

**Research Article****The Paradox of Progress: Energy, Emissions, and the Human Development Index in Bangladesh**Saikat Pande<sup>1,2\*</sup>, Siddharth C. Thaker<sup>3</sup><sup>1</sup>Department of Economics, School of Social Sciences, Gujarat University, Ahmedabad-380009, Gujarat, India.<sup>2</sup>Department of Economics, Dhaka International University, Satarkul, Badda, Dhaka-1212, Bangladesh.<sup>3</sup>Department of Economics, Shri Sahajanand Arts & Commerce College, Panjara Pol, Ambawadi, Ahmedabad-380015, Gujarat, India.\*Corresponding Author, Saikat Pande, Email: [saikatpande.eco@yahoo.com](mailto:saikatpande.eco@yahoo.com)**Abstract**

As one of the world's most climate-vulnerable and rapidly developing nations, Bangladesh faces the urgent task of advancing human development while addressing environmental damage. Designing effective policy requires a clear understanding of what drives its Human Development Index (HDI). This study investigates the dynamic effects of carbon dioxide (CO<sub>2</sub>) emissions, electricity access, nitrous oxide (N<sub>2</sub>O) emissions, and population on the HDI in Bangladesh using data from the World Bank from 1991 to 2023. By using the ARDL bounds testing method, a stable long-run cointegrating relationship was confirmed. The long-run findings are cross-checked for robustness using FMOLS, DOLS, and CCR. This study finds that in the long run, a 1% increase in emissions corresponds to a 0.33% rise in the HDI, showing that development continues to rely on carbon-intensive activities. However, the study also finds that a 1% increase in electricity access is linked to a 0.13% fall in the HDI. This suggests that the environmental externalities of the current fossil-fuel-dependent energy infrastructure may be harming the overall quality of life. The short-run dynamics are complex, characterized by oscillating effects from the explanatory variables and an extremely rapid adjustment to equilibrium (ECT = -0.990). Policy efforts should therefore focus on decoupling human development from emissions by accelerating the transition to renewable energy, enhancing energy efficiency, and promoting sustainable agricultural practices. These insights are vital for guiding Bangladesh toward achieving its Sustainable Development Goals (SDGs 3, 4, 7, and 13) and can serve as a model for other developing nations navigating similar challenges. By implementing evidence-based policies, Bangladesh can achieve balanced development, positioning the country as a leader in sustainable development within the region.

**Keywords:** Human Development Index (HDI), Energy Consumption, Environmental Emissions, Sustainable Development, ARDL, Bangladesh

**1. Introduction**

Bangladesh stands as a powerful global emblem of a 21st-century paradox. On one hand, the nation is heralded as a paragon of economic resilience, having achieved an average GDP growth rate exceeding 6% for much of the last decade and making extraordinary strides in poverty reduction [1]. On the other hand, this remarkable economic dynamism unfolds against a backdrop of acute climate peril. Situated on the world's largest and most densely populated delta, its future is perpetually threatened by sea-level rise, Himalayan glacial melt, and the increasing ferocity of tropical cyclones, a vulnerability consistently highlighted by international financial institutions [2]. This situation presents a significant dilemma: the industrial and agricultural activities that have contributed to socio-economic growth are simultaneously increasing the carbon footprint, linking the development model to ecological instability that may adversely affect these achievements [3]. Contemporary research has increasingly concentrated on exploring pathways to a decoupled development model, wherein human progress is independent of environmental degradation [4]. As a signatory to the Paris Agreement and committed to the Sustainable Development Goals [5], it is essential for Bangladesh to accurately assess the complex drivers of well-being to effectively navigate its future.

This study deliberately moves beyond traditional economic metrics like GDP, instead focusing on the Human Development Index (HDI), a more meaningful measure of national progress that includes health and education [6]. A key part of Bangladesh's development story has been the massive expansion of electricity access, which is crucial for empowering

communities and improving health and education outcomes [7-8]. However, this progress comes with a serious trade-off. The nation's energy grid relies heavily on fossil fuels, which generate carbon dioxide (CO<sub>2</sub>) emissions that not only fuel climate change but also cause severe local air pollution [8, 37]. In fact, this particulate pollution is now considered the single greatest threat to public health in Bangladesh. Estimates suggest that it reduces the average citizen's life expectancy by several years, a direct impact on the health component of the HDI [9]. The latest Air Quality Life Index report reveals that it shortens the life of the average Bangladeshi by 6.8 years, a staggering toll that directly erodes the health pillar of the HDI and surpasses the life-years lost to smoking or unsafe water [10]. This creates a profound and counterintuitive dynamic where a key instrument of modernization may, in its current form, be actively undermining the ultimate goal of a long and healthy life. This direct, detrimental impact on the health component of the HDI creates a profound and counterintuitive dynamic that this study seeks to untangle. The stagnation in household energy transition further exacerbates this dynamic. Recent data reveal that clean cooking fuel adoption in Bangladesh remains at a critical low of approximately 15.24%, a disparity that significantly drives household air pollution and disproportionately affects the health outcomes of vulnerable populations [11].

Furthermore, Bangladesh's environmental pressures extend beyond the smokestacks of its industries. As an agrarian society, the silent threat of agricultural emissions presents an equally formidable challenge. The immense pressure to achieve food self-sufficiency has driven the intensification of farming, leading to a substantial rise in nitrous oxide (N<sub>2</sub>O) emissions, primarily from the pervasive use of synthetic nitrogen fertilizers [12]. These emissions, with a warming potential nearly 300 times that of, not only accelerate climate change but are also intrinsically linked to the degradation of the nation's fragile deltaic soil and water systems, thereby threatening the health and livelihoods of its vast rural populace [13]. Superimposed on these sectoral pressures is the relentless force of demography. The country's large and growing population amplifies resource consumption and environmental impact, a relationship well-established within the IPAT and STIRPAT frameworks [14, 15]. The inexorable shift from rural to urban living further transforms consumption patterns and places immense strain on the infrastructure of sprawling megacities like Dhaka, creating new hotspots of environmental stress [16].

The main goal of this study is to employ robust empirical methods to untangle the complex, often contradictory, pathways through which carbon dioxide emissions, electricity access, nitrous oxide emissions, and population growth collectively shape the Human Development Index (HDI) in Bangladesh from 1991 to 2023. While previous research has focused mainly on a factor-by-factor analysis or centered on GDP, this article is poised to be the first to address this gap by integrating these multiple effects within a single, dynamic econometric framework focused on a holistic measure of well-being. This study seeks to establish both the short-term dynamics and the long-term equilibrium relationships between these drivers and the HDI by utilizing the ARDL bounds testing method. The objective is to furnish a systems-level perspective, highlighting the interconnections among energy infrastructure, environmental quality, demographic change, and human development. The results are anticipated to provide granular and significant policy insights into achieving a balance between Bangladesh's ecological sustainability agenda and its human development aspirations.

While a significant body of scholarly work has explored Bangladesh's environment-energy-growth nexus (e.g., Alam et al, Rahman & Kashem) [17, 18], this literature often remains siloed. Many studies concentrate on Gross Domestic Product (GDP) as the sole indicator of progress, thereby overlooking the broader, multidimensional nature of human well-being. Furthermore, the analytical scope is frequently limited to a single pollutant, typically industrial (CO<sub>2</sub>) or relies on static, linear models that are ill-equipped to capture the complex, evolving dynamics and crucial feedback loops between different environmental pressures and development outcomes [19]. This can lead to an incomplete picture, particularly in a country where agricultural emissions and energy infrastructure quality are central to the development challenge.

This research breaks from this tradition in two fundamental ways. First, shifting the analytical focus away from economic output and placing the Human Development Index (HDI) at the core of our investigation. This allows us to construct a more sophisticated econometric framework that integrates emissions from both industrial (CO<sub>2</sub>) and agricultural (N<sub>2</sub>O) sources. This methodological choice more accurately reflects the dual pressures on Bangladesh's ecosystem. To capture these complex dynamics, this paper employs the autoregressive distributed lag (ARDL) model. Then rigorously validate our long-run findings

using a suite of robustness checks (FMOLS, DOLS, and CCR), a practice recommended for ensuring reliable policy inference in contemporary time-series analysis [20].

Crucially, our analysis is explicitly designed to uncover the complex and often counterintuitive trade-offs inherent in Bangladesh's development path. The paper goes beyond simply measuring correlations to expose underlying tensions, such as the paradoxical finding that expanded electricity access, in its current form, may negatively impact overall well-being in the long run. By doing so, this study provides robust empirical evidence that is not a statistical artifact but a reflection of genuine structural realities. This paper's goal is to offer new evidence to help reconcile Bangladesh's formidable development trajectory with its urgent sustainability commitments, a challenge highlighted as critical for the future of South Asia [21].

By doing so, this study provides robust empirical evidence reflecting genuine structural dynamics, which can help reconcile the country's impressive development trajectory with its urgent sustainability commitments.

## **2. Literature Review**

The existing literature on the nexus between development, energy, and the environment is vast. This review synthesizes previous studies under key themes relevant to this analysis, focusing on the shift from economic growth to the more holistic concept of human development.

### **2.1. Human Development and Energy Consumption**

The link between energy consumption and human development is foundational. Access to modern energy services is crucial for powering hospitals, schools, and industries, thereby directly improving the health, education, and income components of the HDI [21, 7]. However, studies such as Rahman et al. [4] emphasize that the type of energy is critical. This is particularly relevant for Bangladesh, which utilized the ARDL approach to confirm that electricity access remains a primary contributor to CO<sub>2</sub> emissions. Such reliance on fossil fuels can lead to adverse health impacts from local air pollution, creating a negative relationship with HDI in the long run [33].

### **2.2. Environmental Emissions and Human Development**

The Environmental Kuznets Curve (EKC) hypothesis, which posits an inverted U-shaped relationship between income and pollution, was empirically pioneered by Grossman et al. [23] and has been extensively tested [24]. However, its applicability to Bangladesh is questionable due to the country's continued reliance on polluting industries [17]. When shifting the focus to HDI, the impact of emissions becomes more direct. Pollutants like and not only contribute to climate change [25] but are also linked to environmental degradation that directly affects life expectancy, a core component of the HDI. For instance, particulate matter pollution, often co-emitted with CO<sub>2</sub> [39], significantly reduces life expectancy in Bangladesh [9]. Most studies focus narrowly on, neglecting pollutants from agriculture, which is a significant research gap for agrarian economies like Bangladesh [26].

### **2.3. Population Growth and Resource Use**

Rapid population growth in densely populated nations like Bangladesh places immense pressure on natural resources and public services, which can constrain human development [16]. This relationship is often conceptualized through frameworks like the IPAT identity ( $\text{Impact} = \text{Population} \times \text{Affluence} \times \text{Technology}$ ), which demonstrates how population scale multiplies environmental pressures [14, 13]. Population growth can have an ambiguous effect on HDI: it increases the labor force but can also strain educational and healthcare systems, potentially diluting the quality of human capital.

### **2.4. Gaps in the Literature and This Study's Contribution**

Despite extensive research, critical gaps remain. Most studies for Bangladesh focus on the energy-environment-growth nexus, while the more comprehensive energy-environment-human development relationship is less explored. Furthermore, the dynamic short- and long-run impacts of key emissions sources, particularly from agriculture, are often overlooked. This study addresses these gaps by:

- Employing the HDI as a holistic measure of development.
- Including emissions from both industrial and agricultural sources.
- Using the ARDL model to analyse both short- and long-term dynamics robustly.

### 3. Methodologies

#### 3.1. Data and Variables

This study utilises annual time-series data for Bangladesh covering the period from 1991 to 2023. The data for the Human Development Index (HDI) is sourced from the United Nations Development Program (UNDP) [37], a premier authority on this metric. All other macroeconomic and environmental variables, namely, CO<sub>2</sub>, Access to electricity, nitrous oxide emissions (N<sub>2</sub>O), and Total Population, are obtained from the World Bank's comprehensive World Development Indicators (WDI) database. To ensure the estimated coefficients can be interpreted as elasticities and to mitigate potential issues of heteroskedasticity, all variables are transformed into their natural logarithms, except for N<sub>2</sub>O, which is already expressed as a percentage change. The variables employed in the analysis are detailed in Table 1.

Table 1. Variable Description and Sources.

Variables	Description	Logarithmic form	Unit of Measure	Data Sources
HDI	Human Development Index — a composite measure of life expectancy, education, and income per capita.	LNHDI	Index (0–1)	World Bank (WB), World Development Indicators (WDI)
ELEC	Access to electricity represents the share of the population with a reliable power supply.	LNELEC	Percentage of total population (%)	World Bank (WB), World Development Indicators (WDI)
CO <sub>2</sub>	Total carbon dioxide emissions excluding land-use, land-use change, and forestry (LULUCF).	LNCO <sub>2</sub>	Million metric tons of CO <sub>2</sub> equivalent (MtCO <sub>2</sub> e)	World Bank (WB), World Development Indicators (WDI)
N <sub>2</sub> O	Total nitrous oxide emissions excluding LULUCF are used as a proxy for agricultural emissions.	LNN <sub>2</sub> O	Percentage change from 1990	World Bank (WB), World Development Indicators (WDI)
POP	Total resident population of Bangladesh.	LNPOP	Number of persons	World Bank (WB), World Development Indicators (WDI)

#### 3.2. Econometric Framework and Model Specification

This study employs the Autoregressive Distributed Lag (ARDL) modelling approach developed by Pesaran et al. [27] as its analytical foundation. The ARDL framework is particularly well-suited for this investigation, offering robustness in small-sample contexts and flexibility in handling variables with mixed integration orders, specifically, a combination of stationary  $I(0)$  and first-difference stationary  $I(1)$  series. Its ability to simultaneously estimate both short- and long-run dynamics makes it an effective econometric tool for capturing complex interactions within time-series data.

Accordingly, the baseline functional relationship for Bangladesh can be expressed as follows, linking the human development index (HDI) to its key economic, environmental, and energy-related determinants:

$$LNHDI_t = f(\beta_1 LNCO_{2t}, \beta_2 LNELEC_t, \beta_3 LNN_2O_t, \beta_4 LNPOP_t) \quad (1)$$

This relationship is formalized into a log-linear econometric model to allow for the interpretation of coefficients as elasticities:

$$LNHDI_t = \beta_0 + \beta_1 LNCO_{2t} + \beta_2 LNELEC_t + \beta_3 LNN_2O_t + \beta_4 LNPOP_t + \varepsilon_t \quad (2)$$

Where:

- $LNHDI_t$  is the natural logarithm of the Human Development Index at time  $t$ .
- $\beta_1 LNCO_{2t}$ ,  $\beta_2 LNELEC_t$ ,  $\beta_3 LNN_2O_t$ , and  $\beta_4 LNPOP_t$  are the natural logarithms of their respective variables.
- $\beta_1, \beta_2 \dots$  are the coefficients to be estimated, and  $\varepsilon(t)$  is the stochastic error term.

### 3.3. Unit Root Testing

Before applying the ARDL model, it is essential to assess the stationarity of each time series to prevent misleading results from spurious regression. For this purpose, this study relies on three well-established unit root tests: the Augmented Dickey-Fuller (ADF) [28], the Phillips-Perron (PP) [29], and the Dickey-Fuller Generalized Least Squares (DF-GLS) test [28]. The paper examined each variable at both its level,  $I(0)$ , and its first difference,  $I(1)$ . The ARDL approach is valid for this study because it requires that none of the variables are integrated of order two,  $I(2)$ .

### 3.4. ARDL Cointegration Analysis

Having confirmed the mixed order of integration among the variables, the crucial next step was to determine if they share a stable long-run relationship (cointegration). To do this, the study employed the ARDL bounds testing procedure. This approach works by estimating an Unrestricted Error Correction Model (UECM), which is specified as follows:

$$\begin{aligned} \Delta LNHDI_t = & \alpha_0 + \sum_{i=1}^p \delta_i \Delta LNHDI_{t-i} + \sum_{j=0}^{q_1} \phi_j \Delta LNCO_{2t-j} + \sum_{k=0}^{q_2} \theta_k \Delta LNELEC_{t-K} + \\ & \sum_{l=0}^{q_3} \gamma_l \Delta LNN_2O_{t-1} + \sum_{m=0}^{q_4} \zeta_m \Delta LNPOP_{t-m} + \lambda_1 LNHDI_{t-1} + \lambda_2 LNCO_{2t-1} + \lambda_3 LNELEC_{t-1} + \\ & \lambda_4 LNN_2O_{t-1} + \lambda_5 LNPOP_{t-1} + \mu_t \end{aligned} \quad (3)$$

In this equation,  $\Delta$  represents the first difference operator,  $p$  and  $q$  are the optimal lag lengths, the coefficients  $\Delta, \phi, \gamma, \theta, \xi$  capture the short-run dynamics, and the coefficients  $\lambda_1$  through  $\lambda_5$  represent the long-run relationship. The bounds test involves conducting a joint F-test on the null hypothesis of no cointegration,  $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$ . The calculated F-statistic is then compared against the critical value bounds provided by Pesaran et al. [26]. If the F-statistic exceeds the upper bound, the null hypothesis is rejected, providing conclusive evidence of a long-run relationship.

### 3.5. Estimation of Long- and Short-Run Coefficients

Following the confirmation of cointegration, the long-run coefficients are derived from the estimated ARDL model. The long-run equation is specified as:

$$LNHDI_t = \gamma_0 + \gamma_1 LNCO_{2t} + \gamma_2 LNELEC_t + \gamma_3 LNN_2O_t + \gamma_4 LNPOP_t + \nu_t \quad (4)$$

The short-run dynamics and the speed of adjustment back to the long-run equilibrium are captured through an Error Correction Model (ECM):

$$\Delta \text{LNHDI}_t = \pi_0 + \sum_{i=0}^p \omega_i \Delta \text{LNHDI}_{t-i} + \sum_{j=0}^q K_j \Delta X_{t-j} + \psi \text{ECT}_{t-1} + \xi_t \quad (5)$$

Where  $X$  is the vector of independent variables, and  $\text{ECT}_{t-1}$  is the lagged error correction term derived from the long-run relationship. The coefficient  $\psi$  is the crucial speed of adjustment parameter; it is expected to be negative and statistically significant, indicating how quickly the system corrects any disequilibrium from the previous period.

### 3.6. Diagnostic and Robustness Checks

To validate the statistical integrity of the final model, a comprehensive suite of diagnostic tests is conducted. These include the Breusch-Godfrey LM test for serial correlation, the Breusch-Pagan-Godfrey test for heteroskedasticity [30], the Jarque-Bera, [31] test for normality of residuals, and the Ramsey RESET test for model specification. The CUSUM and CUSUMSQ tests [32] are used to check the stability of the parameters even more. Lastly, to make sure the long-term estimates are strong, they are checked against three other single-equation cointegration estimators: Fully Modified OLS (FMOLS) [34], Dynamic OLS (DOLS) [35], and Canonical Cointegrating Regression (CCR) [36].

## 4. Results and Discussion

This section presents the empirical findings of the study, starting with descriptive statistics and unit root tests, followed by the core ARDL model results, the Robustness Check of Long-Run Estimates using FMOLS, DOLS, and CCR. To ensure the validity of the ARDL model, a suite of diagnostic tests was conducted.

### 4.1. Summary Statistics

Table 2 presents the summary statistics of the log-transformed variables used in the analysis. The mean and median values are closely aligned across most variables, suggesting the absence of extreme outliers and a generally balanced data distribution. The standard deviation values indicate moderate variability, with  $\text{LNCO}_2$  (0.675) and  $\text{LNELEC}$  (0.652) showing relatively higher dispersion, reflecting fluctuations in emissions and electricity access over the study period. Skewness and kurtosis coefficients reveal that most variables are approximately symmetric and normally distributed, with skewness values lying within the conventional range of  $\pm 1$ . However,  $\text{LNN}_2\text{O}$  (−1.373) displays pronounced left skewness and leptokurtic behaviour (kurtosis = 4.219), indicating occasional sharp declines or shocks in agricultural emissions. The Jarque–Bera (JB) test supports the normality assumption for all variables except  $\text{LNN}_2\text{O}$  ( $p = 0.002$ ), where the null hypothesis of normality is rejected. Overall, the descriptive results suggest that the data exhibit stable statistical properties, justifying the use of log-transformed series to mitigate heteroskedasticity and enable elasticity-based interpretation in the subsequent ARDL analysis.

Table 2. Descriptive Statistics of Variables.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
LNHDI	-0.629	-0.627	-0.373	-0.929	0.164	-0.108	1.830	1.945	0.378
LNCO <sub>2</sub>	3.844	3.833	4.827	2.644	0.675	-0.125	1.764	2.186	0.335
LNELEC	3.781	3.922	4.605	2.293	0.652	-0.598	2.408	2.447	0.294
LNN <sub>2</sub> O	3.840	4.140	4.687	1.634	0.773	-1.373	4.219	12.409	0.002
LNPOP	18.788	18.813	18.960	18.550	0.121	-0.450	2.036	2.393	0.302

## 4.2. Unit Root Test

To ensure the suitability of the ARDL framework, unit root tests were conducted to determine the order of integration for each variable. Table 3 presents the results from the ADF, PP, and DF-GLS tests. The findings indicate that LNHDHI and LNCO<sub>2</sub> are integrated of order one, I(1), becoming stationary after the first difference. LNELEC, LNN<sub>2</sub>O, and LNPOP are found to be stationary at their levels, I(0). As the variables are a mix of I(0) and I(1) and none are I(2), the ARDL methodology is appropriate for this analysis.

Table 3. Unit Root Test Results.

Variables	ADF I(0)	ADF I(1)	P-P I(0)	P-P I(1)	DF-GLS I(0)	DF-GLS I(1)	Decision
LNHDHI	-1.633	-6.522***	-1.555	-6.597***	-1.675	-6.316***	I(1)
LNCO <sub>2</sub>	-0.493	-6.570***	-1.429	-8.025***	-0.548	-1.050	I(1)
LNELEC	-2.364	-3.611**	-2.988**	-3.035**	-1.209	-1.607	I(0)
LNN <sub>2</sub> O	-1.633	-5.170***	-4.153***	-7.462***	0.147	1.274	I(0)
LNPOP	-2.005	-8.703***	-8.993***	-6.955***	0.221	-0.168	I(0)

Note: \*\*\* $p < 0.01$  and \*\* $p < 0.05$ .

## 4.3. ARDL Cointegration and Long-Run Results

The ARDL bounds test was performed to determine the existence of a long-run relationship among the variables. As shown in Table 4, the calculated F-statistic (9.704) is substantially higher than the upper bound critical value (4.37) at the 1% significance level. This allows for the decisive rejection of the null hypothesis of no cointegration, confirming a stable long-run equilibrium relationship.

Table 4. ARDL F-Bounds Test for Cointegration.

Test Statistic	Value	
F-statistic	9.703507	
Significance	Lower Bound I(0)	Upper Bound I(1)
10%	2.20	3.09
5%	2.56	3.49
2.5%	2.88	3.87
1%	3.29	4.37

## 4.4. Estimated Long-Run Coefficients

The estimated long-run coefficients are presented in Table 5. The results indicate that LNCO<sub>2</sub> has a positive and highly significant long-run impact on LNHDHI. Specifically, a 1% increase in carbon emissions is associated with a 0.33% increase in the HDI, suggesting that the economic activities driving development remain carbon-intensive. Conversely, LNELEC has a negative and significant long-run coefficient, implying that a 1% increase in electricity access is associated with a 0.13% decrease in the HDI. This finding aligns with recent empirical evidence that electricity access in Bangladesh acts as a significant

driver of CO<sub>2</sub> emissions due to the grid's heavy reliance on fossil fuels. These environmental costs appear to outweigh the direct developmental benefits in the long run, negatively impacting the health component of the HDI. The other variables are not statistically significant in the long-run model [33].

Table 5. Estimated Long-Run Coefficients.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCO <sub>2</sub>	0.330	0.037	8.857	0.000***
LNELEC	-0.128	0.038	-3.379	0.008***
LNN <sub>2</sub> O	0.037	0.034	1.094	0.302
LNPOP	0.052	0.275	0.189	0.854
C (Constant)	-1.103	2.161	-0.510	0.622

*Note: Coefficients represent long-run elasticities. \*\*\* denotes significance at the 1% level. Dependent Variable: LN<sub>HDI</sub>*

- LNCO<sub>2</sub>: In the long run, a 1% increase in CO<sub>2</sub> emissions is associated with a 0.33% increase in the Human Development Index (HDI). This suggests that the economic activities generating emissions are positively linked to long-term development.
- LNELEC: In the long run, a 1% increase in access to electricity is associated with a 0.13% decrease in the HDI. While counterintuitive, the finding is consistent with those who utilized the ARDL approach to demonstrate that electricity access in Bangladesh is a significant driver of CO<sub>2</sub> emissions due to the grid's heavy reliance on fossil fuels. This suggests that the environmental degradation and associated health costs linked to current energy generation outweigh the direct developmental benefits in the long run [33].
- Other variables are not statistically significant in the long run.

#### 4.5. Short-Run Dynamics

The short-run dynamics are estimated through the Error Correction Model (ECM), with results presented in Table 6. The Error Correction Term (ECT), denoted as CointEq(-1), is negative (-0.990) and statistically significant at the 1% level. This significance confirms a stable long-run relationship among the variables. The magnitude of the coefficient (-0.990) indicates an extremely rapid speed of adjustment, suggesting that 99% of any disequilibrium from the previous year is corrected within the current annual period. This implies that the human development system in Bangladesh is highly resilient, quickly returning to its equilibrium path following short-term shocks. Furthermore, the model reveals highly complex and significant short-run dynamics. Changes in CO<sub>2</sub>, electricity access, N<sub>2</sub> O<sub>3</sub> and population all have significant impacts on the change in HDI, with effects that often oscillate between positive and negative across different lags.

#### 4.6. ARDL Model Summary Statistics

The model has an exceptionally high R-squared and Adjusted R-squared, indicating an excellent overall fit (Table 7). The F-statistic is highly significant, confirming the joint significance of the explanatory variables. The SIC value of -9.1442 confirms this is the statistically preferred model. The Durbin-Watson statistic is close to 2, suggesting no first-order serial correlation.

Table 6. Error Correction Model (Short-Run Dynamics).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Error Correction Term (ECT)	-0.990	0.1050	-9.5166	0.000***
D(LNCO <sub>2</sub> )	0.099	0.0151	6.5337	0.000***
D(LNCO <sub>2</sub> (-1))	-0.1604	0.0235	-6.8127	0.000***
D(LNCO <sub>2</sub> (-2))	-0.1718	0.0229	-7.4824	0.000***
D(LNCO <sub>2</sub> (-3))	-0.0814	0.0171	-4.7479	0.001***
D(LNELEC)	-0.0532	0.0119	-4.4402	0.001***
D(LNELEC(-1))	0.0661	0.0093	7.1054	0.000***
D(LNN <sub>2</sub> O)	-0.0094	0.0075	-1.2470	0.243
D(LNN <sub>2</sub> O(-1))	-0.0189	0.0060	-3.1124	0.012**
D(LNN <sub>2</sub> O(-2))	-0.0121	0.0064	-1.9010	0.089*
D(LNN <sub>2</sub> O(-3))	-0.0320	0.0052	-6.0487	0.000***
D(LNPOP)	-2.2617	1.3528	-1.6718	0.128
D(LNPOP(-1))	5.3314	2.9520	1.8060	0.104
D(LNPOP(-2))	-10.907	3.3718	-3.2347	0.010**
D(LNPOP(-3))	11.735	2.0972	5.5955	0.000***

Note: D denotes the first difference. CointEq (-1) represents the Error Correction Term (ECT). \*\*\* denotes significance at 1%, \*\* at 5%, and \* at 10% level. Dependent Variable: D(LNHDI)

Table 7. ARDL Model Summary Statistics.

Statistic	Value
R-squared	0.999
Adjusted R-squared	0.999
F-statistic	2810.580
Prob(F-statistic)	0.000
Schwarz criterion (SIC)	-9.1442
Durbin-Watson stat	2.536

#### 4.7. Robustness Check of Long-Run Estimates using FMOLS, DOLS, and CCR

To corroborate the long-run estimates from the ARDL model and ensure the reliability of the findings, this study employs three alternative cointegration estimators: Fully Modified OLS (FMOLS), Dynamic OLS (DOLS), and Canonical Cointegrating Regression (CCR). The broadly consistent results are presented in the table above. The coefficient for  $\text{LNCO}_2$  is positive and statistically significant at the 1% level across all three methodologies. A 1% increase in carbon emissions is associated with a 0.201%, 0.198%, and 0.156% increase in the Human Development Index (LNHDI) in the FMOLS, DOLS, and CCR estimations, respectively. This consistently positive relationship suggests that the economic activities generating  $\text{CO}_2$  emissions are strongly linked to long-term improvements in human development.

In contrast, the impact of  $\text{LNN}_2\text{O}$  is found to be negative and significant in both the DOLS (at the 5% level) and CCR (at the 1% level) frameworks. It is negative but borderline insignificant in the FMOLS model. A 1% rise in nitrous oxide emissions correlates with a decrease in LNHDI by 0.019% (DOLS) and 0.055% (CCR), indicating that emissions from sources such as agriculture pose a tangible threat to long-term well-being. The variable  $\text{LNPOP}$  exhibits a positive and significant relationship with LNHDI across all estimators. A 1% increase in population corresponds with increases in the LNHDI of 0.330% (significant at 10%), 0.353% (significant at 10%), and a notably larger 1.153% (significant at 1%) in the FMOLS, DOLS, and CCR results, respectively. Conversely,  $\text{LNELEC}$  does not demonstrate a statistically significant long-run relationship with LNHDI in any of the employed models.

Collectively, these findings provide a robust confirmation of a complex long-run dynamic. While economic and demographic growth, proxied by  $\text{LNCO}_2$  and  $\text{LNPOP}$ , are positively associated with human development, the environmental degradation represented by  $\text{LNN}_2\text{O}$  emissions presents a significant countervailing pressure on these developmental gains.

Table 8. Robustness Check of Long-Run Estimates using FMOLS, DOLS, and CCR.

Variable	FMOLS	DOLS	CCR
$\text{LNCO}_2$	0.201*** (0.000)	0.197*** (0.000)	0.155*** (0.000)
$\text{LNELEC}$	0.009 (0.753)	0.005 (0.859)	-0.035 (0.270)
$\text{LNN}_2\text{O}$	-0.022 (0.110)	-0.0186** (0.044)	-0.055*** (0.004)
$\text{LNPOP}$	0.330* (0.074)	0.353* (0.063)	1.153*** (0.000)
C	-3.279** (0.027)	-3.463** (0.023)	-9.819*** (0.000)
R-squared	0.996	0.996	0.999

Note: The table presents the long-run coefficients. P-values are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

#### 4.8. Diagnostic and Stability Test Results

To ensure the validity of the ARDL model, a suite of diagnostic tests was conducted. The results, summarised in Table 9, confirm that the model is well-specified. The model passes tests for normality of residuals (Jarque-Bera), serial correlation (Breusch-Godfrey LM), and heteroskedasticity. The Ramsey RESET test also indicates no model specification error.

#### 4.9. CUSUM and CUSUM of Squares Test

The stability of the estimated ARDL model's parameters was rigorously assessed using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests. An examination of the CUSUM and CUSUMSQ plots shows that both statistics lie well within the 5% critical boundaries across the entire sample period. This finding provides strong evidence for parameter

constancy, confirming the structural stability of the model. Therefore, the estimated long-run and short-run coefficients are robust and reliable for policy analysis.

Table 9. Diagnostic tests.

Diagnostic tests	Coefficient	p-Value	Decision
Jarque–Bera for Normality test	0.737	0.692	Residuals are normally distributed.
Breusch–Godfrey LM (Lagrange multiplier) test	1.461	0.295	No serial correlation exists.
Breusch–Pagan–Godfrey test for Heteroscedasticity	14.081	0.661	No heteroscedasticity exists.
Ramsey RESET test	0.581	0.577	No specification error.

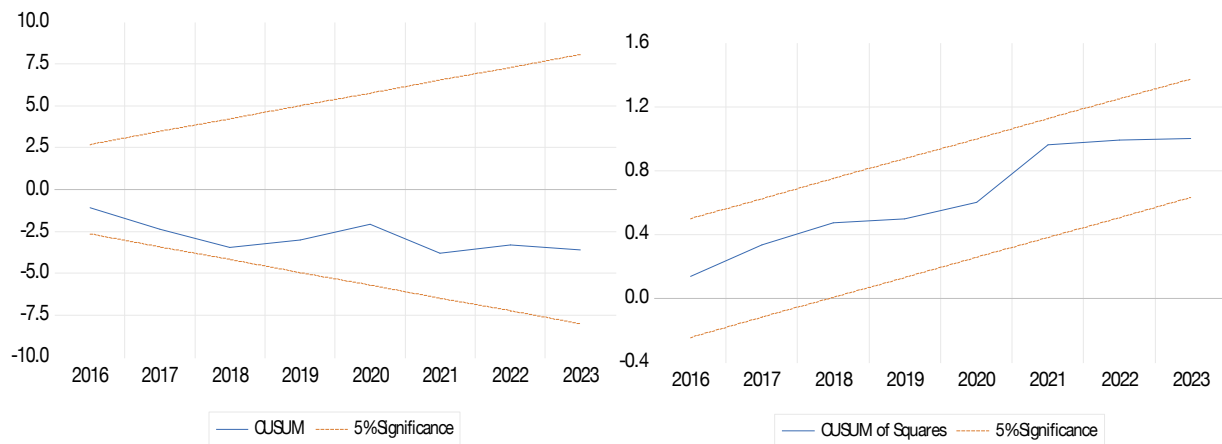


Figure 1. CUSUM and CUSUM of Squares.

## 5. Conclusion and Policy Implications

This study's examination of Bangladesh from 1991 to 2023 exposes a profound development paradox. While the long-run analysis reveals that rising carbon emissions are closely intertwined with improvements in human development, it also highlights the troubling reality that Bangladesh's progress remains dependent on carbon-intensive growth. Paradoxically, increased access to electricity, often seen as a hallmark of modernization, shows a negative long-run relationship with the Human Development Index (HDI), suggesting that the environmental and health costs of the existing energy infrastructure may be undermining the very well-being it aims to enhance. Robustness tests using FMOLS, DOLS, and CCR methods reaffirm the stability of these results and further uncover the harmful long-run effects of agricultural emissions ( $\text{N}_2\text{O}$ ) on human welfare. Together, these findings illuminate an urgent humanitarian challenge: Bangladesh must learn not merely to grow, but to grow sustainably and compassionately by decoupling human progress from environmental degradation. The path forward lies in embracing cleaner technologies, greener energy, and policies that ensure that the pursuit of prosperity no longer comes at the expense of planetary and human health [22]. The findings of the current study present multiple specific policy implications for Bangladesh's sustainable development agenda.

1. First, the persistent positive link between HDI and carbon highlights the critical necessity of strategically decoupling development from carbon: To achieve this, policymakers should accelerate the transition to renewable energy. This can be achieved by creating a favorable investment climate for utility-scale solar and wind projects, inspired by the success

of Germany's Energiewende policy, which used feed-in tariffs and tax incentives to dramatically increase its renewable energy share [7].

2. Second, the counterintuitive negative long-run impact of electricity access on HDI underscores the importance of greening the grid: It is not enough to expand access; the quality and source of that energy are paramount. Policymakers should implement mandatory energy efficiency standards for industries and households, drawing lessons from Japan's highly successful Top Runner program. Simultaneously, for remote and underserved regions, deploying off-grid solutions like solar home systems and mini-grids, as successfully implemented in Kenya, can provide clean energy access without overburdening the national grid [1]. However, expanding infrastructure is insufficient if economic barriers persist. A recent study argues that overcoming the high upfront costs of these clean technologies requires targeted financial incentives, specifically the implementation of subsidies and micro-loan frameworks to ensure equitable access for low-income households [11].
3. Third, the observed mitigating effect of reducing agricultural emissions (N<sub>2</sub>O) on long-term well-being warrants a focus on sustainable agriculture: As agricultural intensification continues, Bangladesh needs to promote practices that enhance food security without compromising environmental health. This includes training farmers in efficient fertilizer use and providing subsidies for organic farming techniques, following the model of India's Zero Budget Natural Farming (ZBNF) initiative [26].
4. Fourth, as population growth and urbanisation continue to exert pressure, urban and demographic planning policies are crucial: Policies should prioritise the creation of compact, low-carbon cities that incorporate sustainable transportation systems and promote efficient energy utilisation. This can be complemented by strengthening family planning services and integrating population education into curricula, inspired by Rwanda's success in sustainably managing demographic trends [8].

A comprehensive strategy that integrates renewable energy transition, energy efficiency, sustainable agriculture, and integrated spatial planning is crucial for realising Bangladesh's dual objectives of advancing human development and ensuring environmental sustainability. The findings establish a basis for evidence-grounded policymaking focused on achieving Bangladesh's Sustainable Development Goals and fulfilling its global climate commitments.

This study presents specific limitations that provide opportunities for further research. First, the study is exclusively centred on Bangladesh, which restricts the generalizability of its findings to other national contexts with varying economic, institutional, and environmental frameworks. Second, the analysis focused on a select set of macro-level variables while omitting other potentially significant factors such as green finance, institutional quality, trade openness, or the quality of governance. Third, this study utilises national-level annual data, which may not account for the significant regional disparities in development and environmental quality within Bangladesh. Methodologically, although the ARDL and related estimators demonstrate robustness, future research may benefit from the application of nonlinear techniques (such as NARDL) to capture asymmetric relationships more effectively. Future research should therefore focus on regional-level analyses within Bangladesh, incorporate a wider array of institutional and financial variables, and include cross-country comparisons with other South Asian nations to enhance the understanding of sustainable development strategies in the region.

## Declarations

**Ethics approval/declaration:** Not applicable.

Consent to participate: Not applicable.

**Consent for publication:** Not applicable.

**Author Contributions:** Saikat Pande: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing.

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