Systemic Analytics

www.sa-journal.org

Research Expansion Alliance

Syst. Anal. Vol. 4, No. 1 (2026) 13–26.

Paper Type: Original Article

Towards Sustainable Development Goals: An ARDL Analysis of Energy Efficiency, Finance, and Technology in Mitigating CO_2 Emissions in the United States

Shamina Israr Tithi*

Department of Earth and Environmental Sciences, Brooklyn College, CUNY, USA; Shamina.Tithi@brooklyn.cuny.edu.

Citation:

Received: 14 March 2025 *Revised: 17 May 2025* *Accepted: 05 June 2025*	Israr Tithi, Sh. (2026). Towards sustainable development goals: An ARDL analysis of energy efficiency, finance, and technology in mitigating CO_2 emissions in the united states. *Systemic Analytics*, *4*(1), 13-26.

Abstract

This paper examines the changing associations among economic growth, Energy Efficiency (EE), and access to finance, Information and Communication Technology (ICT), and Urbanization (URBA), and their joint impacts on Carbon Dioxide (CO_2) emissions in the United States (US) between 1990 and 2022. The analysis employs unit root and cointegration tests to estimate the short- and long-run dynamics. It applies the Autoregressive Distributed Lag (ARDL) model with error-correction terms and Granger causality tests. Results show that Gross Domestic Product (GDP) growth and URBA significantly worsen environmental quality, as rising economic activity and expanding urban populations intensify fossil fuel consumption and carbon emissions. In contrast, EE, Financial Accessibility (FA), and ICT adoption mitigate emissions, highlighting their potential to advance environmental sustainability. Specifically, access to finance facilitates investment in cleaner technologies, ICT applications reduce energy intensity, and renewable energy innovations enhance efficiency. Causality analysis further indicates unidirectional effects of GDP, ICT, EE, and FA on CO_2 emissions, whereas URBA shows a bidirectional causal link with emissions. These findings highlight the importance of technological development, sustainable finance, and green energy in ensuring that U.S. development aligns with the global climate agenda. The research is relevant to Sustainable Development Goals (SDG 7: Affordable and Clean Energy, SDG 9: Industry, Innovation, and Infrastructure, SDG 11: Sustainable Cities and Communities, and SDG 13: Climate Action) because it provides empirical data on how to strike a balance between economic growth and environmental sustainability. Policymakers are urged to prioritize green finance, ICT infrastructure, and energy transition policies to achieve long-term carbon neutrality.

Keywords: Sustainable development goals, Carbon emissions, Energy efficiency, Green finance, United States.

1 | Introduction

Environmental degradation and climate change are burning global issues that impose a dire burden on the environment, economies, and human lives. Increasing rates of Greenhouse Gas (GHG) emissions, especially

Corresponding Author: Shamina.Tithi@brooklyn.cuny.edu
https://doi.org/10.31181/sa41202667

Carbon Dioxide (CO_2), pose a threat to global climate security, despite international efforts. To reach the Sustainable Development Goals (SDGs), in particular, Affordable and Clean Energy (SDG 7), Industry, Innovation, and Infrastructure (SDG 9), Sustainable Cities and Communities (SDG 11), and Climate Action (SDG 13), immediate actions are necessary to balance economic growth with ecological sustainability [1], [2]. The global reliance on fossil fuels remains the primary driver of rising CO_2 emissions. According to recent evidence, worldwide CO_2 outputs rose modestly by 0.1% in 2023 after consecutive increases of 5.4% and 1.9% in 2021 and 2022, reaching nearly 35.8 Gt [3]. This upward trajectory highlights the difficulty of achieving climate stabilization targets despite technological innovations and international agreements. As the second-largest global emitter, the United States (US) alone accounts for more than 15% of total CO_2 emissions, making its role central to advancing global decarbonization [4]. The current level of urgency in lowering emissions is also reflected in the U.S. government's climate agenda, which aims to reduce GHG emissions by 27% from 2005 levels by 2025 and to eliminate them by 2050 [5–7]. Reaching these targets is vital not only for U.S. sustainability but also for meeting international climate goals and the SDG framework.

The US occupies a unique position in the global climate challenge. Despite extensive technological advancement and international cooperation, fossil fuels have remained the backbone of U.S. energy consumption, accounting for about 87% in 1990 and still 83% by 2020 [8]. This heavy reliance on non-renewable energy has made the country a consistent contributor to global carbon pollution. In 2022, the U.S. Gross Domestic Product (GDP) per capita reached $61,349, marking steady economic expansion, yet such growth has been accompanied by intensified industrial production, rising energy demand, and higher emissions[1]. Despite the increase in the use of renewable energy and Energy Efficiency (EE) initiatives, there are not enough. To illustrate, in 2019, the proportion of renewable energy to total electric energy was only 17.7 percent, and the year-on-year EE increase over 2010-2019 was only 1.9 percent, which was much lower than the rate needed to meet international targets.

Additionally, U.S. Urbanization (URBA) continues to accelerate, reshaping land use, increasing household energy demand, and intensifying transport-related emissions [9]. These trends underscore a fundamental dilemma: while economic expansion, technological progress, and urban growth have supported prosperity, they have simultaneously placed significant pressure on environmental systems. It raises a critical question for policymakers and scholars: Can Financial Accessibility (FA), Information and Communication Technology (ICT) adoption, and EE be leveraged effectively to offset the environmental costs of U.S. development and align with its carbon-neutrality goals?[2]

Prior studies show mixed results on the drivers of CO_2 emissions. Regarding GDP, many confirm a positive link with emissions due to industrial growth and reliance on fossil fuels [2], [10–12]. Yet others suggest that growth can reduce emissions by supporting clean technologies and the adoption of renewable energy [13]. EE is also debated. Several studies find that conservation policies reduce CO_2 emissions [14–16]. However, others note rebound effects where efficiency gains raise total energy use [17]. FA presents similar contradictions. Some evidence links finance to greener investment and lower emissions [18]. Conversely, other studies associate financial development with higher energy consumption and pollution [19–21]. ICT adoption has shown potential to reduce emissions through EE [19], [22], [23]. Still, several studies caution that ICT diffusion may increase energy demand in energy-intensive economies [9], [24]. URBA effects also vary. While many studies link urban growth with ecological decline [25–27], others identify U-shaped or mitigating effects depending on regional conditions [28], [29]. Overall, prior work rarely integrates GDP, EE, FA, ICT, and URBA within one framework for the US. This gap motivates the present study, which jointly examines these drivers using robust econometric techniques. Based on these gaps, the research problem of this study is to examine how the combination of GDP growth, EE, FA, ICT adoption, and URBA has impacted CO_2 in the US between 1990 and 2022. Through the Autoregressive Distributed Lag (ARDL)

[1]https://www.cmegroup.com/markets.html?utm_source=google&utm_medium=paid_search&utm_campaign

model, which has been used in error correction and causality analysis, the study determines short- and long-run dynamics. The study makes three key contributions. First, it integrates multiple socioeconomic and technological drivers into a single framework, offering a more comprehensive assessment than prior studies that focused on isolated variables. Second, it provides fresh empirical evidence for the US, the world's second-largest emitter, where sustainable growth policies are of global significance. Third, it highlights the role of green finance, ICT, and EE as tools for aligning economic progress with environmental sustainability. These can be directly related to global climate goals and the SDGs, such as SDG 7, SDG 9, SDG 11, and SDG 13. The results will guide policymakers in developing combined policies that consider the development and long-term sustainability of the environment.

The rest of this paper is as follows. Section 2 is a literature review of the relationship between GDP, EE, FA, ICT, URBA, and CO_2 emissions. Section 3 describes the data, variable characterization, and econometric approach. Section 4 presents and discusses the empirical results, and Section 5 provides a conclusion with important policy recommendations and explains how they align with the SDGs.

2|Literature Review

Decarbonization outcomes hinge on how growth, technology, finance, and settlement patterns interact. Prior evidence is mixed, often context-specific, and rarely estimated jointly for the US. This review synthesizes mechanisms and contradictions for five drivers to motivate testable hypotheses. Economic growth is often cited as a key contributor to rising carbon emissions. Several studies emphasize a positive correlation between GDP and environmental deterioration, as industrial growth and energy consumption are often based on fossil fuels. For example, Pattak et al. [10] found that in Italy, a 1% change in GDP increased CO_2 emissions by 8%. Likewise, Raihan et al. [12] in the case of Malaysia, Ridwan et al. [2] in the case of South Asia, and Ahmad et al. [11] in the case of China established that long-term GDP growth increases carbon pollution. Similar findings were reported by Islam et al. [30] in nuclear energy-consuming nations and by Raihan et al. [20] in Vietnam, who noted that increased output worsens emissions in both developed and emerging economies. However, other scholars suggest that under certain conditions, economic expansion may support environmental improvement. Similarly, Mehmood et al. [13], examining G-7 countries, observed a negative correlation between GDP and carbon emissions, implying that higher income levels can fund greener infrastructure and energy transitions. Taken together, the literature presents contradictory evidence. While the majority emphasizes the emission-enhancing role of GDP, some findings suggest the possibility of a decoupling effect when technological upgrading accompanies growth. Given the US's high reliance on fossil fuels and its mixed record in decoupling growth from emissions, the relationship remains an open empirical question.

EE is widely regarded as a critical tool for reducing emissions by lowering the amount of energy required per unit of output. Several studies provide strong evidence that improvements in EE curb CO_2 emissions. Shahzadi et al. [14], using a Panel ARDL approach for G-7 economies, found that efficient energy use consistently reduced carbon emissions. Similarly, Wenlong et al. [15] reported that across 10 Asian regions, EE significantly improved environmental quality. Evidence from the EU also confirms this outcome, with Bilgili et al. [16] and Jin et al. [31] demonstrating that investments in EE and green R&D reduce emissions.

Nevertheless, not all findings are consistent. Robaina and Arshad [17], examining Association of Southeast Asian Nations (ASEAN) countries, showed that efficiency gains sometimes generated a "rebound effect," where reduced energy costs increased demand for energy services, ultimately raising emissions in the short run. Likewise, Raihan et al. [32] argued that rapid technological progress, while boosting efficiency, can also raise aggregate energy consumption, thereby offsetting environmental benefits. These contrasting results suggest that the impact of EE is context dependent. In advanced economies with strong environmental policies, EE is more likely to deliver net reductions, whereas in regions with high energy demand, rebound effects may dominate. For the US, where efficiency standards are relatively advanced but fossil fuel dependence remains high, the net outcome remains uncertain and warrants empirical testing.

The relationship between FA and environmental quality has attracted growing attention, though results remain inconsistent. On the positive side, several studies show that improved access to finance facilitates investment in cleaner technologies, renewable energy projects, and energy-efficient infrastructure. Raihan et al. [33], analyzing G-7 countries, demonstrated that financial inclusion supports environmental sustainability by channeling resources into green sectors. Similarly, Akhter et al. [24] found that in the US, FA positively influenced environmental health by enabling households and firms to adopt greener practices. Chaudhry et al. [18], using data from OECD countries, further confirmed that enhanced financial inclusion reduces CO_2 emissions in both the short- and long-run. By contrast, other studies present evidence that financial development may worsen environmental outcomes. Ridwan [34], focusing on the U.S., revealed that financial progress was associated with higher environmental degradation when capital flows supported carbon-intensive industries. Raihan et al. [33] showed similar results in the G-7, where access to finance increased emissions rather than reducing them. Likewise, Raihan et al. [35] concluded that in Indonesia, financial development stimulated economic growth but simultaneously led to higher CO_2 emissions. These mixed results highlight two competing channels: finance can accelerate green transformation, but it can also fund carbon-heavy consumption and production. For the U.S. with advanced financial markets and emerging green finance instruments the net effect remains uncertain and needs empirical verification.

ICT plays a dual role in shaping environmental outcomes. On the one hand, ICT is frequently linked to emission reductions through dematerialization, energy optimization, and digital innovations. Rahman et al. [36] found that in the U.S., ICT adoption improved ecological sustainability by enhancing efficiency across production and service sectors. Sun et al. [22] reported that the long-term benefits of ICT were particularly pronounced in high-income countries, where digitalization reduced emissions at a scale nearly 10 times that in middle-income economies. Similarly, Xie et al. [23] showed that ICT adoption in Belt and Road countries significantly mitigated CO_2 emissions, reinforcing its potential role in sustainable transitions. However, not all evidence is favorable. Rahman and Ferdaous [9], using a panel ARDL approach, argued that ICT development in certain regions raised CO_2 emissions due to increased electricity consumption from data centers and digital infrastructure. Akther et al. [24] also identified a positive link between ICT use and emissions in the U.S., suggesting that digital growth can intensify energy demand. In addition, Godil et al. [37] observed similar results for Pakistan, where ICT diffusion contributed to environmental degradation rather than alleviating it. Taken together, the literature indicates mixed impacts of ICT: while it has strong potential to enable EE and sustainability, its rapid expansion may increase electricity consumption if not powered by renewable sources. For the US, where digitalization is advanced, but fossil fuels remain dominant, the direction of impact remains empirical.

URBA is another critical factor influencing environmental quality, but the literature presents highly divergent outcomes. Several studies argue that urban growth contributes to higher CO_2 emissions by increasing energy demand in transportation, housing, and industry. Ridwan [25] highlighted that rapid urban expansion intensifies ecological degradation by increasing fossil fuel consumption. Similar findings were reported by Raihan et al. [26] for Bangladesh, showing that URBA raises CO_2 emissions. Song et al. [27] also found that urban development in China had a direct and significant negative impact on environmental sustainability.

In contrast, some scholars suggest that URBA can, under certain conditions, reduce emissions. Shahbaz et al. [28] studied Malaysia and identified a U-shaped relationship: early stages of URBA lowered emissions through efficiency gains, but beyond a threshold, urban growth increased pollution. Anser et al. [29], focusing on Finland, reported that URBA contributed to emission reduction when supported by renewable energy integration and sustainable planning. Likewise, Zhang et al. [38] found that new forms of URBA in northern China decreased CO_2 emissions by improving efficiency and infrastructure. Overall, these contrasting results highlight the complex role of URBA: it may either exacerbate or alleviate emissions depending on the quality of infrastructure, energy mix, and urban design. In the U.S., characterized by high dependence on private vehicles and sprawling urban forms, the relationship is likely to be emission-increasing in the short run, but empirical testing is required.

The review reveals that prior studies provide contradictory evidence on the drivers of CO_2 emissions. While GDP growth also presents two opposing channels: it can finance green investments or intensify carbon-intensive activities. ICT demonstrates similar duality, with evidence of both emission mitigation and escalation depending on the energy mix. Finally, URBA is associated with rising emissions in many cases, though some studies identify U-shaped or even reducing effects when sustainable infrastructure is in place. Despite these insights, two gaps remain. First, most analyses treat these drivers in isolation, offering a limited understanding of their combined influence. Second, although the US is the world's second-largest emitter, few studies have found an increase in emissions; in some contexts, technological progress accompanies expansion, leading to decoupling. EE is widely credited with lowering emissions, yet rebound effects may offset these gains. FA assessed GDP, EE, FA, ICT, and URBA within one empirical framework. Closing these gaps is essential to inform policies that would respond to global sustainability commitments to the SDGs.

3 | Methodology

3.1 | Data and Variables

In this case, time series are used annually, using US data from 1990 to 2022. The information was obtained from credible sources, including the World Development Indicators (WDI), the International Monetary Fund (IMF), and Our World in Data, to ensure consistency and reliability. Economic growth is measured by real GDP per capita, which reflects the scale of economic activity and is linked to Decent Work and Economic Growth (SDG 8). EE is proxied by renewable energy-related patents, reflecting technological innovation to reduce energy intensity and supporting SDG 7. FA is the share of domestic credit to the private sector of GDP that reflects the contribution of finance to sustainable investment, which is in line with SDG 9. ICT imports as a percentage of GDP reflect digital penetration, which can optimize energy use and support SDG 9 and Responsible Consumption and Production (SDG 12). URBA is calculated as the proportion of the urban population to the total population, as a population measure of demographic change for SDG 11. To provide a clear overview, *Table 1* presents the variables, their proxies, expected signs, data sources, and their alignment with the SDGs.

Table 1. Variables, measurements, expected effects, sources, and relevant SDGs.

Variable	Proxy/Measurement	Expected Effect	Source	Relevant SDG(s)
CO_2	CO_2 emissions per capita	Dependent variable	WDI/OWID	SDG 13
GDP	Real GDP per capita	Positive (+)	WDI	SDG 8
EE	Renewable energy patents	Negative (–)	WDI/IMF	SDG 7
FA	Domestic credit to private sector (% of GDP)	Ambiguous	WDI	SDG 9
ICT	ICT imports (% of GDP)	Negative (–)	WDI	SDG 9, SDG 12
URBA	Urban population (% of total)	Positive (+)	WDI	SDG 11

3.2 | Theoretical Framework

The analysis is based on the IPAT identity, which connects environmental impact (I) to population (P), affluence (A), and technology (T). IPAT, though helpful, is deterministic and cannot reflect stochastic fluctuations. To overcome this shortcoming, Dietz and Rosa [39] generalized it into the STIRPAT model, which can be tested and hypotheses formulated using econometric techniques. This model has been widely applied to explain the environmental impacts of socioeconomic and technological forces across various settings. The fundamental structure of this model is as follows:

$$\mathrm{I} = \int \mathrm{PAT}. \tag{1}$$

The Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model allows the addition of additional independent variables, such as power consumption and business structure, to investigate the implications of different factors on the natural world [40]. In this article, we have used CO_2 emissions as proxy measures of ecological harm.

$$I_i = C.P_i^{\beta}.A_i^{\gamma}.T_i^{\delta}.\varepsilon_i \quad (2)$$

The empirical background presented in this paper is the culmination of an intricate review that led to the following characterizations.

$$\text{ED} = f(\text{Population}, \text{Affluence}, \text{Technology}). \quad (3)$$

Also, alongside the exogenous features, we incorporated the ecological impacts and employed CO_2 emissions as an alternative measure. To obtain *Eq. (4)*, run the following process:

$$CO_{2_{it}} = \gamma_0 + \gamma_1 GDP_{it} + \gamma_2 EE_{it} + \gamma_3 FA_{it} + \gamma_4 ICT_{it} + \gamma_5 URBA_{it}. \quad (4)$$

In this case, GDP depicts the growth of the economy; EE stands for EE; FA is access to finance; ICT is technological innovation; and URBA is URBA. In our *Eq. (4)*, we denoted the coefficient of the exogenous factors by γ_1 to γ_5 and γ_0 is the intercept term. In *Eq. (5)*, the elements are put in a logarithmic form to ensure normal distribution.

$$LCO_{2_{it}} = \gamma_0 + \gamma_1 LGDP_{it} + \gamma_2 LEE_{it} + \gamma_3 LFA_{it} + \gamma_4 LICT_{it} + \gamma_5 LURBA_{it}. \quad (5)$$

3.3 | Empirical Strategy

To ensure trend stationarity, unit root tests determine whether non-stationary data should be incorporated before regression [41]. Time trends in series may yield spurious results [42], [43]. This study applied P-P, DF-GLS, and ADF tests [44], with the ADF favored for handling serial correlation. Both levels and first differences were examined. The ARDL bounds test [45] assessed cointegration, offering robustness to serial correlation and endogeneity [46]. It is effective with small samples [47] and applicable for I(0)/I(1) data [19]. The following *Eq. (6)* represents the long-run scenario:

$$\Delta LCO_{2t} = \delta_0 + \delta_1 LCO_{2t-1} + \delta_2 LGDP_{t-1} + \delta_3 LEE_{t-1} + \delta_4 LFA_{t-1} + \delta_5 LICT_{t-1} + \delta_6 LURBA_{t-1} + \sum_{i=1}^{p} \gamma_1 \Delta LCO_{2t-i} + \sum_{i=1}^{p} \gamma_2 \Delta LGDP_{t-i} + \sum_{i=1}^{p} \gamma_3 \Delta LEE_{t-i} + \sum_{i=1}^{p} \gamma_4 \Delta LFA_{t-i} + \sum_{i=1}^{p} \gamma_5 \Delta LICT_{t-i} + \sum_{i=1}^{p} \gamma_6 \Delta LURBA_{t-i} + \varepsilon_t \quad (6)$$

Once we have long-term associations, we examine the ECT and short-term linkages following the ECM structure proposed by Engle and Granger [48]. *Eq. (7)* utilizes the ARDL, which uses the ECM term to explain the short-term relationship between the factors.

$$\Delta LCO_{2t} = \delta_0 + \delta_1 LCO_{2t-1} + \delta_2 LGDP_{t-1} + \delta_3 LEE_{t-1} + \delta_4 LFA_{t-1} + \delta_5 LICT_{t-1} + \delta_6 LURBA_{t-1} + \sum_{i=1}^{p} \gamma_1 \Delta LCO_{2t-i} + \sum_{i=1}^{p} \gamma_2 \Delta LGDP_{t-i} + \sum_{i=1}^{p} \gamma_3 \Delta LEE_{t-i} + \sum_{i=1}^{p} \gamma_4 \Delta LFA_{t-i} + \sum_{i=1}^{p} \gamma_5 \Delta LICT_{t-i} + \sum_{i=1}^{p} \gamma_6 \Delta LURBA_{t-i} + \varphi ECM_{t-1} + \varepsilon_t \quad (7)$$

To address potential issues that may affect the coefficient's reliability, the study used various diagnostic tests, including the Lagrange Multiplier (LM), Jarque-Bera, and Breusch-Pagan-Godfrey tests. The normal distribution of the residuals was confirmed by the Jarque-Bera test [49]. The LM test was applied to detect serial correlation, ensuring that residual errors were not dependent on time, thereby avoiding biased inferences. Similarly, the BPG test assessed heteroscedasticity, as uneven error variances can distort standard errors and predictions. In addition, causal relationships were explored using the Pairwise Granger causality framework [47], which provides robust predictive insights within time-series analysis.

4 | Results and Discussion

Table 3 reports the descriptive statistics of the log-transformed variables for the period 1990–2022. The average value of $lnCO_2$ is 2.66, ranging from 2.48 to 2.82, indicating moderate variation in per capita emissions across the sample period. lnGDP records a mean of 10.86, with values ranging from 10.50 to 11.14, reflecting steady income growth. lnEE shows greater variability, with a mean of 4.42 and a spread from 3.75 to 5.24, consistent with fluctuations in renewable-related patenting activity. lnFA averages 4.92, ranging from 4.62 to 5.15, highlighting considerable differences in financial sector depth. lnICT is relatively stable, with a mean of 0.98 and bounds of 0.64-1.50. Finally, lnURBA exhibits minimal dispersion, averaging 4.39, with values ranging from 4.36 to 4.42, reflecting the already high level of URBA in the U.S.

Table 2. Summary statistics.

Variable	Mean	Std. Dev.	Min	Max	Obs
$lnCO_2$	2.66	0.09	2.48	2.82	33
lnGDP	10.86	0.18	10.5	11.14	33
lnEE	4.42	0.37	3.75	5.24	33
lnFA	4.92	0.14	4.62	5.15	33
lnICT	0.98	0.22	0.64	1.5	33
lnURBA	4.39	0.02	4.36	4.42	33

As shown in *Table 4*, the correlation results of the log variables remain consistent with expectations. lnGDP is positively and significantly correlated with $lnCO_2$ (0.59***), confirming the scale effect of growth. Ln EE exhibits a negative correlation with $lnCO_2$ (–0.41**), suggesting its role in mitigating emissions. Ln ICT is also negatively correlated (–0.36**), consistent with its energy-optimizing potential. lnFA displays an insignificant correlation (–0.11), reflecting its ambiguous impact, while ln URBA shows a significant positive correlation with ln CO_2 (0.39**). These preliminary associations support the formulated hypotheses but do not imply causality.

Table 3. Correlation matrix.

Variables	$lnCO_2$	lnGDP	lnEE	lnFA	lnICT	lnURBA
$lnCO_2$	1					
lnGDP	0.59***	1				
lnEE	–0.41**	–0.34*	1			
lnFA	–0.11	0.17	0.29	1		
lnICT	–0.36**	–0.40**	0.31*	0.27	1	
lnURBA	0.39**	0.43**	–0.21	–0.07	–0.28*	1

Before estimating the ARDL model, the series' stationarity must be investigated. To avoid bias from a single procedure, three complementary tests were used: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and DF-GLS. The findings, as shown in *Table 5*, indicate that the variables are of mixed order: some are stationary at the level [I(0)], and others at the first level [I(1)]. None of the variables is I(2), which supports the appropriateness of the ARDL method. In particular, $lnCO_2$ and lnGDP became stationary following initial differencing, indicating I(1) processes. lnEE and lnICT also showed mixed behavior, but both remained stationary after initial differencing. Such results support the adoption of the ARDL bounds testing methodology that supports a combination of I(0) and I(1) regressors.

Table 4. Unit root test.

Variable	ADF		P-P		DF-GLS		Order
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
$lnCO_2$	–2.11	–5.72***	–2.24	–5.83***	–1.94	–5.45***	I(1)
lnGDP	–2.42	–6.13***	–2.35	–6.07***	–2.18	–6.02***	I(1)
lnEE	–3.41**	–	–3.55**	–	–3.22**	–	I(0)
lnFA	–2.07	–5.31***	–2.19	–5.24***	–2.02	–5.11***	I(1)
lnICT	–3.12**	–	–3.27**	–	–3.05**	–	I(0)
lnURBA	–2.18	–4.89***	–2.25	–4.92***	–2.08	–4.77***	I(1)

Once the order of integration was determined, the ARDL bounds test was used to assess the existence of a long-run relationship among the variables. *Table 6* indicates that the calculated F-statistic (6.72) is greater than the upper critical values of the 1% level and affirms the existence of cointegration between $lnCO_2$, ln GDP, lnEE, lnFA, lnICT, and lnURBA. It justifies the use of the ARDL to estimate the long- and short-run dynamics.

Table 5. ARDL bound test.

	F=6.7680	k=5
Significance level	I(0)	I(1)
10%	2.08	3
5%	2.39	3.38
2.50%	2.7	3.73
1%	3.06	4.15

The ARDL results confirm that economic growth significantly contributes to environmental degradation in the US. In the long run, GDP elasticity is positive (0.362, p=0.004), indicating that a 1% rise in income increases per capita CO_2 emissions by 0.36%. Similarly, the short-run coefficient (0.214, p=0.014) also shows a positive effect, though smaller in magnitude, suggesting that both immediate and persistent growth effects are environmentally harmful. These findings imply that expansion in industrial output, transport, and consumption increases reliance on fossil fuels, thereby accelerating carbon emissions. This result is consistent with the scale effect hypothesis, which posits that higher output raises energy demand and intensifies ecological pressure. The findings closely align with several studies in the literature. Pattak et al. [12] and Raihan et al. [14] reported that GDP growth increases CO_2 emissions in Italy and Malaysia, respectively, while Polcyn et al. [50] and Ahmad et al. [11] confirmed similar outcomes for South Asia and China, respectively. Islam et al. [30] also found growth-induced emissions in nuclear energy-consuming nations. However, contrasting results exist, such as Raihan et al. [35] for Indonesia and Mehmood et al. [13] for the G-7, who argue that at higher development stages, growth can facilitate investments in green technology and renewable energy, thereby decoupling economic performance from emissions. For the US, the positive GDP–CO_2 nexus suggests that current growth patterns are unsustainable without structural transformation. This finding underscores the importance of integrating SDG 8 with SDG 13 by promoting growth strategies aligned with renewable energy deployment, energy efficiency improvements, and low-carbon innovation.

The ARDL estimates indicate that EE significantly mitigates CO_2 emissions in the US. In the long run, the coefficient is negative (–0.214, p=0.026), indicating that a 1% increase in renewable energy–related patents, as a proxy for efficiency, reduces per capita CO_2 emissions by 0.21%. In the short run, the effect remains negative (–0.143, p=0.041), though smaller in magnitude, confirming that efficiency improvements generate both immediate and persistent environmental benefits. These results suggest that innovation and diffusion of renewable energy technologies, improved industrial processes, and efficiency standards contribute to lowering energy intensity, thereby curbing carbon emissions. These findings are consistent with a large body of empirical research. Shahzadi et al. [14], focusing on G-7 economies, and Wenlong et al. [15], examining Asian regions, found that efficiency initiatives substantially improve environmental quality. Similarly, Bilgili et al. [16] and Jin et al. [31] reported that EE and green R&D in European contexts significantly reduce emissions. However, other studies caution that efficiency gains may not always yield net benefits. Robaina and Arshad [17] observed rebound effects in ASEAN economies, where improved efficiency lowered costs and induced higher energy consumption. Ridzuan et al. [41] further argued that rapid technological progress could increase aggregate demand, offsetting some of the efficiency gains. For the U.S., the consistent negative coefficients imply that EE policies are functioning as intended, though vigilance against rebound effects remains necessary. This outcome aligns strongly with SDG 7 and SDG 13, highlighting efficiency-driven innovation as a pathway to a low-carbon economy.

The ARDL estimates reveal that FA contributes to lowering CO_2 emissions in the US, although the effect differs in magnitude across time horizons. In the long run, the coefficient is negative (–0.129, p=0.063), suggesting that a 1% increase in domestic credit to the private sector reduces per capita CO_2 emissions by 0.13%. The short-run effect is slightly weaker but still negative (–0.092, p=0.081), indicating that enhanced access to finance facilitates immediate investments in cleaner technologies, renewable energy projects, and energy-efficient infrastructure, while also supporting sustained environmental gains over time. These findings imply that credit availability enables firms and households to adopt sustainable practices. The results align with the literature showing that financial development can serve as a channel for green transformation. Raihan et al. [33] found that financial inclusion supports sustainability across G-7 economies, while Akther et al. [24] reported similar effects for the U.S., emphasizing that financial resources can ease the transition toward greener practices. Chaudhry et al. [18] also confirmed that financial development in OECD countries significantly reduces CO_2 emissions in both the short- and long-run. However, contrasting evidence exists. Ridwan et al. [19] documented that in the U.S., financial progress sometimes increased emissions when capital was directed toward carbon-intensive industries. Raihan et al. [33], Voumik et al. [51], and Ismail et al. [52] similarly showed that finance in some contexts can expand consumption and energy use, thereby worsening environmental quality. Overall, the U.S. results suggest that the "green enabling" channel of finance dominates, making FA an important driver of SDG 9 and SDG 13 by linking financial systems with sustainable investments.

Table 6. ARDL long-run estimation.

Variable	Coefficient	Std. Error	t-Statistic	p-Value
lnGDP	0.362***	0.118	3.07	0.004
lnEE	–0.214**	0.091	–2.35	0.026
lnFA	–0.129*	0.067	–1.93	0.063
lnICT	–0.176**	0.082	–2.15	0.04
lnURBA	0.407***	0.139	2.93	0.006
C	1.692***	0.558	3.03	0.005

Table 7. ARDL Short-run estimation.

Variable	Coefficient	Std. Error	t-Statistic	p-Value
ΔlnGDP	0.214**	0.082	2.61	0.014
ΔlnEE	–0.143**	0.067	–2.13	0.041
ΔlnFA	–0.092*	0.051	–1.80	0.081
ΔlnICT	–0.121**	0.058	–2.09	0.044
ΔlnURBA	0.238**	0.094	2.53	0.017
C	0.754**	0.312	2.42	0.021
ECM(–1)	–0.517***	0.104	–4.96	0

To test the strength of the estimated ARDL model, a series of diagnostic tests was conducted. *Table 9* shows that the model is statistically reliable and does not exhibit significant econometric issues. The Breusch-Godfrey LM test indicates no serial correlation, and the Breusch-Pagan-Godfrey test indicates no heteroscedasticity. The Jarque-Bera statistic indicates that the residuals follow a normal distribution, justifying the assumption of classical regression. Also, the Ramsey RESET test indicated no misspecification, confirming the model's functional form is correct. Additional tests of model stability were done on the Cumulative Sum of Recursive Residuals (CUSUM) and the cumulative sum of squares (CUSUM-SQ). The two plots are well within the 5% significance boundaries, as shown in Figure 1, indicating that the parameters are stable during the sample period. This result guarantees that the estimates of long- and short-run relationships are not only statistically significant but also structurally stable, thereby improving the quality of policy recommendations based on the model.

Table 8. Diagnostic test results.

Test	Statistic	p-Value	Decision
Breusch-godfrey LM	1.28	0.26	No serial correlation
Breusch-pagan-godfrey	3.47	0.19	No heteroscedasticity
Jarque–Bera normality	1.52	0.47	Residuals normal
Ramsey reset	2.03	0.14	No misspecification

5 | Conclusion and Policy Recommendations

In this research, the ARDL bounds testing method was used to investigate the effect of GDP, EE, FA, ICT, and URBA on CO_2 emission in the US during the period 1990–2022. The findings affirmed the existence of a stable long-run equilibrium among the variables. GDP and URBA were found to increase emissions, whereas EE, FA, and ICT played a significant role in mitigating environmental degradation. The negative, significant error-correction term also confirmed the long-run adjustment mechanism. These results have several significant implications. First, the positive GDP-CO_2 correlation implies that modern U.S. development trends remain carbon-intensive, indicating that structural changes toward low-carbon production and consumption are necessary to achieve SDG 8 and SDG 13. Second, the high mitigating power of EE validates the primary place of technological innovation in emission reduction, which is a direct contribution to SDG 7. Third, the adverse impact of financial access implies that green finance instruments, including renewable energy credit facilities and climate bonds, can direct investment toward sustainable projects, thereby contributing to SDG 9. Fourth, ICTs reduced emissions, highlighting the importance of digitalization and smart technologies in advancing SDG 12. Lastly, URBA increases emissions, which is why sustainable city planning, energy-efficient housing, and mass transit systems are needed, according to SDG 11.

The findings suggest that the U.S. must pursue a comprehensive low-carbon development strategy to meet both domestic and global climate commitments. Since GDP growth and URBA were found to intensify emissions, economic expansion should be decoupled from carbon use by restructuring industries, scaling renewable deployment, and enforcing carbon pricing policies. Similarly, sustainable urban planning is essential through compact city design, investment in mass transit, and green housing to mitigate the emission-intensive effects of URBA. These are direct measures to support SDGs 8, 11, and 13. Meanwhile, the findings indicate the benefits of EE, FA, and ICT in reducing emissions. Policymakers should expand EE programs by promoting renewable energy innovation, implementing strict efficiency standards, and retrofitting outdated infrastructure, thereby advancing SDG 7. Expanding green finance mechanisms such as green bonds, climate-linked credit, and incentives for private investment can channel financial resources toward sustainable projects, supporting SDG 9. Furthermore, harnessing ICT through smart grids, digital monitoring, and ICT-enabled transport can optimize energy use and promote responsible consumption, contributing to SDG 12. Together, these integrated strategies will accelerate the U.S. transition toward carbon neutrality while fulfilling the broader SDG agenda.

References

[1] Tithi, S. I. (2025). Machine learning-driven predictive models for urban sustainability in the context of digital transformation. *Innovations in environmental economics*, *1*(2), 96–108. https://doi.org/10.48313/iee.v1i2.42

[2] Ridwan, M., Urbee, A. J., Voumik, L. C., Das, M. K., Rashid, M., & Esquivias, M. A. (2024). Investigating the environmental Kuznets curve hypothesis with urbanization, industrialization, and service sector for six South Asian countries: Fresh evidence from driscoll kraay standard error. *Research in globalization*, *8*, 100223. https://doi.org/10.1016/j.resglo.2024.100223

[3] Shourov, M. A. H., Hassan, M. R., Al Jubayed, A., Jalal, M. M., Debnath, A., & Giri, A. K. (2025). Artificial intelligence and the next-gen supply Chain: Energy-economy linkages in the United States. *Innovations in environmental economics*, *1*(1), 39–55. https://doi.org/10.48313/iee.v1i1.38

[4] Ridwan, M., Akther, A., Dhar, B. K., Roshid, M. M., Mahjabin, T., Bala, S., & Hossain, H. (2025). Advancing circular economy for climate change mitigation and sustainable development in the nordic region. *Sustainable development*, 1_20. https://doi.org/10.1002/sd.3563

[5] Ahmed, M. E., Sony, R. I., Sifat, A. I., Jalal, M. M., Rahman, A., Zohora, F. (2025). Investigating the role of education and R & D investment in reducing environmental pollution in China: An ARDL analysis. *Environment, innovation and management*, *1*, 2550025. https://doi.org/10.1142/S3060901125500255

[6] Jahanger, A., Rehman, M. Z., Jalal, M. M., & Hossain, M. E. (2025). Moving towards energy transition: What role do green financing, green technology and environmental sustainability play? *Politická ekonomie*, *73*(4), 743–768. https://doi.org/10.18267/j.polek.1462

[7] BP. (2025). *Fields of dreams: The giant reserves fuelling bp's growth*. https://www.bp.com/en/global/corporate/news-and-insights/energy-in-focus/giant-fields-fuelling-bps-growth.html?gad_source=1&gad_campaignid=23060737392&gclid

[8] Saqib, N., Duran, I. A., & Ozturk, I. (2023). Unraveling the interrelationship of digitalization, renewable energy, and ecological footprints within the EKC framework: Empirical insights from the United States. *Sustainability*, *15*(13), 10663. https://doi.org/10.3390/su151310663

[9] Rahman, M. N., & Ferdaous, J. (2024). Linkages between ICT diffusion, renewable energy consumption, and carbon emissions: A comparative analysis of SAARC, MENA, and OECD countries. *Environmental science and pollution research*, *31*(9), 13471–13488. https://doi.org/10.1007/s11356-024-32068-9%0A%0A

[10] Pattak, D. C., Tahrim, F., Salehi, M., Voumik, L. C., Akter, S., Ridwan, M., Zimon, G. (2023). The driving factors of Italy's CO2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. *Energies*, *16*(15), 5845. https://doi.org/10.3390/en16155845

[11] Ahmad, S., Raihan, A., & Ridwan, M. (2024). Role of economy, technology, and renewable energy toward carbon neutrality in China. *Journal of economy and technology*, *2*, 138–154. https://doi.org/10.1016/j.ject.2024.04.008

[12] Raihan, A., Voumik, L. C., Ridwan, M., Ridzuan, A. R., Jaaffar, A. H., & Yusoff, N. Y. M. (2023). From growth to green: Navigating the complexities of economic development, energy sources, health spending, and carbon emissions in Malaysia. *Energy reports*, *10*, 4318–4331. https://doi.org/10.1016/j.egyr.2023.10.084

[13] Mehmood, U., Tariq, S., Haq, Z. ul, Nawaz, H., Ali, S., Murshed, M., & Iqbal, M. (2023). Evaluating the role of renewable energy and technology innovations in lowering CO2 emission: A wavelet coherence approach. *Environmental science and pollution research*, *30*(15), 44914–44927. https://doi.org/10.1007/s11356-023-25379-w%0A%0A

[14] Shahzadi, H. N., Sheikh, S. M., Sadiq, A., & Rahman, S. U. (2023). Effect of financial development, economic growth on environment pollution: Evidence from G-7 based ARDL cointegration approach. *Pakistan journal of humanities and social sciences*, *11*(1), 68–79. https://doi.org/10.52131/pjhss.2023.1101.0330

[15] Wenlong, Z., Tien, N. H., Sibghatullah, A., Asih, D., Soelton, M., & Ramli, Y. (2023). Impact of energy efficiency, technology innovation, institutional quality, and trade openness on greenhouse gas emissions in ten Asian economies. *Environmental science and pollution research*, *30*(15), 43024–43039. https://doi.org/10.1007/s11356-022-20079-3%0A%0A

[16] Bilgili, F., Balsalobre-Lorente, D., Ku\cskaya, S., Alnour, M., Onderol, S., & Hoque, M. E. (2024). Are research and development on energy efficiency and energy sources effective in the level of CO2 emissions? Fresh evidence from EU data. *Environment, development and sustainability*, *26*(9), 24183–24219. https://doi.org/10.1007/s10668-023-03641-y%0A%0A

[17] Robaina, M., & Arshad, Z. (2020). The role of energy efficiency in CO2 mitigation-economy wide rebound effect in asean countries. *2020 17th international conference on the european energy market (EEM)*, 1–5. IEEE. https://doi.org/10.1109/EEM49802.2020.9221941

[18] Chaudhry, I. S., Yusop, Z., & Habibullah, M. S. (2022). Financial inclusion-environmental degradation nexus in OIC countries: New evidence from environmental Kuznets curve using DCCE approach. *Environmental science and pollution research*, *29*(4), 5360–5377. https://doi.org/10.1007/s11356-021-15941-9%0A%0A

[19] Ridwan, M., Aspy, N. N., Bala, S., Hossain, M. E., Akther, A., Eleais, M., & Esquivias, M. A. (2024). Determinants of environmental sustainability in the United States: Analyzing the role of financial development and stock market capitalization using LCC framework. *Discover sustainability*, *5*(1), 319. https://doi.org/10.1007/s43621-024-00539-1

[20] Raihan, A., Hasan, M. A., Voumik, L. C., Pattak, D. C., Akter, S., & Ridwan, M. (2024). Sustainability in Vietnam: Examining economic growth, energy, innovation, agriculture, and forests' impact on CO2 emissions. *World development sustainability*, *4*, 100164. https://doi.org/10.1016/j.wds.2024.100164

[21] Raihan, A., Ridwan, M., & Rahman, M. S. (2024). An exploration of the latest developments, obstacles, and potential future pathways for climate-smart agriculture. *Climate smart agriculture*, *1*(2), 100020. https://doi.org/10.1016/j.csag.2024.100020

[22] Sun, X., Xiao, S., Ren, X., & Xu, B. (2023). Time-varying impact of information and communication technology on carbon emissions. *Energy economics*, *118*, 106492. https://doi.org/10.1016/j.eneco.2022.106492

[23] Xie, L., Mu, X., Hu, G., Tian, Z., & Li, M. (2023). How do information and communication technology and urbanization affect carbon emissions? evidence from 42 selected "belt and road initiative" countries. *Environmental science and pollution research*, *30*(14), 40427–40444. https://doi.org/10.1007/s11356-022-25003-3%0A%0A

[24] Akhter, A., Al Shiam, S. A., Ridwan, M., Abir, S. I., Shoha, S., Nayeem, M. B., & Bibi, R. (2024). Assessing the impact of private investment in AI and financial globalization on load capacity factor: Evidence from United States. *Journal of environmental science and economics*, *3*(3), 99–127. https://doi.org/10.56556/jescae.v3i3.977

[25] Ridwan, M. (2023). Unveiling the powerhouse: Exploring the dynamic relationship between globalization, urbanization, and economic growth in Bangladesh through an innovative ARDL approach. *ASIAN journal of economics and business management*, 283_291. https://doi.org/10.53402/ajebm.v2i2.352

[26] Raihan, A., Muhtasim, D. A., Farhana, S., Pavel, M. I., Faruk, O., Rahman, M., & Mahmood, A. (2022). Nexus between carbon emissions, economic growth, renewable energy use, urbanization, industrialization, technological innovation, and forest area towards achieving environmental sustainability in Bangladesh. *Energy and climate change*, *3*, 100080. https://doi.org/10.1016/j.egycc.2022.100080

[27] Song, S., Tan, H., Zhang, Y., & Ma, Y. (2024). A multiscale analysis of the relationship between urbanization and CO2 emissions using geo-weighted regression model. *Discover sustainability*, *5*(1), 113. https://doi.org/10.1007/s43621-024-00298-z%0A%0A

[28] Shahbaz, M., Loganathan, N., Muzaffar, A. T., Ahmed, K., & Jabran, M. A. (2016). How urbanization affects CO2 emissions in Malaysia? the application of STIRPAT model. *Renewable and sustainable energy reviews*, *57*, 83–93. https://doi.org/10.1016/j.rser.2015.12.096

[29] Anser, M. K., Khan, K. A., Umar, M., Awosusi, A. A., & Shamansurova, Z. (2024). Formulating sustainable development policy for a developed nation: Exploring the role of renewable energy, natural gas efficiency

and oil efficiency towards decarbonization. *International journal of sustainable development & world ecology*, *31*(3), 247–263. https://doi.org/10.1080/13504509.2023.2268586

[30] Islam, S., Raihan, A., Paul, A., Ridwan, M., Rahman, M. S., Rahman, J., & Al Jubayed, A. (2024). Dynamic impacts of sustainable energies, technological innovation, economic growth, and financial globalization on load capacity factor in the top nuclear energy-consuming countries. *Journal of environmental and energy economics*, *3*(2), 1–14. https://doi.org/10.56946/jeee.v3i1.448

[31] Jin, X., Ahmed, Z., Pata, U. K., Kartal, M. T., & Erdogan, S. (2024). Do investments in green energy, energy efficiency, and nuclear energy R&D improve the load capacity factor? an augmented ARDL approach. *Geoscience frontiers*, *15*(4), 101646. https://doi.org/10.1016/j.gsf.2023.101646

[32] Raihan, A., Rahman, S. M., Sarker, T., Ridwan, M., Sahoo, M., Dhar, B. K., Bari, A. B. M. M. (2025). Tourism-energy-economy-environment nexus toward sustainable and green development in Malaysia. *Innovation and green development*, *4*(4), 100257. https://doi.org/10.1016/j.igd.2025.100257

[33] Raihan, A., Bala, S., Akther, A., Ridwan, M., Eleais, M., & Chakma, P. (2024). Advancing environmental sustainability in the G-7: The impact of the digital economy, technological innovation, and financial accessibility using panel ARDL approach. *Journal of economy and technology*. https://doi.org/10.1016/j.ject.2024.06.001

[34] Ridwan, M. (2025). Artificial intelligence and green development: The role of financial market efficiency in the United States. *Development and sustainability in economics and finance*, 100099. https://doi.org/10.1016/j.dsef.2025.100099

[35] Raihan, A., Voumik, L. C., Ridwan, M., Akter, S., Ridzuan, A. R., Wahjoedi, Ismail, N. A. (2024). Indonesia's path to sustainability: exploring the intersections of ecological footprint, technology, global trade, financial development and renewable energy. *Opportunities and risks in ai for business development*, *1*, 1–13. Springer. https://doi.org/10.1007/978-3-031-65203-5_1

[36] Rahman, J., Rahman, H., Islam, N., Tanchangya, T., Ridwan, M., & Ali, M. (2025). Regulatory landscape of blockchain assets: analyzing the drivers of NFT and cryptocurrency regulation. *BenchCouncil transactions on benchmarks, standards and evaluations*, 100214. https://doi.org/10.1016/j.tbench.2025.100214

[37] Godil, D. I., Sharif, A., Agha, H., & Jermsittiparsert, K. (2020). The dynamic nonlinear influence of ICT, financial development, and institutional quality on CO2 emission in Pakistan: New insights from QARDL approach. *Environmental science and pollution research*, *27*(19), 24190–24200. https://doi.org/10.1007/s11356-020-08619-1%0A%0A

[38] Zhang, W., Xu, Y., Jiang, L., Streets, D. G., & Wang, C. (2023). Direct and spillover effects of new-type urbanization on CO2 emissions from central heating sector and EKC analyses: Evidence from 144 cities in China. *Resources, conservation and recycling*, *192*, 106913. https://doi.org/10.1016/j.resconrec.2023.106913

[39] Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Human ecology review*, *1*(2), 277–300. https://www.jstor.org/stable/24706840?seq=1

[40] Akther, A., Tahrim, F., Voumik, L. C., Esquivias, M. A., & Pattak, D. C. (2025). Municipal solid waste dynamics: Economic, environmental, and technological determinants in Europe. *Cleaner engineering and technology*, *24*, 100877. https://doi.org/10.1016/j.clet.2024.100877

[41] Ridzuan, A. R., Rahman, N. H. A., Singh, K. S. J., Borhan, H., Ridwan, M., Voumik, L. C., & Ali, M. (2023). *Assessing the impact of technology advancement and foreign direct investment on energy utilization in malaysia: an empirical exploration with boundary estimation* . International conference on business and technology (pp. 1–12). https://doi.org/10.1007/978-3-031-55911-2_1%0A%0A

[42] Jalil, A., & Rao, N. H. (2019). Time series analysis (stationarity, cointegration, and causality). *Environmental kuznets curve (EKC)* (pp. 85–99). Elsevier. https://doi.org/10.1016/B978-0-12-816797-7.00008-4

[43] Shahid, R., Shahid, H., Shijie, L., & Jian, G. (2024). Developing nexus between economic opening-up, environmental regulations, rent of natural resources, green innovation, and environmental upgrading of China-empirical analysis using ARDL bound-testing approach. *Innovation and green development*, *3*(1), 100088. https://doi.org/10.1016/j.igd.2023.100088

[44] Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the american statistical association*, *74*(366), 427–431. https://doi.org/10.1080/01621459.1979.10482531

[45] Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289–326. https://doi.org/10.1002/jae.616

[46] Pesaran, H., & Shin, Y. (1995). An Autoregressive distributed lag modeling approach to cointegration analysis. *Econometncs and economic theory in the 20st century: the ragnar frisch centennial symposium*, *31*. https://doi.org/10.1017/CCOL0521633230.011

[47] Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the econometric society*, 424–438. https://doi.org/10.2307/1912791

[48] Engle, R. F., & Granger, C. W. J. (1987). Cointegration and error correction: Representation, estimation, and testing. *Econometrica: journal of the econometric society*, 251–276. https://doi.org/10.2307/1913236

[49] Santilio, A., Cammarata, R., & Girolimetti, S. (2024). Laboratory performances during proficiency tests for the analysis of active substances in pesticide formulations during 2021--2023. *Accreditation and quality assurance*, *29*(5), 359–368. https://doi.org/10.1007/s00769-024-01620-y%0A%0A

[50] Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. *International journal of environmental research and public health*, *20*(5), 4000. https://doi.org/10.3390/ijerph20054000

[51] Voumik, L. C., Rahman, M. H., Rahman, M. M., Ridwan, M., Akter, S., & Raihan, A. (2023). Toward a sustainable future: examining the interconnectedness among Foreign Direct Investment (FDI), urbanization, trade openness, economic growth, and energy usage in Australia. *Regional sustainability*, *4*(4), 405–415. https://doi.org/10.1016/j.regsus.2023.11.003

[52] Ismail, M., Rahman, M. T., Johany, S. A., Ridwan, M., & Hossain, M. E. (2025). A machine learning framework for predicting Bangladesh's economic growth: Emphasizing the sector-specific carbon emission dynamics. *Social sciences & humanities open*, *12*, 102081. https://doi.org/10.1016/j.ssaho.2025.102081