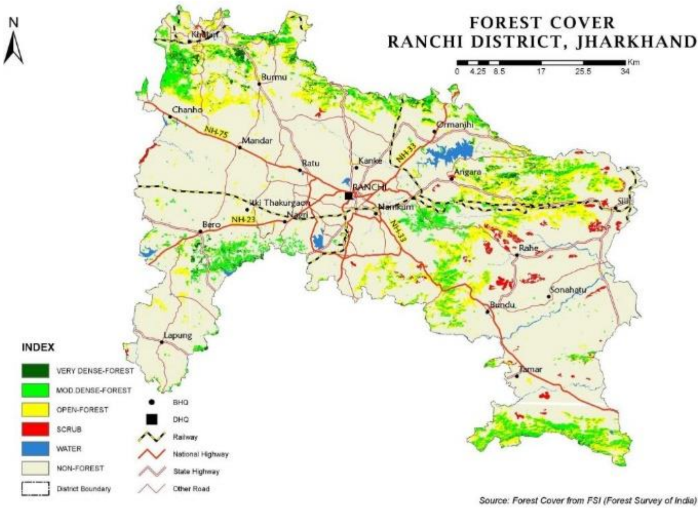



**Fig. 1 Location map of the study area**

## 2. Data and Methodology

In this study, we analyzed the forestry greenhouse gas emissions, carbon emissions, and value-added for the period 2001-2023, utilizing the Mann-Kendall test, the Sequential Mann-Kendall test, Pearson's Correlation Coefficients, and the Autoregressive Integrated Moving Average model. The data on forestry greenhouse gas and carbon emissions are obtained from the Global Forest Watch website (www.globalforestwatch.org) for the period 2001-2023. The forestry value-added data is taken from the "Directorate of Economic and Statistics, Government of Jharkhand, State Income Book, 2022," and from icrisat.org. The trend analysis of the selected variables is conducted using the Mann-Kendall test [17] and Sen's slope method

[18]. To identify the shifting point in the time series, we apply the Sneyers Mann-Kendall test [19]. Correlation analysis between forestry emissions and value added is performed using Pearson's Correlation Coefficient [20]. The Autoregressive Integrated Moving Average (ARIMA) model is used to predict the forestry emissions and value-added for the years 2024 and 2050. Since the ARIMA model necessitates stationary data, the Augmented Dickey-Fuller test assesses whether the dataset is stationary or non-stationary.

### *2.1. Kendall's Tau (MK) Test*

It is a statistical test for identifying monotonic trends in time series data. This test does not require the data to follow a normal distribution.

Let n data points be in the time series, and $y_i$ and $y_j$ are two subsets of the dataset, where $i = 1,2,3, \dots, (n-1)$ and $j = i+1, i+2, i+3, \dots, n$. Then, Mann Kendall's S statistics $(S_s)$ is calculated as follows:

$$S_s = \sum_{i=1}^{(n-1)} \sum_{j=i+1}^{n} \operatorname{sgn}(y_j - y_i)$$

where, $\operatorname{sgn}(y_j - y_i) = \begin{cases} 1; \text{ if } (y_j - y_i) > 0 \\ 0\,; \text{if } (y_j - y_i) = 0 \\ -1; \text{ if } (y_j - y_i) < 0 \end{cases}$ and $y_j$ and $y_i$ are the annual values in years j and i, $j > i$, respectively.

The $S_s$ has the following mean and variance and is generally distributed:

$$E(S_s) = 0 \text{ and } \operatorname{Var}(S_s) = \frac{n(n-1)(2n+5) - \sum t_i(i)(i-1)(2i+5)}{18}$$

where $t_i$ refers to the number of ties to an extent i.

The standard test statistics $(Z_s)$ It is given as follows:

$$Z_s = \begin{cases} \dfrac{S_s - 1}{\sqrt{\operatorname{Var}(S_s)}}; \text{ for } S_s > 0 \\ 0\,; \text{for } S_s = 0 \\ \dfrac{S_s + 1}{\sqrt{\operatorname{Var}(S_s)}}; \text{ for } S_s < 0 \end{cases}$$

The value $Z_s > 0$ indicates a monotone positive trend, and $Z_s < 0$ implies a monotone negative trend in the dataset, respectively.

### *2.2. Sen's Slope Method*

The slope of n pairs of data points was computed using Theil–Sen's estimator, which is given by the equation below:

$$\beta = \text{Median}\left(\frac{y_j - y_i}{j - i}\right) \forall\, i \le j$$

where 'β' is the trend magnitude's reliable estimate. A positive value of $'\beta'$ signifies an 'upward trend', while a negative value of $'\beta'$ indicates a 'downward trend'.

### *2.3. Sneyers-Mann-Kendall's Test*

This test detects sudden changes in trends by creating progressive and retrograde series. A statistically significant trend is indicated when these series intersect and then diverge beyond a specific threshold value. The intersection point provides a reasonable estimate as to when the trend starts. The study's limits are set at specific levels $(\pm 1.96)$, with the crossing point serving as an idea for the year the trend starts.

This test is conducted as follows:

a) We maintain a log of the number of occurrences for every assessment, where $s_m > s_n$ and suppose it as $l_m$, and in a series, $s_m$ and $s_n$; $m, n = 1,2, \dots, p$ are progressive values.
b) Estimating the t-Stats $'t_m'$ is done by

$$t_m = \textstyle\sum_{k=1}^{m} l_k$$

c) The test's variance $\operatorname{var}(t_m)$ and mean $E(t_m)$ are provided by

$$E(t_m) = \frac{m(m-1)}{4}$$

$$\operatorname{var}(t_m) = \frac{m(m-1)(2m+5)}{72}$$

d) A simple method for calculating a sequential progressive value is given by

$$u(t_m) = \frac{t_m - E(t_m)}{\sqrt{var(t_m)}}$$

Additionally, $u'(t_m)$ is computed from the end of the sequence in reverse order.

### 2.4. Persons's Correlation Test

This test quantifies the linear connection between two variables by calculating the ratio of their covariance to the product of their standard deviations.

The correlation between the two variables, U and V, is estimated as follows:

$$Correlation(U, V) = \frac{Cov(U,V)}{\sigma_U \sigma_V}$$

Where, $Cov(U, V)$ is the covariance of U and V and is defined as

$$Cov(U, V) = \frac{1}{(N-1)} \sum_{i=1}^{N} (u_i - \bar{u})(v_i - \bar{v})$$

Where the data set size is N, and $\bar{u}$ and $\bar{v}$ denotes the mean of the variables U and V, respectively. $\sigma_u$ and $\sigma_v$ represents the standard deviations of the variables U and V, respectively. The Pearson correlation coefficient represents the magnitude and direction of a correlation between two variables. The significance level, indicated by the p-value (Sig. 2-tailed), helps to determine whether this correlation is statistically significant. The significant correlation shows a meaningful relationship between the two datasets if the $p - value < 0.05$. On the other hand, the correlation is not significant if the $p - value > 0.05$, indicating that the data sets do not strongly correlate.

### 2.5. Unit Root Test

This test detects whether a selected time series is stationary. It concludes that the selected time series is stationary if it exhibits no unit root [21].

In general, the Augmented Dickey-Fuller equation is in the form mentioned below.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta y_t + \varepsilon_t$$

Where '$y_t$' is the selected time series, 'p' is the optimal lag order, α is the intercept, and β is the coefficient of trend. If $\gamma = 0$, the series has a unit root, which means the selected series is not stationary. Again, if $\gamma < 0$, then the series is stationary. Again, if $\gamma > 0$, the series is explosive.

### 2.6. ARIMA Model

ARIMA stands for Autoregressive Integrated Moving Average [22]. This model is used to predict future values in time series data sets. It consists of three components: Autoregressive (AR), Integrated (I, which refers to the order of integration), and Moving Average (MA). The ARIMA model is represented as ARIMA (p, d, q), where 'p' indicates the optimal lag order of the autoregressive component, 'd' denotes the order of differencing in the time series data, and 'q' represents the optimal lag order of the moving average component$(p, d, q \geq 0)$.

The ARIMA model requires that the time series data be stationary. It also applies to time series data that is not stationary by transforming it into a stationary series through differencing, which involves subtracting the previous observations from the current ones. The ARIMA model is developed for various values of the parameters 'p' (autoregressive), 'd' (differencing), and 'q' (moving average). The best-fitted model is then selected based on the Bayesian Information Criterion (BIC) and the significance of the model's coefficients.

The $ARIMA(p, d, q)$ model can be expressed as follows:

$$\overline{Z_t} = \emptyset_1 \overline{Z_{t-1}} + \emptyset_2 \overline{Z_{t-2}} + \cdots + \emptyset_p \overline{Z_{t-p}} + a_t - \theta_1 \overline{Z_{t-1}} - \theta_2 \overline{Z_{t-2}} - \cdots - \theta_q \overline{Z_{t-q}} \quad (1)$$

Where $\overline{Z_t} = Z_t - \mu$ and $a_t$ is the shock.

Once the backward shift operator (B) has been found, equation (1) can be applied as follows:

$$\emptyset(B)(1 - B)^d Z_t = \theta(B) a_t$$

## 3. Results and Discussion

### *3.1. Descriptive Analysis*

The forestry greenhouse gas and carbon emissions increased from 3,05.4 tonnes and 3,00.1 tonnes in 2001 to 7,60.8 tonnes and 7,37.5 tonnes in 2023, with a yearly average growth rate of 1.24 percent and 1.23 percent, respectively (Figures 2 and 3), while the forestry value added rose from 3,236 ($10^5$ INR) in 2001 to 17,046 ($10^5$ INR) in 2023, with a yearly average growth rate of 0.13 percent (Figure 4). Annually, from 2001 to 2023, the mean, standard deviation, median, and coefficient of variation (CV) are calculated for value-added, carbon, and greenhouse gas emissions from forestry (Table 1). The annual forestry greenhouse gas and carbon emissions means are 8,26.5 and 8,21 tonnes, with a standard deviation of 8,32 and 8,28 tonnes for 2001-2023, respectively. The lowest forestry greenhouse gas and carbon emissions were observed in 2006 (27.568 and 27.6 tonnes), and the highest forestry greenhouse gas and carbon emissions were observed in 2019 (3,223.56 and 3,213.6 tonnes), respectively. There is a 99% fluctuation in the annual forestry carbon and greenhouse gas emissions. However, the yearly forestry value-added mean is 14,507 ($10^5$ INR), with a standard deviation of 9,813 ($10^5$ INR) for the period 2001-2023. The lowest forestry value added was observed in 2001 (3,235($10^5$ INR) ), and the highest forestry value added was observed in 2019 (43,815($10^5$ INR)). The annual value added in forestry shows a variation of 148%, indicating that the data points are widely scattered around the mean, which suggests significant variability and a potential lack of stability.

**Table 1. Descriptive analysis of the raw dataset**

| Variables | Mean | Std. Dev. | Median | Maximum | Minimum | Coeff. of Variation |
|---|---|---|---|---|---|---|
| TE | 826.4846 | 831.8645 | 577.3839 | 3223.558 | 27.56763 | 99% |
| CE | 821.113 | 827.6874 | 575 | 3213.6 | 27.6 | 99% |
| VA | 14507.04 | 9812.883 | 15900 | 43815 | 3236 | 148% |

TE refers to forestry greenhouse gas emissions, CE refers to forestry carbon emissions, and VA refers to forestry value-added.

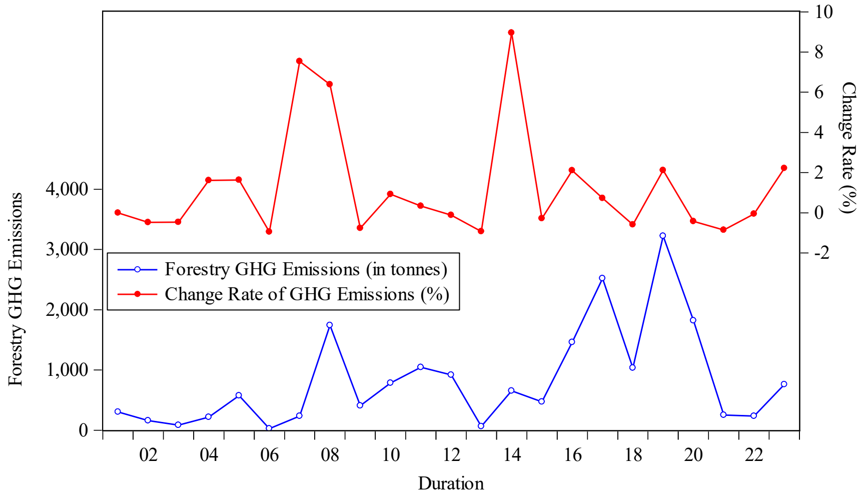



**Fig. 2 Ranchi's forestry greenhouse gas emissions and growth rate during 2001-2023**

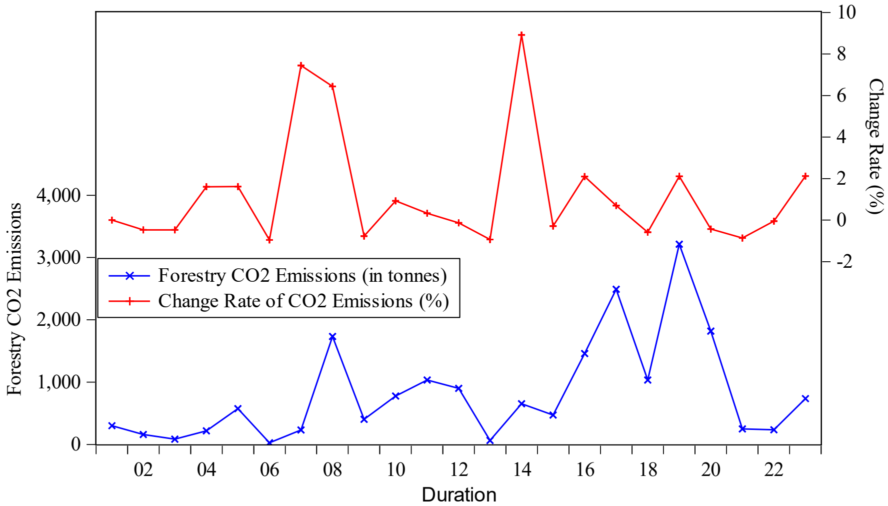



**Fig. 3 Ranchi's forestry carbon emissions and growth rate during 2001-2023**

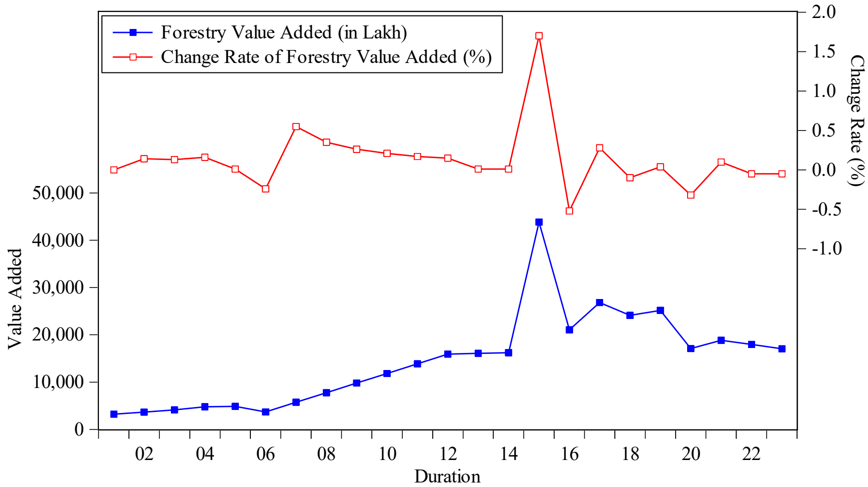



**Fig. 4 Ranchi's forestry value added and growth rate during 2001-2023**

### *3.2. Trend Analysis*

Table 2 shows the trend analysis results of annual forestry greenhouse gas emissions, carbon emissions, and value-added. Both greenhouse gas and carbon emissions have a significant upward trend at a 5% significance level. The shift points for both emissions are observed in 2008 at a 5% significance level, which indicates that the forestry emissions began to rise significantly in an upward direction for greenhouse gas and carbon emissions from 2008, respectively (Table 3). However, the forestry value added has a significant upward trend at a 1% significance level. The shift point is detected for the forestry value added in 2008, but this is statistically insignificant (Table 3).

**Table 2. Trend analysis of annual forestry emissions and economic growth in Ranchi for 2001-2023**

| | | | | Obs: 23 |
|---|---|---|---|---|
| Variables | z-value | Sen's slope | p-value | Remark |
| TE | 2.27 | 42.87 | 0.02 | UT |
| CE | 2.27 | 41.76 | 0.02 | UT |
| VA | 4.91 | 1071.33 | 0.01 | UT |

UT refers to the upward trend in the time series dataset.

**Table 3. Change point detection for forestry emissions and economic growth in Ranchi**

| Variable | Detected Change Point | Sequential Value | Remark |
|---|---|---|---|
| TE | 2008 | 0.743 | Significant |
| CE | 2008 | 0.743 | Significant |
| VA | 2008 | 2.722 | Insignificant |

### *3.3. Correlation Analysis*

The correlation coefficients demonstrate the intrinsic connection between forestry emissions and forestry value added (Table 4). The forestry greenhouse gas emission positively correlates with the forestry value-added, with a correlation coefficient of 0.43 at a 5% significance level. Similarly, the forestry carbon emission positively correlates with the forestry value-added, with a correlation coefficient of 0.43 at a 5% significance level.

**Table 4. Correlation analysis of forestry greenhouse emissions and economic growth**

| Annual Emissions | Correlation Coefficients | p-value | Remark |
|---|---|---|---|
| TE | 0.4307 | 0.04 | Positive Correlation |
| CE | 0.4308 | 0.04 | Positive Correlation |

### *3.4. Forecasting*

The forestry greenhouse gas emissions, carbon emissions, and value-added are projected for 2024-2050, utilizing the best appropriate ARIMA model. The existing data sets from 2001 to 2023 for forestry greenhouse gas emissions, carbon emissions, and forestry value-added are used to detect the perfect model for forecasting from 2024 to 2050. The augmented Dickey-Fuller (ADF) test reveals that the forestry emission and value-added are stationary at 1$^{st}$ Difference (i.e., integrated of order 1, I (0)), which indicates that the differencing parameter of the ARIMA model is set to be 1 (Table 5). The autoregressive and moving average parameters are chosen to ensure that the autoregressive and moving average coefficients are statistically significant while minimizing the ARIMA model's normalized BIC values. ARIMA (1, 1, 0) is identified as the best appropriate model for predicting forestry emissions and forestry value added (Table 6).

**Table 5. Unit root test analysis**

| Variable | Inspection Type | No Difference | | First Difference | | Remark |
|---|---|---|---|---|---|---|
| | (I, T, p) | t-statistics | p-value | t-statistics | p-value | |
| TE | (I, T, 1) | -3.51 | 0.063 | -4.767 | 0.01 | Stationary at 1st Difference |
| CE | (I, T, 1) | -3.49 | 0.065 | -4.768 | 0.01 | Stationary at 1st Difference |
| VA | (I, T, 2) | -1.41 | 0.83 | -8.133 | 0.01 | Stationary at 1st Difference |

I, T, and p represent intercept, trend, and optimal lag. The AIC criterion determined the optimal lag.

**Table 6. Value of ARIMA coefficients and normal BIC**

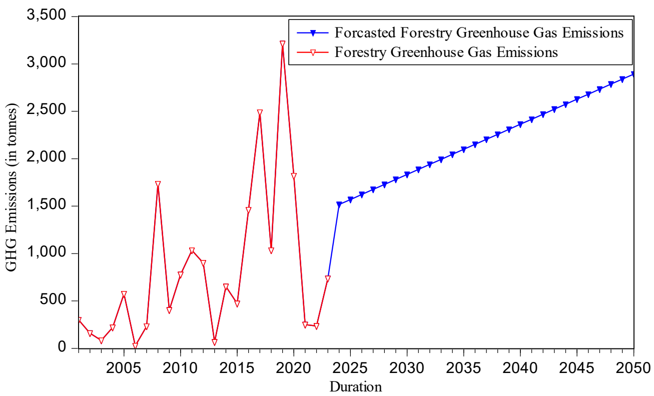
| Model | Forestry Carbon Emissions | | | | | Forestry Greenhouse Gas Emissions | | | | | Forestry Economic Growth | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AR-Coeff. | | MA-Coeff. | | BIC | AR-Coeff. | | MA-Coeff. | | BIC | AR-Coeff. | | MA-Coeff. | | BIC |
| | t-stats | p-value | t-stats | p-value | | t-stats | p-value | t-stats | p-value | | t-stats | p-value | t-stats | p-value | |
| ARIMA (1,1,1) | 0.823 | 0.421 | 0.242 | 0.811 | 13.833 | 0.815 | 0.430 | 0.282 | 0.781 | 13.844 | -0.960 | 0.349 | 0.703 | 0.490 | 18.135 |
| ARIMA (0,1,1) | 0.000 | 0.000 | 0.003 | 0.998 | 13.860 | 0.000 | 0.000 | 0.003 | 0.998 | 13.687 | 0.000 | 0.000 | 2.671 | 0.015 | 17.993 |
| ARIMA (1,1,0) | -1.820 | 0.084 | 0.000 | 0.000 | 13.900 | -1.837 | 0.081 | 0.000 | 0.000 | 13.912 | -2.889 | 0.009 | 0.000 | 0.000 | 17.976 |

The forecasted forestry greenhouse gas emissions, carbon emissions, and value-added are plotted in Figure 5, and the value of forecasted forestry emissions and value added is presented in Table 8. The trend analysis of projected forestry emissions and value-added indicates a significant upward trend in both greenhouse gas and carbon emissions from the forestry sector and in forestry value-added for the period from 2024 to 2050 in Ranchi, Jharkhand. This trend is significant at the 1% significance level (Table 7).

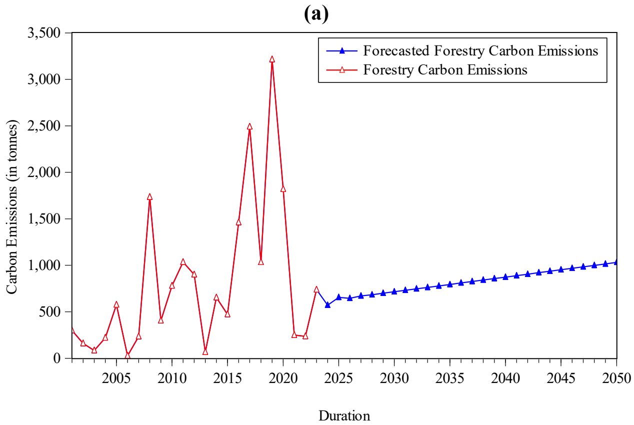
**Table 7. Trend Analysis of the annually forecasted forestry greenhouse gas emissions, carbon emissions, and value-added**

| | | | | Obs: 27 |
|---|---|---|---|---|
| Variables | z-value | Sen's slope | p-value | Remark |
| CE | 7.25 | 15.78 | 0.01 | UT |
| TE | 7.25 | 16.37 | 0.01 | UT |
| VA | 7.29 | 655.93 | 0.01 | UT |

UT refers to the upward trend in the time series dataset.




**(a)**

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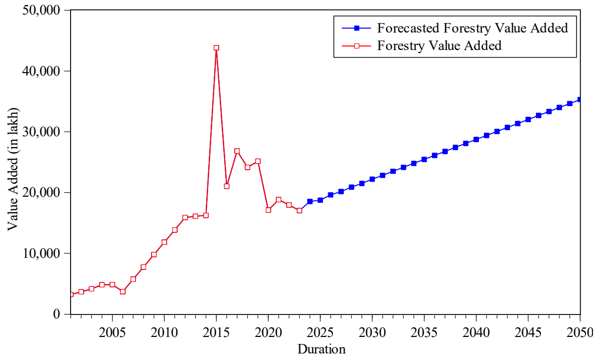


**(c)**

**Fig. 5 Plot of forecasted forestry (a) Greenhouse gas emissions, (b) Carbon emissions, and (c) Value added**

**Table 8. Forecasted values through the ARIMA Model**

| Duration | Forestry Carbon Emissions (Tonnes) | Forestry GHG Emissions (Tonnes) | Forestry Value-Added $(10^5$ INR$)$ |
|---|---|---|---|
| 2024 | 570.35 | 584.07 | 18538.12 |
| 2025 | 655.09 | 673.81 | 18745.53 |
| 2026 | 644.88 | 662.29 | 19642.04 |
| 2027 | 670.46 | 689.25 | 20168.94 |
| 2028 | 682.55 | 701.59 | 20894.08 |
| 2029 | 699.73 | 719.49 | 21512.89 |
| 2030 | 714.98 | 735.27 | 22188.74 |
| 2031 | 730.97 | 751.86 | 22833.99 |
| 2032 | 746.68 | 768.14 | 23495.65 |
| 2033 | 762.49 | 784.54 | 24148.51 |
| 2034 | 778.26 | 800.89 | 24806.09 |
| 2035 | 794.05 | 817.26 | 25461.14 |
| 2036 | 809.83 | 833.63 | 26117.55 |
| 2037 | 825.61 | 850.00 | 26773.23 |
| 2038 | 841.40 | 866.36 | 27429.29 |
| 2039 | 857.18 | 882.73 | 28085.15 |
| 2040 | 872.97 | 899.09 | 28741.13 |
| 2041 | 888.75 | 915.46 | 29397.04 |
| 2042 | 904.53 | 931.83 | 30052.98 |
| 2043 | 920.32 | 948.19 | 30708.91 |
| 2044 | 936.10 | 964.56 | 31364.84 |
| 2045 | 951.88 | 980.92 | 32020.78 |
| 2046 | 967.67 | 997.29 | 32676.71 |
| 2047 | 983.45 | 1013.66 | 33332.64 |
| 2048 | 999.23 | 1030.02 | 33988.57 |
| 2049 | 1015.02 | 1046.39 | 34644.51 |
| 2050 | 1030.80 | 1062.75 | 35300.44 |

## 4. Conclusion

The annual forestry emissions and value-added for the period 2001-2023 have been analyzed, and it has been observed that the yearly forestry greenhouse gas and carbon emissions means are 8,26.5 and 8,21 tonnes, with a standard deviation of 8,32 and 8,28 tonnes, respectively, while the yearly forestry value-added mean is 14,507 $(10^5$ INR$)$, with a standard deviation of 9,813 $(10^5$ INR$)$. Trend analysis suggests that both forestry greenhouse gas and carbon emissions have a significant upward trend at a 5% significance level. However, the forestry value added has a significant upward trend at a 1% significance level. Correlation analysis of the forestry emissions and value-added revealed that the forestry greenhouse gas and carbon emissions positively correlate with the forestry value-added, with a correlation coefficient of 0.43 at a 5% significance level. The forecasting of annual forestry emissions and value added is done using an appropriate ARIMA model, and it was found that ARIMA (1,1,0) was the most suitable model for the projection. The future yearly forestry emissions trend analysis indicates a significant increase in greenhouse gas and carbon emissions for 2024-2050. The future forestry value-added shows a significant upward trend for 2024-2050.

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