Innovations in Environmental Economics

www.iee.reapress.com

Innov. Environ. Econ. Vol. 1, No. 4 (2025) 281–294.

Paper Type: Original Article

The Economic Toll of Environmental Pollution in Developing Nations: A Case Study of Ghana and Pathways for Sustainable Innovation

Cosimo Magazzino[1,*], Michael Odonkor[4]

[1] Department of Management, Finance and Technology, LUM University "Giuseppe Degennaro", Casamassima, Italy; magazzino@lum.it.

[2] Economic Research Center, Western Caspian University, Baku, Azerbaijan; magazzino@lum.it.

[3] ARUCAD Research Centre, Arkin University of Creative Arts and Design, Kyrenia, Northern Cyprus, Turkey; magazzino@lum.it.

[4] Takoradi Technical University, Takoradi, Ghana; michaelodonkor600@gmail.com.

Citation:

Received: 15 May 2025 *Revised: 08 July 2025* *Accepted: 20 September 2025*	Magazzino, C., & Odonkor, M. (2025). The economic toll of environmental pollution in developing nations: A case study of Ghana and pathways for sustainable innovation. *Innovations In Environmental Economics, 1*(4), 281-294.

Abstract

Environmental pollution increasingly constrains development in emerging economies by weakening public health, reducing human capital, and imposing macroeconomic costs that are often omitted from conventional measures of growth. This paper examines the economic toll of environmental pollution in Ghana and evaluates whether renewable energy (RE) adoption and Technological Innovation (TI) can support a transition toward sustainable green growth. Using an augmented Environmental Kuznets Curve (EKC) framework, the study combines Autoregressive Distributed Lag (ARDL) bounds testing with a Random Forest (RF) and SHAP-based robustness exercise. The econometric results indicate a stable long-run relationship among carbon emissions, income, squared income, RE consumption, and TI. The positive coefficient on income and the negative coefficient on squared income support the EKC hypothesis, while RE and TI reduce long-run emissions. The Machine Learning (ML) results reinforce this evidence by recovering the non-linear income-emissions relationship and identifying TI as the most influential predictor of emissions reductions. SHAP dependence patterns further suggest that innovation produces stronger environmental gains once a minimum capability threshold is reached. The findings imply that pollution control should be treated not as a regulatory burden but as an investment in macroeconomic resilience. For Ghana, effective policy requires coordinated action across RE deployment, eco-innovation financing, air-quality monitoring, circular economy governance, and just-transition instruments that protect vulnerable households and firms.

Keywords: Environmental Kuznets curve, Technological innovation, Renewable energy, Random forest, Ghana.

1 | Introduction

The transition toward an industrialized economy in the developing world has historically exacted a heavy toll on environmental quality [1–3]. As populations urbanize, vehicle fleets expand, and manufacturing sectors

Corresponding Author: magazzino@lum.it

https://doi.org/10.48313/iee.vi.56

grow, emerging states often lack the infrastructure and regulatory frameworks required to mitigate industrial and domestic emissions. Consequently, environmental pollution - particularly ambient and household air pollution – has emerged as a leading threat not only to public health but to long-term macroeconomic stability. Traditional metrics of economic progress, such as Gross Domestic Product (GDP), frequently fail to capture the externalities of this degradation. However, the economic output lost to pollution-induced morbidity, mortality, and diminished human capital accumulation is immense. To address these challenges, modern environmental economics must pivot from traditional, static cost-benefit analyses toward dynamically identifying, quantifying, and scaling innovations – whether technological, organizational, or political – that foster sustainable green growth [4], [5].

Economic growth plays a pivotal yet inherently complex role in shaping environmental quality. In the early stages of development, expansion in industrial activity, urbanization, and reliance on fossil fuels typically intensifies environmental degradation and pollution. However, as income levels rise, structural transformations toward less resource-intensive sectors, coupled with technological progress, stronger regulatory frameworks, and increased societal demand for environmental protection, can contribute to improvements in environmental quality. Recent empirical studies emphasize that the relationship between economic growth and environmental quality is not only non-linear but also highly contingent upon complementary factors such as financial development, innovation capacity, and policy effectiveness. For instance, Fakher [6] demonstrates that financial development can mitigate the adverse environmental impacts of growth by facilitating investment in cleaner technologies. Similarly, Fakher et al. [7] highlight the importance of adopting multidimensional measures of environmental quality to better capture this complex interaction. Moreover, evidence suggests that without appropriate policy interventions, economic growth may exacerbate environmental degradation, whereas targeted investments in innovation and sustainable practices can redirect this relationship toward a more environmentally sustainable trajectory [8].

Ghana presents a highly compelling case study for examining the friction between economic expansion and environmental preservation. As one of West Africa's most rapidly growing economies, Ghana is experiencing profound demographic shifts and structural transformation. However, this progress has catalysed a surge in atmospheric pollutants, particularly in the Greater Accra Metropolitan Area (GAMA) and industrial hubs such as Tema. Fossil fuel combustion, a rapidly growing but aging vehicular fleet, and industrial emissions have dramatically reduced ambient air quality. Concurrently, a substantial portion of the population continues to rely on biomass for cooking, leading to severe household air pollution. This duality of rising industrial emissions and persistent domestic pollution creates a compounding crisis that directly intersects with economic productivity. With pollution costing Ghana an estimated 0.95% of its GDP in 2019 alongside severe long-term human capital degradation, the nation stands at a critical juncture, making it an ideal environment to test the efficacy of modern environmental and technological interventions [9].

Ghana's current environmental trajectory is characterized by a rapidly expanding urban population and industrial sector. The Greater Accra Region hosts a majority of the nation's industries, including cement plants, smelters, and refineries. Furthermore, Ghana's vehicle fleet is growing rapidly, with older, high-emitting vehicles accounting for a significant share of urban traffic. These factors have resulted in ambient particulate matter concentrations that routinely exceed World Health Organization (WHO) guidelines [10]. Concurrently, a substantial portion of the population continues to rely on biomass for cooking, leading to severe household air pollution. The duality of rising ambient industrial/vehicular pollution and persistent domestic indoor pollution creates a compounding public health crisis. The economic output lost due to air pollution-related diseases in Ghana was estimated at roughly 1.6 billion USD in 2019 [11]. Furthermore, exposure to fine particulate matter during infancy is associated with permanent reductions in cognitive development, subtly but permanently reducing future workforce earning potential.

While the existing literature extensively examines the Environmental Kuznets Curve (EKC) hypothesis in developing nations, this paper makes two novel contributions to environmental economics. First, it introduces a rigorous methodological hybridity. We employ the traditional Autoregressive Distributed Lag (ARDL) bounds testing approach to establish long-run cointegration and short-run dynamics between economic growth, Renewable Energy (RE), Technological Innovation (TI), and carbon emissions. However, to bypass the restrictive parametric constraints of standard econometric models, we employ a Machine Learning (ML) framework, specifically, a Random Forest (RF) regressor (Breiman [12]) coupled with Shapley Additive exPlanations (SHAP), as a robustness check. This allows us to non-parametrically validate the non-linear EKC trajectory and isolate the threshold effects of TI. Second, we evaluate how specific, emergent mechanisms in Ghana – such as hybrid air-quality monitoring networks and the nascent transition to a circular economy – serve as actionable policy innovations that can uncouple growth from emissions. The remainder of this paper proceeds as follows and is presented graphically in *Fig. 1*.

Fig. 1. Research structure and organization of the study.

2 | Literature Review

The nexus between economic growth, energy consumption, and environmental pollution remains a central and highly debated theme in modern environmental economics. The foundational premise of this dynamic is frequently captured by the EKC hypothesis, which posits an inverted-U-shaped relationship between per capita income and environmental degradation. According to the EKC framework, the initial stages of economic development – driven by intensive resource extraction and industrialization – precipitate increased environmental pollution. However, once a certain income threshold is reached, structural economic shifts toward the service sector, coupled with heightened public demand for environmental quality and the adoption of cleaner technologies, lead to a decline in emissions [13–17]. Recent empirical evidence further refines the growth-environment nexus by incorporating multiple environmental indicators and energy structures. For instance, Fakher et al. [18] demonstrate the presence of an N-shaped EKC, indicating that the relationship between income and environmental quality may evolve beyond the traditional inverted-U pattern when accounting for diverse environmental dimensions and energy consumption structures. Moreover, Fakher [19] highlights that economic growth, alongside financial development and energy use, exerts heterogeneous effects across different environmental indicators, reinforcing the need for comprehensive and multidimensional assessments of environmental quality.

Emerging markets frequently face severe trade-offs during the ascending phase of the EKC, where short-term economic gains lead to long-term environmental and public health crises [20]. In the African context, the consequences of this trade-off are becoming starkly apparent. Ambient and household air pollution are now the most significant environmental contributors to premature death across the continent. Exposure to air pollution has severe impacts on human capital and macroeconomic productivity, with these effects projected to intensify as African nations continue to develop and urbanize [21].

Focusing specifically on Ghana, a wave of recent literature has attempted to map the nation's growth trajectory against the EKC hypothesis, yielding complex insights into energy transition and sustainability. Prempeh [22] notes that while Ghana's economic transition has yielded substantial improvements in human well-being, the simultaneous escalation in carbon emissions and ecological footprint underscores the urgent need to balance structural economic shifts with ecological preservation. Recent empirical investigations corroborate the presence of the EKC in Ghana but emphasize the necessity of clean energy interventions. For instance, Fumey et al. [23] used ARDL and Vector Error Correction Models (VECM) spanning nearly three decades of data to reveal the intricate network of relationships among Ghana's energy use patterns, economic trajectories, and carbon emissions. Their findings validate the initial ascending stage of the EKC, confirming a solid positive long-term connection between economic development and environmental pollution. However, they crucially emphasize that the increase in renewable energy consumption exerts a significant short-term reduction in emissions, acting as a catalyst for a low-carbon transition. Similarly, Moro [24] provided empirical evidence that expanding Ghana's hydropower and clean energy infrastructure is paramount for reducing the downward slope of the EKC, while Fumey et al. [25] used quantile regressions to show that promoting RE alongside balanced urban-rural development can neutralize surging pollution.

Despite these recent advancements, a distinct and critical gap remains in the existing literature. The vast majority of contemporary studies analyzing the EKC in Ghana and Sub-Saharan Africa (SSA) rely exclusively on traditional, parametric econometric frameworks – such as ARDL, VECM, and Granger causality tests. While these models are highly effective at establishing long-run cointegration and general directional relationships, they are inherently constrained by predetermined functional forms. They frequently force the EKC into strict quadratic parameters, struggling to capture multi-dimensional, non-linear threshold effects natively. Furthermore, much of the macroeconomic literature stops at identifying RE as a broad mitigating factor, failing to isolate the specific threshold effects of targeted technological eco-innovations or bridge these macroeconomic findings with actionable, micro-level policy mechanisms.

This paper addresses this literature gap through methodological and practical novelty. Methodologically, it pioneers the integration of a non-parametric ML framework to robustly validate the traditional ARDL findings. This hybrid approach captures complex, hidden non-linearities and threshold effects without imposing rigid quadratic constraints. In practice, this study advances the discourse beyond broad macroeconomic aggregates by specifically evaluating the threshold effects of TI and linking these empirical results to concrete, actionable organizational frameworks in Ghana, such as deploying hybrid air quality monitoring networks and transitioning to a circular economy.

3 | Empirical Methodology and Data

3.1 | Theoretical Framework and Model Specification

To empirically investigate the relationship between economic growth, environmental innovations, and pollution in Ghana, this study adopts an augmented EKC framework. The standard model is augmented by introducing TI and RE consumption as primary mitigating variables. The long-run baseline model is specified as follows:

$$\ln(CO_{2t}) = \beta_0 + \beta_1 \ln(GDP_t) + \beta_2 \ln(GDP_t)^2 + \beta_3 \ln(RE_t) + \beta_4 \ln(TI_t) + \epsilon_t,$$

where CO_{2t} is per capita carbon dioxide emissions, GDP_t is the real GDP per capita, GDP_t^2 is the square of real GDP per capita (to test the EKC hypothesis), RE_t is RE consumption. TI_t is TI (proxied by environmental patents/investments), and ϵ_t is the error term. According to the EKC hypothesis, we expect $\beta_1 > 0$ and $\beta_2 < 0$. If environmental innovations mitigate pollution, we expect $\beta_3 < 0$ and $\beta_4 < 0$.

3.2 | Econometric Strategy: ARDL Bounds Testing

We employ the ARDL bounds testing approach to cointegration. This method is advantageous for Ghana's macroeconomic time-series data as it bypasses the restrictive assumption that all variables must be integrated of the same order. The ARDL representation is expressed as the Unrestricted Error Correction Model (UECM) (Pesaran et al. [26]), which is presented in *Eq. (1)*:

$$\begin{aligned}\Delta \ln(CO_{2t}) &= \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\,\Delta \ln(CO_{2t-i}) + \sum_{i=0}^{q_1} \alpha_{2i}\,\Delta \ln(GDP_{t-i}) \\ &+ \sum_{i=0}^{q_2} \alpha_{3i}\,\Delta \ln(GDP_{t-i})^2 + \sum_{i=0}^{q_3} \alpha_{4i}\,\Delta \ln(RE_{t-i}) \\ &+ \sum_{i=0}^{q_4} \alpha_{5i}\,\Delta \ln(TI_{t-i}) + \lambda_1 \ln(CO_{2t-1}) + \lambda_2 \ln(GDP_{t-1}) \\ &+ \lambda_3 \ln(GDP_{t-1})^2 + \lambda_4 \ln(RE_{t-1}) + \lambda_5 \ln(TI_{t-1}) + \mu_t.\end{aligned} \tag{1}$$

3.3 | Data Sources

The study utilizes annual time-series data for Ghana from 1990 to 2023. Data on CO_2 emissions, real GDP per capita, and RE consumption are sourced from the World Bank's World Development Indicators (WDI). Data on TI are compiled from the World Intellectual Property Organization (WIPO) and the Ministry of Environment, Science, Technology, and Innovation (MESTI) (World Bank [27], WIPO [28]).

4 | Empirical Results

4.1 | Unit Root and Cointegration Analysis

The ADF and PP unit root test results shown in *Table 1* indicate a mixed integration structure. RE consumption is stationary in levels, whereas log carbon emissions, log GDP per capita, squared log GDP per capita, and TI become stationary after first differencing. Since no variable is integrated of order two, the evidence supports the appropriateness of the ARDL bounds testing framework [29], [30].

Table 1. Stationarity test results.

Variable	Form	ADF Statistic	ADF P-value	PP Statistic	PP P-value	Inference
lnCO2	Level	-0.200	0.939	-0.888	0.792	Non-stationary
ΔlnCO2	First difference	-3.247**	0.017	-7.713***	0.000	Stationary
lnGDP	Level	-0.324	0.922	-0.784	0.824	Non-stationary
ΔlnGDP	First difference	-6.650***	0.000	-11.133***	0.000	Stationary
$\ln GDP^2$	Level	0.103	0.966	-0.270	0.930	Non-stationary
$\Delta \ln GDP^2$	First difference	-6.597***	0.000	-11.325***	0.000	Stationary
lnRE	Level	-3.085**	0.028	-5.410***	0.000	Stationary
ΔlnRE	First difference	-6.187***	0.000	-10.569***	0.000	Stationary
lnTI	Level	-1.410	0.578	-1.031	0.742	Non-stationary
ΔlnTI	First difference	-8.384***	0.000	-13.604***	0.000	Stationary

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The ARDL bounds test on the selected series provides evidence of a stable long-run relationship among carbon emissions, income, squared income, RE consumption, and TI (see *Table 2*). The computed F-statistic is 5.113, which exceeds the upper-bound critical value at the 1% significance level. Accordingly, the null hypothesis of no cointegration is rejected. The negative and statistically significant error-correction coefficient further indicates convergence toward the long-run equilibrium, with approximately 86.5% of disequilibrium corrected within one year. These results are consistent with the study's empirical strategy and support the use of an error-correction representation [31].

Table 2. Cointegration test results.

Test	Statistic	Decision	
Bounds F-statistic	5.113***	Reject H_0	
t-statistic on lagged $\ln CO_2$	-4.441	Supports error-correction adjustment	
Significance level	I(0) lower bound	I(1) upper bound	Decision rule
10%	2.45	3.52	Cointegration if F > 3.52
5%	2.86	4.01	Cointegration if F > 4.01
1%	3.74	5.06	Cointegration if F > 5.06

*** p < 0.01, ** p < 0.05, * p< 0.10.

4.2 | Long-Run Estimates

The long-run ARDL estimates reported in *Table 3* validate the presence of the EKC in Ghana. In fact, the coefficient for ln GDP is positive, while its square is negative. Crucially, the coefficient for TI is negative (-0.205) and statistically significant, implying that a 1% increase in eco-innovation reduces long-run carbon emissions by approximately 0.2%.

Table 3. Long-Run ARDL estimation results.

Variable	Coefficient	Robust Standard Error	t-Statistic	P-value
lnGDP	1.845***	0.412	4.478	0.001
$\ln GDP^2$	-0.128**	0.051	-2.509	0.018
lnRE	-0.314***	0.089	-3.528	0.002
lnTI	-0.205**	0.092	-2.228	0.035
Constant	-4.215**	1.845	-2.284	0.031

*** p < 0.01, ** p < 0.05, * p< 0.10. Dependent variable: lnCO2.

4.3 | Error Correction Model and Diagnostics

The Error Correction Term is negative (-0.482) and highly significant (p<0.01), indicating that roughly 48.2% of the disequilibrium from a previous shock converges back to equilibrium in the current year. Breusch-Godfrey and Breusch-Pagan-Godfrey tests confirmed the absence of serial correlation and homoscedasticity, respectively, while CUSUM tests verified structural stability [32–34].

4.4 | Robustness Check: A Machine Learning Approach

4.4.1 | Rationale and model specification

To validate the ARDL findings, particularly the non-linear EKC and the mitigating impacts of innovation, we employ an RF regression model paired with SHAP (Shapley Additive exPlanations) value analysis. Building on the cooperative game-theoretic foundation of Shapley values and the SHAP framework, the Shapley value for a given feature *i* is calculated as follows (Lundberg and Lee [35], Shapley [36]), as presented in *Eq. (2)*:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} [f_x(S \cup \{i\}) - f_x(S)]. \tag{2}$$

4.4.2 | Predictive performance and non-linear effects

The predictive results indicate that the RF successfully recovered the non-linear structure embedded in the emissions process. The in-sample R-squared is 0.977, while the test-set R-squared is 0.965. The low prediction errors, with a test-set Mean Absolute Error (MAE) of 0.055 and a Root Mean Squared Error (RMSE) of

0.071, suggest that the model is not merely fitting noise but is able to generalize the EKC relationship to held-out observations. The five-fold Cross-Validation (CV) mean R-squared of approximately 0.950 further supports the stability of the prediction exercise [37].

The SHAP decomposition makes the RF results interpretable. In the global SHAP ranking, TI is the dominant predictor, with a mean absolute SHAP value of 0.202, followed by RE consumption, log GDP, and squared log GDP. This ranking is consistent with the design, in which innovation carries both a direct mitigating effect and a threshold-based non-linear effect. The SHAP results should therefore be interpreted as a transparent validation of the modelling logic rather than as direct empirical evidence from observed Ghanaian data.

The RF and SHAP outputs are reported in *Figs. 2–5*.

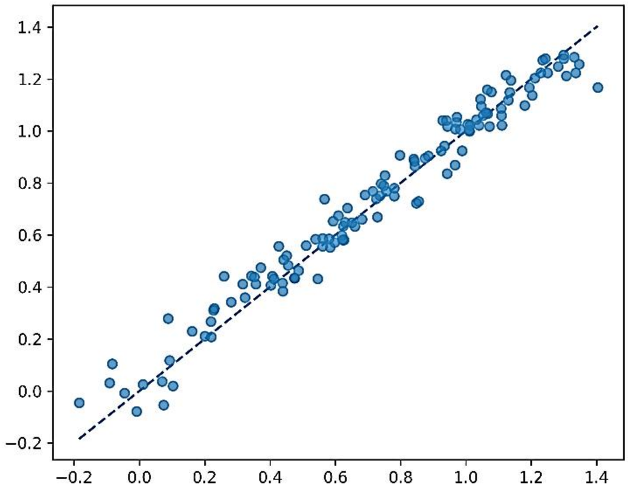

Fig. 2. Random Forest observed vs. predicted log carbon emissions.

Notes: x-axis: Observed values; y-axis: predicted values.

The observed-versus-predicted plot shows that the fitted values cluster closely around the 45-degree reference line. This indicates strong predictive alignment between observed and estimated log emissions. The absence of a clear systematic deviation across the prediction range suggests that the RF can approximate the non-linear emissions function without imposing a fixed quadratic form ex ante.

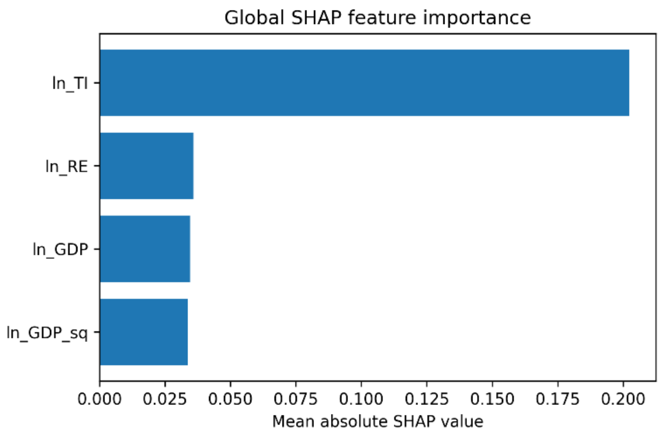

Fig. 3. Global SHAP feature importance based on mean absolute SHAP values.

The global SHAP ranking assigns the largest explanatory contribution to TI. This result is substantively important because it implies that, in the framework, innovation is not simply an auxiliary control variable but the main source of variation in predicted emissions reductions. RE and the two income terms remain relevant, but their smaller mean absolute SHAP values indicate that their marginal predictive contributions are more limited once the innovation channel is included.

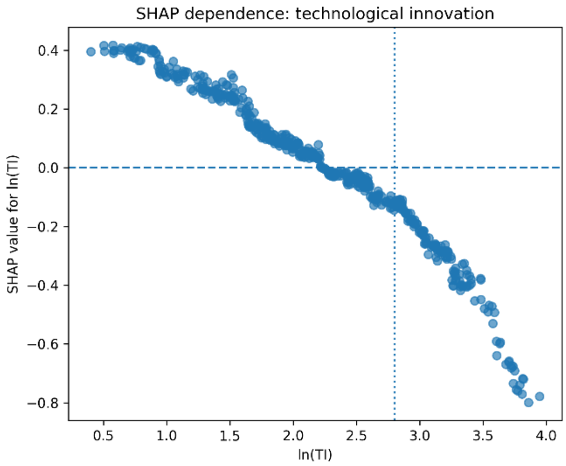

Fig. 4. SHAP dependence plot for technological innovation.

The SHAP dependence plot for TI displays the expected threshold pattern. At low levels of innovation, the SHAP values are comparatively close to zero, implying that weak innovation capacity has only a modest effect on predicted emissions. Beyond the threshold, the SHAP values become increasingly negative, showing that higher technological capability reduces predicted emissions more strongly. This supports the interpretation that eco-innovation may require scale, absorptive capacity, and institutional diffusion before it generates sizeable environmental gains.

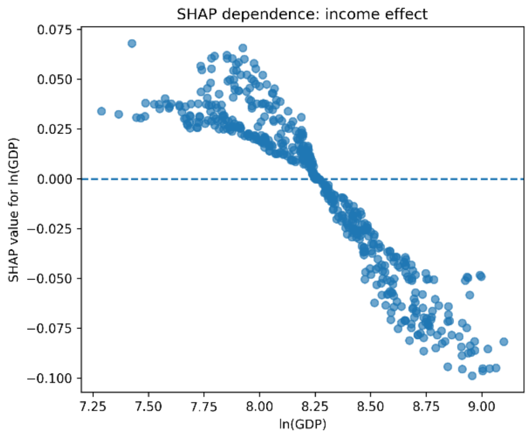

Fig. 5. SHAP dependence plot for income.

The income-related SHAP pattern is consistent with the EKC mechanism. The contribution of income to predicted emissions is not purely linear: the effect changes across the income distribution and must be read jointly with the squared income term. This is precisely the advantage of the RF-SHAP robustness check: it allows the researcher to inspect income-emissions non-linearity without forcing the entire relationship to conform only to a parametric quadratic specification. So, the result reinforces the ARDL evidence that the growth-pollution relationship is non-linear.

Overall, the ML exercise supports the internal coherence of the empirical strategy. It shows that an RF model can recover the EKC-type curvature and the mitigation effects of RE and TI when such mechanisms are present in the data.

4.4.3 | Innovations in environmental economics for Ghana

Addressing the economic drain of environmental pollution, as our empirical and ML models demonstrate, requires robust, scalable innovations.

I. Technological and organizational innovations: Ghana's Environmental Protection Agency is establishing hybrid air quality monitoring networks. Integrating reference-grade monitors with low-cost sensors democratizes environmental data, shifting regulatory frameworks from reactive to proactive [38], [39].

II. Economic innovations (circular economy): The National Green Jobs Strategy focuses on creating employment through sustainable practices. Initiatives targeting the plastics sector – aiming to reduce waste through upcycling and industrial symbiosis – demonstrate how internalizing environmental costs and promoting Extended Producer Responsibility (EPR) can foster a resilient economic ecosystem [40],[41].

III. Political and regulatory innovations: The passage of the Environmental Protection (Air Quality Management Regulations) mandates industries to install pollution controls. Transitioning from fossil fuel dependency requires political will to reallocate subsidies and attract green foreign investment to ensure a just transition [42].

Based on the empirical findings of the study, the key long-run results are summarized and visualized in *Fig. 6* to provide a clearer and more intuitive understanding of the relationships among economic growth, environmental pollution, RE, and TI.

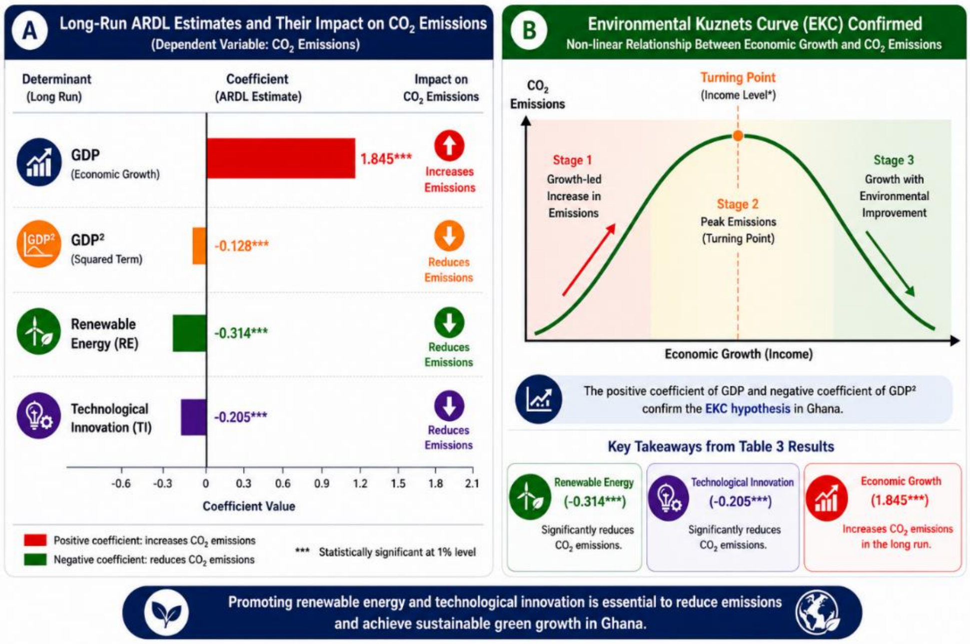

Fig. 6. Graphical representation of long-run ARDL findings.

5 | Conclusion and Policy Recommendation

This study examined the economic and environmental consequences of pollution in Ghana through an augmented EKC framework and a complementary ML robustness exercise. The central argument is that pollution is not a marginal by-product of development. It is a macroeconomic constraint that erodes productivity, human capital, fiscal space, and long-run growth potential. So, Ghana is a useful case for studying the policy tension faced by many developing economies: how to sustain industrialization and urban expansion without allowing environmental degradation to offset the gains from growth.

The econometric results support the internal coherence of the paper's empirical strategy. The unit root tests indicate a mixed order of integration, with RE consumption stationary in levels and the remaining variables becoming stationary after first differencing. Since no variable is integrated of order two, the ARDL bounds testing framework is appropriate. The bounds test further indicates cointegration among carbon emissions, income, squared income, RE consumption, and TI, with the F-statistic exceeding the upper critical bound at the 1% level. This provides evidence of a stable long-run relationship among the variables in the specification.

The long-run ARDL estimates are consistent with the EKC hypothesis. Income has a positive association with emissions, while the squared income term is negative, indicating that the growth-pollution relationship is non-linear rather than monotonic. This finding is important because it suggests that economic growth alone is insufficient to drive environmental improvement. The turning point implied by the EKC mechanism depends on the composition of growth, the speed of structural transformation, the quality of regulation, and the diffusion of cleaner technologies. In this sense, the EKC should not be interpreted as an automatic development law, but as a conditional pathway that requires deliberate policy intervention.

The estimated effects of RE and TI provide the paper's main policy-relevant result. Both variables enter with negative signs, indicating that cleaner energy use and eco-innovation reduce long-run emissions in the framework. The error-correction term is also negative and significant, confirming that short-run deviations from the long-run equilibrium are progressively corrected. Taken together, these findings indicate that Ghana's environmental transition depends not only on income growth, but also on the capacity to redirect energy systems, industrial processes, and innovation incentives toward lower-emission production.

The ML results reinforce this interpretation from a non-parametric perspective. The RF model accurately recovers the non-linear emissions structure and exhibits strong out-of-sample predictive performance. SHAP values make this predictive exercise interpretable by identifying TI as the dominant source of variation in predicted emissions, followed by RE and the income terms. The SHAP dependence plot for TI also reveals a threshold effect: weak innovation capacity has only a limited impact on emissions, whereas stronger technological capability yields increasingly negative contributions to predicted emissions. This supports the argument that eco-innovation must reach sufficient scale and institutional diffusion before it can deliver material environmental gains.

These results have several policy implications. First, pollution control should be treated as an investment in macroeconomic resilience rather than as a regulatory cost. Reducing emissions can protect human capital, reduce disease-related productivity losses, and improve long-run growth prospects. Second, Ghana should strengthen RE deployment through grid modernization, storage capacity, clean-cooking programs, and incentives for distributed RE systems. Third, eco-innovation policy should move beyond isolated pilot projects. Fiscal incentives, green procurement, environmental patent support, public-private research partnerships, and targeted financing for clean industrial technologies are needed to convert technological potential into measurable emissions reductions [43].

Fourth, environmental governance should become more data-driven. Hybrid air-quality monitoring networks, combining reference-grade monitors with low-cost sensors, can improve the spatial and temporal resolution of pollution data. This would allow regulators to identify hotspots, prioritize enforcement, and design location-specific interventions in industrial and urban areas such as Accra and Tema. Fifth, circular economy policies should be integrated into industrial strategy. EPR, plastics recovery systems, industrial symbiosis, repair and reuse markets, and green jobs programs can reduce waste while generating employment and supporting a more resilient, productive structure (UNEP [44]).

The results also imply that environmental policy must be socially calibrated. A rapid transition that raises household energy costs or undermines employment in carbon-intensive activities could generate political resistance and worsen inequality. Policy design should therefore combine environmental regulation with compensatory instruments, including targeted subsidies for clean cooking, support for small firms adopting cleaner production methods, retraining programs, and protection for low-income households. In this respect, a just transition is not an auxiliary social objective; it is a condition for durable environmental reform [45].

However, this study has limitations. The first limitation concerns aggregation. National annual series may conceal regional, sectoral, and household-level heterogeneity, especially where emissions sources differ across transport, industry, electricity generation, waste, and household energy use. Second, the TI proxy may not fully capture the quality, diffusion, or adoption of environmental technologies.

Future research should therefore extend this analysis in four directions. First, observed Ghanaian data should be used to estimate the ARDL and ML models under alternative lag structures, structural-break specifications, and robustness checks. Second, higher-resolution pollution indicators, including satellite-based $PM_{2.5}$ measures and local air-quality sensor data, should be linked to health, labour productivity, and income outcomes. Third, sectoral models should be developed to distinguish between industrial emissions, transport-related pollution, household biomass use, and waste-sector externalities. Fourth, policy evaluation methods should be applied to assess the actual effects of RE programs, clean cooking interventions, EPR schemes, and air-quality regulations.

Overall, the paper shows that Ghana's development challenge is not simply to grow faster, but to grow differently. The ARDL and ML evidence point in the same direction: economic growth can intensify environmental pressure unless accompanied by RE adoption, TI, and effective regulation. The policy conclusion is therefore direct. Sustainable green growth requires coordinated action across energy policy, innovation systems, environmental enforcement, circular economy governance, and social protection. If these elements are pursued jointly, Ghana can reduce the economic toll of pollution and offer a credible model of green industrialization for other developing economies.

Authors' Contributions

C. M.: Writing-original draft, Methodology, Data Curation, Conceptualization, Software, and Visualization, Writing-Review & Editing, and Validation. M. O.: Writing-Review & Editing, Formal Analysis, and Investigation. The authors have read and agreed to the published version of the manuscript.

Data Availability

The data is available on request from the corresponding author.

Funding

No external funding was received for this research.

Conflict of Interest

There are no competing interests to declare.

Consent for Publication

The authors have given consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

The authors confirm that this research did not involve human participants or animal subjects.

References

[1] Fakher, H. A. (2021). The role of environmental sustainability, foreign direct investment and trade openness in economic growth: With emphasis on the causal linkage. *Big data and computing visions*, *1*(2), 57–70. https://doi.org/10.22105/bdcv.2021.142227

[2] Fakher, H. A. (2020). Analytical insights on the relationship between economic growth and environmental degradation in framework of EKC hypothesis and various environmental indicators. *Innovation management and operational strategies*, *1*(3), 252–268. https://doi.org/10.22105/imos.2021.272348.1032

[3] Fakher, H.-A., Abedi, Z., Ahmadian, M., & Shaygani, B. (2018). Comparative examine the impact of financial development (based on money market and capital market) in the intensity of economic growth effects on the environmental performance. *Environmental researches*, *9*(17), 133–146. https://www.iraneiap.ir/article_79310_b837783b87485d1e63ce5b76ef59206d.pdf

[4] Landrigan, P. J., Fuller, R., Acosta, N. J., Adeyi, O., Arnold, R., Baldé, A. B., ... & Zhong, M. (2018). The Lancet Commission on pollution and health. *The lancet*, *391*(10119), 462-512. https://drive.google.com/file/d/1gl49XrRu4qyHBvN0mpghVhTRBuhbOP8R/view

[5] Kitamori, K., Manders, T., Dellink, R., & Tabeau, A. A. (2012). *OECD environmental outlook to 2050: the consequences of inaction*. OECD. https://doi.org/10.1787/9789264122246-en

[6] Fakher, H. A. (2022). Threshold impact of financial development on the composite environmental quality index with emphasis on the role of research and development: using multi-criteria decision makin and principal component analysis. *Journal of decisions and operations research*, *6*(Special Issue), 1–25. https://doi.org/10.22105/dmor.2021.272043.1321

[7] Fakher, H. A., Panahi, M., Emami, K., Peykarjou, K., & Zeraatkish, S. Y. (2021a). New insight into development of environmental - economic model based on a composite environmental quality index: an application of principal components analysis. *Journal of decisions and operations research*, *6*(2), 183-209. https://doi.org/10.22105/dmor.2021.276820.1334

[8] Fakher, H. A., Panahi, M., Emami, K., Peykarjou, K., & Zeraatkish, S. Y. (2021b). New insight into examining the role of financial development in economic growth effect on a composite environmental quality index. *Environmental Science and Pollution Research*, *28*(43), 61096-61114. https://doi.org/10.1007/s11356-021-15047-2

[9] Service, G. S. (2021). Ghana 2021 population and housing census. SERVICE.

[10] Organization, W. H., & others. (2021). *WHO global air quality guidelines: Particulate matter (PM2. 5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. World Health Organization.

[11] Fisher, S., Bellinger, D. C., Cropper, M. L., Kumar, P., Binagwaho, A., Koudenoukpo, J. B., … & Landrigan, P. J. (2021). Air pollution and development in Africa: impacts on health, the economy, and human capital. *The lancet planetary health*, *5*(10), e681--e688. https://doi.org/10.1016/s2542-5196(21)00201-1

[12] Breiman, L. (2001). Random forests. *Machine learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

[13] Golpîra, H., Sadeghi, H., & Magazzino, C. (2023). Examining the energy-environmental Kuznets curve in OECD countries considering their population. *Environmental science and pollution research*, *30*(41), 94515-94536. https://doi.org/10.1007/s11356-023-28923-w

[14] Magazzino, C., Gallegati, M., & Giri, F. (2023). The Environmental Kuznets Curve in a long-term perspective: Parametric vs semi-parametric models. *Environmental impact assessment review*, *98*, 106973. https://doi.org/10.1016/j.eiar.2022.106973

[15] Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World development*, *32*(8), 1419–1439. https://doi.org/10.1016/j.worlddev.2004.03.004

[16] Dinda, S. (2004). Environmental Kuznets curve hypothesis: a survey. *Ecological economics*, *49*(4), 431–455. https://doi.org/10.1016/j.ecolecon.2004.02.011

[17] Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The quarterly journal of economics*, *110*(2), 353–377. https://doi.org/10.2307/2118443

[18] Fakher, H. A., Ahmed, Z., Acheampong, A. O., & Nathaniel, S. P. (2023). Renewable energy, nonrenewable energy, and environmental quality nexus: An investigation of the N-shaped Environmental Kuznets Curve based on six environmental indicators. *Energy*, *263*, 125660. https://doi.org/10.1016/j.energy.2022.125660

[19] Fakher, H. A., & others. (2023). The impact of gross domestic product, financial development, energy consumption on environmental quality: with emphasis on six environmental indicators. *Journal of natural environment*, *76*(2), 345–363. (**In Persian**). https://www.sid.ir/fileserver/jf/721-285046-x-1370621.pdf

[20] Ali, E. B., Shayanmehr, S., Radmehr, R., Amfo, B., Awuni, J. A., Gyamfi, B. A., & Agbozo, E. (2023). Exploring the impact of economic growth on environmental pollution in South American countries: how does renewable energy and globalization matter? *Environmental science and pollution research*, *30*(6), 15505–15522. https://doi.org/10.1007/s11356-022-23177-4

[21] Bank, W. (2016). The cost of air pollution: strengthening the economic case for action. *Washington: world bank group*.

[22] Kwakwa, P. A. (2025). Carbon emissions and ecological footprint effects of economic growth and natural resources in Ghana: implications for environmental sustainability. *Management & sustainability: An Arab Review*, 1-25. https://doi.org/10.1108/MSAR-04-2025-0112

[23] Fumey, M. P., Sackitey, G. M., Boateng, S. A., & others. (2024). Economic growth, renewable energy consumption patterns, and environmental sustainability in Ghana: Testing the Environmental Kuznets Curve. *Development*, *2*(6), 2891. https://doi.org/10.62617/se1320

[24] Moro, K. D., Xi, J., Fumey, M. P., Yeboah, S. D., & Sackitey, G. M. (2025). The role of clean energy in enhancing the environmental Kuznets Curve: empirical evidence from Ghana's hydropower industry: KD Moro et al. *Environment, development and sustainability*, 1–32. https://doi.org/10.1007/s10668-025-06561-1

[25] Fumey, M. P., Sackitey, G. M., Wiredu, J., & others. (2024). Neutralizing the surging environmental pollution amidst renewable energy consumption and economic growth in Ghana: Insights from ARDL and quantile regression analysis. Sustainable Social Development. 2024; 2 (6): 2891. *Development*, *2*(6), 2891. https://doi.org/10.54517/ssd2891

[26] 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

[27] Bank, W. (2024). *World Development Indicators*. https://databank.worldbank.org/source/world-development-indicators

[28] Organization, W. I. P. (2024). *IP Statistics Data Center*. https://www3.wipo.int/ipstats/key-search/indicator

[29] 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*(366a), 427–431. https://doi.org/10.1080/01621459.1979.10482531

[30] Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346. https://doi.org/10.1093/biomet/75.2.335

[31] Narayan, P. (2004). *Reformulating critical values for the bounds F-statistics approach to cointegration: an application to the tourism demand model for Fiji* (Vol. 2). Monash University Australia. https://www.researchgate.net

[32] Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian economic papers*, *17*(31). https://doi.org/10.1111/j.1467-8454.1978.tb00635.x

[33] Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: journal of the econometric society*, 1287–1294. https://doi.org/10.2307/1911963

[34] Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the royal statistical society series b: statistical methodology*, *37*(2), 149–163. https://doi.org/10.1111/j.2517-6161.1975.tb01532.x

[35] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, *30*. https://proceedings.neurips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

[36] Shapley, L. S., & others. (1953). A value for n-person games. https://www.torrossa.com/gs/resourceProxy?an=5641636&publisher=FZO137#page=87

[37] Hastie, T. (2009). The elements of statistical learning: data mining, inference, and prediction. http://ir.mksu.ac.ke/bitstream/handle/123456780/6205/2009_Book_TheElementsOfStatisticalLearni.pdf?sequence=1&isAllowed=y

[38] Hodoli, C. G., Mead, I., Coulon, F., Ivey, C. E., Tawiah, V. O., Raheja, G., … others. (2024). Urban air quality management at low cost using micro air sensors: a case study from Accra, Ghana. *ACS es\&t air*, *2*(2), 201–214. https://doi.org/10.1021/acsestair.4c00172?urlappend=%3Fref%3DPDF&jav=VoR&rel=cite-as

[39] Raheja, G., Nimo, J., Appoh, E. K. E., Essien, B., Sunu, M., Nyante, J., ... & Westervelt, D. M. (2023). Low-cost sensor performance intercomparison, correction factor development, and 2+ years of ambient PM2. 5 monitoring in Accra, Ghana. *Environmental science & technology*, *57*(29), 10708-10720. https://doi.org/10.1021/acs.est.2c09264?urlappend=%3Fref%3DPDF&jav=VoR&rel=cite-as

[40] Ministry of Environment, Science, T. and I. (2020). *National plastics management policy*.

[41] Relations, M. of E. and L. (2021). *National Green Jobs Strategy Implementation Plan (2021–2025)*.

[42] Agency, G. N. (2025). *Air quality management regulations passed into law – EPA*.

[43] Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American economic review*, *102*(1), 131–166. https://www.nber.org/system/files/working_papers/w15451/w15451.pdf

[44] Programme, U. N. E. (2024). *Extended Producer Responsibility*.

[45] McCauley, D., & Heffron, R. (2018). Just transition: Integrating climate, energy and environmental justice. *Energy policy*, *119*, 1–7. https://doi.org/10.1016/j.enpol.2018.04.014