

Impact of Renewable Energy Adoption on CO₂ Emissions in India

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Abstract

This study uses Autoregressive Distributed Lag (ARDL) bounds and the Toda–Yamamoto Granger causality test to assess the impact of renewable energy on CO₂ emissions in India using annual data from 1970 to 2024. The findings of this study showed that India follows a carbon-intensive growth trajectory since GDP growth increases CO₂ emissions. Hydropower consumption has a positive impact on CO₂ emissions, thereby showing limited mitigation potential. Nuclear energy consumption is negatively correlated with CO₂ emissions. The Toda–Yamamoto Granger causality analysis showed unidirectional causality from GDP to CO₂ emissions, nuclear energy, and hydropower, while bidirectional causality (feedback) exists between CO₂ emissions and both nuclear energy and hydropower. The findings suggest that India needs an integrated energy and environmental policy, as the effectiveness of renewable and low-carbon energy sources is outweighed by rapid economic growth.

Keywords: CO₂ emissions, renewable energy, Hydro energy, nuclear energy.

JEL: Q42, Q43, Q53, O13, Q54

1. Introduction

Renewable energy use is very important for curbing CO₂ emissions in India, especially in heavy industries such as Iron and steel, Cement, Power generation, and mining. The use of solar and wind power sources brings long-term benefits to India's power sector, which is strengthened by Solar Parks and the UJALA plan. These initiatives show India's dedication to increasing renewable energy and energy efficiency. To address carbon leakage across nations, coal and other fossil fuels are replaced with solar and wind power, but the adoption of these renewable energy sources is constrained by their intermittent nature and limited capacity. Swain & Karimu [1] focused on the link between energy use (both renewable and nonrenewable), environmental damage, and economic growth and showed that renewable energy is crucial for achieving sustainability and fulfilling the SDGs.

This study examines the link between renewable energy and CO₂ emissions in India using annual data from 1970 to 2024. This study uses Autoregressive Distributed Lag (ARDL) bounds and the Toda–Yamamoto Granger causality test to assess the impact of renewable energy on CO₂ emissions in India. However, the literature on energy, environment, and growth is divided into two branches. The first one focuses on the link between energy and growth [2, 3]. The second one explores the environment-growth relationship using the environmental Kuznets curve (EKC) theory, initially proposed in 1991, and various other econometric techniques. According to Grossman and Krueger's study, environmental damage increases as a country's GDP grows, but declines once it reaches a tipping point. In general, ecological quality will deteriorate before improving economic growth [4]. This finding is supported by several empirical studies [5, 6, 7] and is fundamentally solid. The relationship among economic growth, energy expenditure, economic expansion & environmental degradation has been studied over the last decade, but the role of green energy in reducing carbon emissions has not been studied in the Indian context using such an extensive database and empirical methods.

The world's economy, particularly in emerging countries, has sought to provide environmental security even though global atmospheric issues have continued to deteriorate. South Asia hosts various rapidly expanding economic hubs which now rank among the world's most polluted areas while India maintains its position as the third biggest greenhouse gas emitter (World Population Review, 2022). In recent years, however, India has committed to developing appropriate solutions to reduce its annual carbon dioxide (CO₂) emissions and aims to become carbon neutral in the future. During the twenty-sixth Conference of the Parties (COP26) in Glasgow, India's PM promised to significantly cut the country's CO₂ emissions in order to achieve carbon neutrality by the year 2070. India has pledged to achieve sustainable environmental development through 2030 by accepting the

Sustainable Development Goals which are known as the SDGs. India has not achieved success in creating working carbon reduction plans despite its numerous declarations about environmental protection. As a result, the country faces noncompliance with its national & international environmental duties, which places enormous strain on the well-being of its environmental indicators year after year.

2. Literature Review

Ghosh [11] investigates the link between renewable energy usage, inequality, & CO₂ emissions in Brazil, Russia, India, China, & South Africa. Scientists have investigated the connection between worldwide energy usage and World War occurrences. The results from the panel enhance mean group (AMG) & common correlation effects mean group (CCEMG) support the societal Kuznets curve. According to statistics, every 1% rise in Gini inequality results in 0.240% more CO₂ emissions (AMG) & 0.17% more CCEMG emissions (method). Renewable energy has a moderating effect on the Gini measure of inequality, with estimates of -0.10 using the AMG and CCEMG methods. Manocha [12] applies an ARDL model which unites autoregressive components with distributed lag elements to analyze Indian greenhouse gas emission reactions against renewable energy consumption (REC) during 1990-2020. The research team created two prototype systems which included the EKC model and a version without this model. The result for the REC variable was negative but minor with the EKC paradigm & negative & considerable without the EKC constraints, indicating a reduction in CO₂ emissions from the use of energy from renewable sources. The findings suggest that increasing the use of green energy sources may help improve the impact of the REC coefficient on India's environment.

According to Alam [13] research on the possible nonlinear relationship between renewable energy usage & air pollution contributes to eco-culture. Using quarterly frequencies from 1990q1 to 2018q4, as well as appropriate sophisticated techniques to address structural break issues, real-world results show that trade liberalisation, farm output increases, & higher density of population density all contribute to long-term greenhouse gas emissions through economic and social channels. The relationship between renewable energy consumption and air quality exists as an inverted-U shape pattern. The projection shows green power will become the dominant energy source in India by reaching 45.75% of total energy consumption while exceeding the current renewable energy usage in the country. Justice et al., [14] research employs a mediation model to study how green energy systems create direct and indirect effects on carbon emissions which result from globalisation. The study's data covers the years 1990 to 2020. Study found that, while renewable electricity has no discernible influence on trade openness, it has an immediate & negative effect on CO₂ emissions. However, FDI has a direct & considerable positive impact on CO₂ emissions, whereas trade openness has no noticeable effect. The indirect conclusion showed that green power with FDI has an adverse effect on CO₂ emissions, whereas innovative energy sources through trade openness have a positive impact on emissions. The government should establish trade restrictions which would block the market entry of equipment that generates emissions.

Onakpojeru [15] examines the relationship between India's economic growth & CO₂ emissions, as well as the effects of population trends, energy efficiency, and renewable & non-renewable energy consumption on CO₂ levels. To investigate these links, the study uses an autonomous distributed lag (ARDL) study of 1990–2019 data. The research data indicates that NREC produces major CO₂ emissions through its standard energy systems which require immediate solutions through mitigation strategies. The research demonstrates how various components establish complex connections which determine the amount of carbon dioxide emissions in India. The research data indicates that renewable energy sources (RECs) and efficient energy use would reduce CO₂ emissions yet the measured results show different results. Furthermore, we detect a negative correlation between the number of inhabitants (POP) & CO₂ levels, although further research is needed to fully explain this relationship.

3. Research Methodology

The research examines how hydro-nuclear and economic development factors influence Indian carbon emission levels through a thorough investigation. The data for this study came from two sources: the BP statistics & the World Development Indicators. The data requires log-linear transformation for normalization because this method produces stable estimation results. Table I summarises the variable descriptions.

Table I: Variables

Variables		Symbol	Measurement	Sources
Dependent	Carbonemissions	CO ₂	Mtoe	BP statistics
Independent	Gross domestic product	GDP	Constant2010US\$	WDI
	Hydro electricity consumption	Hydro	Mtoe	BP statistics
	Nuclear Force	Nuclear	Mtoe	BP statistics

The study used a model which studied the relationship between renewable power generation and atmospheric CO₂ emissions. The model examines which renewable energy sources result in modifications to CO₂ emission levels. The model's functional form may be described as follows:

$$\ln\text{CO}_2t = f(\ln\text{GDP}t, \ln\text{Hyd}t, \ln\text{Nuct}) \dots \dots \dots (1)$$

Then, Equation (1) can be rewritten as:

$$\ln\text{CO}_2t = \alpha + \beta_1 \ln\text{GDP}t + \beta_2 \ln\text{Hyd}t + \beta_3 \ln\text{Nuct} + \epsilon_t \dots \dots \dots (2)$$

where $t=1,2,\dots,T$ denotes the time period;

α represents the intercept term;

β_1, β_2 , and β_3 are the long-run elasticities of CO₂ emissions with respect to GDP, hydropower, and nuclear energy consumption, respectively; and

ϵ_t is a white-noise error term.

Before applying any regression analysis, it is essential to conduct a preliminary test. Unit root tests, such as the ADF & PP tests used in Table 2, have the disadvantage of ignoring structural breaks as external factors. Perron discovered that, while the permanent option is viable, the ability to reject a unit root decreases as the crack in the structure is ignored. Zivot and Andrews propose updating the first Perron test to describe the actual break-point time. Instead, a data-intensive approach is used to replace Perron's random technique for determining break sites. With this in mind, Zivot & Andrew [16] developed three models to establish the permanence of variables in the absence of an architectural stoppage in series. (a) This model allows for a single alteration in variable level, (b) a one-time modification in slope of the trend component, i.e., formula, & (c) a one-time shift in timing & trend dependence of each variable used to make empirical judgments.

Zivott & Andrew [16] adapted models to test the series hypothesis of a single structural break as follows:

Model A: Break in Intercept

$$\Delta X_t = a + aX_{t-1} + bt + cDU_t + \sum_{j=1}^k d_j \Delta X_{t-j} + u_t \dots \dots \dots (3)$$

Model B: Break in Trend

$$\Delta X_t = b + bX_{t-1} + ct + bDU_t + \sum_{j=1}^k d_j \Delta X_{t-1} + u_t \dots \dots \dots (4)$$

Model C: Break in Both Intercept and Trend

$$\Delta X_t = c + cX_{t-1} + dt + dDU_t + \sum_{j=1}^k d_j \Delta X_t + u_t \dots \dots \dots (5)$$

where DU_t shows random variables representing mean change at each stage with timebreak & DT shows trendshift indicators.

$$DU_t = \begin{cases} t - TB & \text{if } t > TB \\ 0 & \text{if } t < TB \end{cases}$$

The null value for the unit root break date is $C=0$ which shows that the series contains a drift but lacks any breaking points. The $C<0$ hypothesis states that all variables are trend-stationary with an unknown break time. The Zivott-Andrews unit root test determines all possible future points. Following the determination of the series's stationary attributes, we employ Pesaran (2001) ARDL bound testing technique to investigate its integration in the Indian economy and to identify a long-term relationship among green power use, prosperity, and emissions. To assess the stability of variable co-integration, we used several co-integration tests, including the Hansen parameter instability test, the Engle-Granger [17] cointegration test, & the Phillips-Ouliaris [18] co-integration test. The ARDL bound testing methodology outperforms other standard co-integration approaches. For example, it appears flexible with respect to the stationary properties of variables. The method produces its best results when variables exist in $I(1)$ or $I(0)$ or $I(1)/I(0)$ forms. The ARDL testing method provides precise and understandable technical support for small sample sizes, such as those from India [19]. The system tracks both short-term and long-term operational problems which appear in real-world system environments. The ARDL model implementation of unbounded error correction is shown below.

$$\ln CO_{2,t} = \beta_0 + \beta_1 Dum_t + \beta_2 \ln CO_{2,t-1} + \beta_3 \ln GDP_{t-1} + \beta_4 \ln Hyd_{t-1} + \beta_5 \ln Nuc_{t-1} + \sum_{k=0}^c \beta_j \Delta \ln CO_{2,t-k} + \sum_{k=0}^d \beta_k \Delta \ln Hyd_{t-k} + \sum_{k=0}^e \beta_l \Delta \ln Nuc_{t-k} + u_t \dots \dots \dots (6)$$

$$\ln GDP_t = \beta_0 + \beta_1 Dum_t + \beta_2 \ln GDP_{t-1} + \beta_3 \ln CO_{2,t-1} + \beta_4 \ln Hyd_{t-1} + \beta_5 \ln Nuc_{t-1} + \sum_{k=0}^c \beta_j \Delta \ln GDP_{t-k} + \sum_{k=0}^d \beta_k \Delta \ln CO_{2,t-k} + \sum_{k=0}^e \beta_l \Delta \ln Hyd_{t-k} + \sum_{k=0}^f \beta_l \Delta \ln Nuc_{t-k} + u_t \dots \dots \dots (7)$$

$$\ln Hyd_t = \beta_0 + \beta_1 Dum_t + \beta_2 \ln Hyd_{t-1} + \beta_3 \ln GDP_{t-1} + \beta_4 \ln CO_{2,t-1} + \beta_5 \ln Nuc_{t-1} + \sum_{k=0}^c \beta_j \Delta \ln Hyd_{t-k} + \sum_{k=0}^d \beta_k \Delta \ln GDP_{t-k} + \sum_{k=0}^e \beta_l \Delta \ln CO_{2,t-k} + \sum_{k=0}^f \beta_l \Delta \ln Nuc_{t-k} + u_t \dots \dots \dots (8)$$

$$\ln Nuc_t = \beta_0 + \beta_1 Dum_t + \beta_2 \ln Nuc_{t-1} + \beta_3 \ln GDP_{t-1} + \beta_4 \ln Hyd_{t-1} + \beta_5 \ln CO_{2,t-1} + \sum_{k=0}^c \beta_j \Delta \ln Nuc_{t-k} + \sum_{k=0}^d \beta_k \Delta \ln GDP_{t-k} + \sum_{k=0}^e \beta_l \Delta \ln Hyd_{t-k} + \sum_{k=0}^f \beta_l \Delta \ln CO_{2,t-k} + u_t \dots \dots \dots (9)$$

Δ represents the initial differentiating operator, Dum_t represents the structural break dummy variable, and u_t is a white-noise error term. The Akaike information criterion (AIC) is used to determine the optimal lag length for first-difference regression. The F-statistics are substantially more likely to choose the lag order. Incorrectly setting the lag duration may provide misleading results. The authors of Pesaran used F-statistics to determine the reciprocal value of the variable' lagged-level coefficient. For example, no partner assumption for each of variables in equation (6) is

$$H_0 = \beta_{CO_2} = \beta_{Hyd} = \beta_{Nuc} = \beta_{GDP} = 0$$

while the alternate hypothesis is

$$H_0 = \beta_{CO_2} \neq \beta_{Hyd} \neq \beta_{Nuc} \neq \beta_{GDP} \neq 0.$$

Pesaran [20] defines twin critical asymptotic values: the UCB & the LCB, which are used to assess if the data points are cointegrated. When the entire series integration is performed at $I(0)$, a lower critical limit is used to ensure harmonic integration. A UCB follows this. If the observed F-statistics exceed the UCB, the long-term relationship between variables will continue. There is no cointegration amongst series unless our estimated F-statistic's lower critical limit (LCB) is met. When we examined F-statistics between LCB and UCB, we were unsure whether cointegration was present. The assessment of variable collaboration through mistake correction becomes a simple and valid method in this situation.

4. Results & Discussions

Before beginning the long-term ARDL model, we confirm the stationarity of each variable. The research results contradict the initial hypothesis about unit root stability because all studied variables including carbon dioxide

emissions and GDP and hydroelectricity and nuclear energy consumption show no change in their level I or initial differential values. Because none of the variables in the study are combined without order two or intermediate variability, we reject the null explanation of nonstationarity in I(1) & conclude that all variables are fixed, as shown in Table II.

Table II. ADF & PP Unit Root Test Results

Variable	ADFTest		PP test		Order of integration
	Phillips–Pearsontest				
	Level	1stdifference	Level	1stdifference	
LnCO ₂	0.814 [0.994]	−5.046 [0.000]	0.874 [0.995]	−8.638 [0.000]	(1)
LnGDP	4.676 [1.000]	−7.317 [0.000]	6.261 [1.000]	−7.325 [0.000]	(1)
LnHyd	−1.848 [0.354]	−6.727 [0.000]	−1.878 [0.394]	−6.715 [0.000]	(1)
LnNuc	−1.416 [0.565]	−9.977 [0.000]	−11.497 [0.525]	−10.215 [0.000]	(1)

Note: Values in brackets [] denote probability (p-values)

The ZA unit root tests enable us to detect when the data structure undergoes modifications. The financial regulations which government agencies create aim to boost macroeconomic efficiency through structural transformations according to their assessment. The findings are presented in Table III.

Table III. Zivot and Andrews' Unit Root Test Results

Variables	At level		At 1 st difference		Order of integration
	Tstatistics	Break	Tstatistics	Break	
LnCO ₂	−2.574	1996	−124*	1988	(1)
LnGDP	−3.005	1987	−9.122**	1974	(1)
LnHyd	−3.557	1976	−7.734*	1983	(1)
LnNuc	−3.755	1995	−5.301*	1990	(1)

Note: * & ** represent 1 & 5 per cent levels of significance.

The ZA unit root test indicates that all variables are stationary at the level & after first differencing, are I(1). We tested the parameters' long-term stability using Hansen, & results are reported in Table IV.

Table IV. Co-Integrations Tests

Hansen stability test	Engel–Granger	Phillips–Qularis
5.198 [0.254]	−7.596 [0.013]	−7.646 [0.012]

Note: Values in brackets [] denote probability (p-values)

Using the unconstrained VAR technique, we selected the lag length that minimized the AIC criterion. The Hansen instability test assumes that long-run parameters are stable when the alternative hypothesis is that they are unstable. The Engle-Granger & Phillips-Qualidaris cointegration tests will then be used to analyse the cointegration of CO₂ emissions, GDP, & hydro energy use in India. The null hypothesis for both tests states that the data points are not cointegrated, whereas the alternative hypothesis claims that they are. The model shows that the Engle-Granger & Phillips-Qualid tests might reject the null hypothesis of no cointegration amongst variables. As a result, in India, the previously mentioned components have cointegrated throughout time. In the following stage, we used the bound testing method to test for co-integration. The estimated F statistics are shown in Table V, & ARDL OLS regressions identify each variable as a dependent (normalised) variable.

Table V. Bound Test Results

Model	F statistics	Decision
$FC(CO_2/GDP, Hyd, Nuc)$	07.113[4,2,3,0]	Yes1
$FG(GDP/Hyd, Nuc, CO_2)$	15.123 [3,0,4,0]	Yes1
$FH(Hyd/Nuc, CO_2, 1GDP)$	02.223 [1,0,0,2]	No1
$FN(Nuc/Hyd, 1GDP, CO_2)$	05.123 [2,1,4,1]	Yes1
CV	LL	UL
1%	3.58	5.13
5%	2.34	4.56
10%	1.13	3.12

Note: Values in brackets [] denote probability (p-values)

The model operates with these specific parameter values which it uses for its operations. The value of $FC(CO_2/GDP, Hyd, Nuc)$ in Equation (6) equals 7.113. The value of $FG(GDP/Hyd, Nuc, CO_2)$ in Equation (7) equals 15.123. The value of $FH(Hyd/Nuc, CO_2, GDP)$ in Equation (8) equals 02.223. The value of $FN(Nuc/Hyd, GDP, 1CO_2)$ in Equation (9) equals 5.123. When CO_2 is the dependent variable, the F statistic is 7.015, which is more than Pesaran's (2001) upper bound. Except for Equation (8), we can reject the null hypothesis of no cointegration among variables. After verifying the reciprocal relationship between the variables, we estimate the elasticities of the long-run and short-run strategies using the ARDL model, as shown in Table VI.

Table VI. ARDL Long-Run & Short Run Results

Long-run estimates				Short-run estimates			
VARIABLES	COEFFICIENT	T-STATISTIC	PROB.	VARIABLES	COEFFICIENT	t- STATISTIC	PROB.
L _{GDP}	1.115	3.111	0.001	D(L _{GDP})	0.125	1.512	0.247
L _{Hyd}	0.811	1.078	0.112	D(L _{Hyd})	0.055	1.363	0.207
L _{Nuc}	-0.124	-1.421	0.134	D(L _{Nuc})	-0.006	-1.365	0.602
C	-25.561	-3.452	0.001	CointEq(-1)	-0.145	-1.467	0.234

In the model, we examined the relationship between CO_2 emissions and the consumption of renewable energy sources, such as hydroelectric & nuclear energy, as well as other variables, such as GDP. The extended data analysis shows that hydropower operations produce a small beneficial effect which results in decreased CO_2 emissions. The power generation process of hydroelectric dams produces methane and carbon dioxide emissions which exceed the emissions that traditional fossil-fuel power plants produce. These findings support those of Ummalla & Samal [21]. Nonetheless, nuclear energy seems to have a negative impact on greenhouse gas emissions. The research shows that revenue expansion creates a direct positive relationship which results in major increases of CO_2 emissions. It shows that a 1% rise in economic growth results in a 1.11% increase in carbon dioxide emissions in India. The research results match the findings of Al Mulali (2015) who studied how green

electricity affects European carbon emissions across 23 European nations. Table 7 displays tests performed on the long-run scenario throughout the model study.

Table VII: Diagnostic Test

Normality	Serial correlation	Heteroscedasticity	RESET test
1.115 [0.262]	1.216 [0.449]	2.152 [0.731]	2.042 [0.602]

The results show that the model distribution follows a normal pattern and does not show serial correlation. We use the LMtest to calculate the series correlation between the error term & each independent variable. The test shows that the equation has no serial association; still, the second option is serial correlation, and since its p-value is negligible, we cannot reject the null hypothesis. The model functions at its highest operational level because of its particular organizational structure which determines its maximum processing ability. Table 8 displays the findings of Toda & Yamaamoto's Granger causality test, which determines the pattern of causality.

Table VIII. Toda Yamamoto Granger Causality

Null Hypothesis	Chi-Square	Probability	Direction of Casuality
GDP does not granger causes CO2	6.734**	0.011	GDP to CO2
CO2 does not granger causes GDP	1.842	0.398	No causality
GDP does not granger causes Nuclear	6.762**	0.011	GDP to Nuclear
Nuclear does not granger causes GDP	2.116	0.347	No causality
GDP does not granger causes Hydro	1.967	0.374	No causality
Hydro does not granger causes GDP	4.912*	0.073	Hydro to GDP
CO2 does not granger causes Hydro	12.334***	0.001	CO2 to Hydro
Hydro does not granger causes CO2	4.654*	0.069	Hydro to CO2
CO2 does not granger causes Nuclear	09.127***	0.004	CO2 to Nuclear
Nuclear does not granger causes CO2	08.566***	0.007	Nuclear to co2

Table 8 reports the results of the Toda–Yamamoto Granger causality tests, which examine the dynamic causal relationships among GDP, CO₂ emissions, nuclear energy, and hydropower in India. In each case, the null hypothesis assumes the absence of Granger causality between the variables. The Chi-square statistic produces a probability value (p-value) which falls under the typical significance thresholds (1%, 5% or 10%) to prove directional causality exists [23,24]. The research data demonstrates that GDP establishes a single direction of cause-effect which results in higher CO₂ emissions. The test results show that GDP does not Granger-cause CO₂ emissions because the null hypothesis was rejected at a χ^2 value of 6.734 with a p-value of 0.011. The research results showed no evidence to confirm that GDP causes CO₂ emissions because the statistical relationship between these variables was not significant ($p = 0.398$). The data shows that economic growth creates environmental problems instead of emission restrictions preventing economic growth. Research findings from previous studies validate the growth-driven emissions hypothesis which operates in emerging economies including India according to [2, 25]. Second the data shows that GDP creates a one-way effect which leads to increased nuclear energy usage. The researchers rejected the null hypothesis because the calculated χ^2 value (6.762) reached statistical significance at $p = 0.011$. The study results demonstrate that nuclear energy development does not create economic growth because no reverse causality effect exists ($p = 0.347$). The data indicates that nuclear energy development tracks economic growth patterns instead of generating economic expansion. The results match the findings which Saidi et al. [26], who find that nuclear energy expansion in developing economies is largely growth-driven. Third, no evidence is found for causality running from GDP to hydropower consumption ($p = 0.374$). The reverse null

hypothesis receives rejection at the 10% significance level because the test result shows $\chi^2 = 4.912$ with a p-value of 0.073. The results show hydropower causes GDP growth according to unidirectional causality. The research shows that hydropower development leads to economic growth because it provides stable power supply which makes a nation less dependent on fossil fuels and reduces manufacturing expenses during long periods. The research by Gozgor et al. [3] and Ummalla and Samal [21] shows that renewable energy creates conditions which support economic development. The research data demonstrates that CO₂ emissions and hydropower usage exist in a reciprocal relationship because each variable affects the other. The data shows that CO₂ emissions create a causal relationship with hydropower usage because the χ^2 value equals 12.334 while the p value reaches 0.001. The analysis indicates that environmental pressure growth leads people to select alternative clean energy systems. The research shows that hydropower operations create CO₂ emissions through Granger causality ($\chi^2 = 4.654$, $p = 0.069$). The study reveals that hydropower production levels affect the amount of emissions that occur. The feedback system demonstrates how renewable energy systems monitor environmental results which in turn influence these environmental outcomes according to [9,11]. The study reveals that nuclear energy usage creates a direct link with carbon dioxide emissions which also affect each other through a mutual relationship. The analysis shows that nuclear energy usage follows CO₂ emissions patterns because nuclear energy usage responds to changes in CO₂ emissions ($\chi^2 = 9.127$, $p = 0.004$). The study shows that environmental concerns about climate change and emissions drive nations to choose nuclear power as their low-carbon energy solution. The data shows that nuclear energy production creates a causal relationship which leads to CO₂ emissions ($\chi^2 = 8.566$, $p = 0.007$) because it determines how emissions change through its impact on the energy sector. Research findings confirm previous studies which demonstrate that nuclear power serves two purposes by reducing emissions and helping transform energy systems [5,2].

5. Conclusion

The research examines the relationship between CO₂ emissions and economic growth and clean energy production from hydropower and nuclear energy systems in India. The research data shows that economic growth leads to increasing CO₂ emissions because India needs to use carbon-based resources to develop its economy. The research shows that GDP causes CO₂ emissions to rise because economic growth results in rising energy usage which produces more environmental damage. The long-run analysis demonstrates that hydropower generates a small positive impact on CO₂ emissions which indicates its restricted ability to reduce emissions. The classification of hydropower as a renewable energy source does not guarantee carbon neutrality because reservoirs emit methane and carbon dioxide which affect the environmental benefits of this power source especially when it involves large dam construction. Nuclear energy serves as a vital factor which affects CO₂ emissions because it functions as a low-carbon power source for India's energy sector. The Granger causality results show which variables lead to others according to the analysis. The research shows that GDP creates a single path of cause and effect which leads to increased nuclear energy and hydropower usage. The economic growth of a nation leads to higher investments which result in better capacity development for these two energy sources. The research establishes that CO₂ emissions create a feedback loop which affects both hydropower and nuclear energy usage patterns. People select cleaner energy alternatives because of rising CO₂ emissions which leads to higher clean energy consumption that results in decreased emission levels.

6. Policy Implications

This study have several implications on sustainability, energy efficiency and growth domain. The research shows that GDP causes CO₂ emissions to rise which demonstrates the necessity for economic development to separate from environmental harm. The implementation of energy efficiency measures and cleaner production technologies needs to become part of industrial and economic planning by policymakers to stop emission growth while allowing development to continue. Second the two-way connection between CO₂ emissions and clean energy sources indicates that environmental pressure functions as a force which promotes clean energy implementation. The world will transition to clean energy resources because strict emission rules and carbon pricing systems and climate agreements have been put into place. The third point requires policymakers to improve hydropower environmental performance through better reservoir management and methane reduction techniques and environmental impact assessments during their development of solar and wind energy capacity for renewable energy diversity. Nuclear power plants generate electricity through nuclear reactions which produce no CO₂

emissions so nuclear energy serves as a vital long-term solution for reducing emissions. The expansion of nuclear power generation with improved safety measures and better community support will enable India to reach its climate goals while maintaining its energy stability.

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NA

Declaration of Interest Statement

There is no conflict of interests.

Availability of data and materials

The datasets used during the current study are available from the corresponding author on reasonable request.

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