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Research Article

Unveiling impact of financial development, renewable energy, and technological innovation on ecological footprint in major remittance-receiving economies – A PQARDL approach

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Abstract A nation's financing system is pivotal in fulfilling the demands of sustainable development. Domestic funding sources and international financial flows make substantial contributions to both economic growth and environmental quality, with their influence being of paramount significance. The objective of this study is to analyze the complex linkage between financial development, renewable energy consumption, technological innovation, on ecological footprint in top remittance-receiving economies, namely Indonesia, Bangladesh, Vietnam, Pakistan, Egypt, Mexico, Philippines, China, and India, over the period 1990-2022. Using Panel Quantile Autoregressive Distributed Lag (PQARDL) method, our findings challenge the universal applicability of the Environmental Kuznets Curve (EKC) hypothesis and reveal complex interactions among variables. The long-term empirical results reveal inconsistent relationships between environmental degradation across different quantiles, challenging the universal applicability of the Environmental Kuznets Curve (EKC) hypothesis. Therefore, financial development reveals a mixed impact on ecological footprint across different quantiles, renewable energy consumption advertises a consistently negative association, suggesting its potential as a sustainable development lever. Moreover, technological innovation's influence varies across quantiles, indicating heterogeneous effects on ecological footprint reduction. Therefore, the validity of an inverted U-shaped or N-shaped Environmental Kuznets Curve pointed complexity of income's impact on environmental outcomes. The validity of the N-shaped EKC in all quantiles, acclaiming that policymakers should incorporating renewable energy and technology innovation into respect when formulating environmental calends.

Keywords: Sustainability; Financial development; Technology innovation; Remittances PQARDL.

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1. Introduction

Sustainable development goals have recently gained importance in maintaining socioeconomic and environmental well-being. Environmental sustainability has particularly attracted the attention of scholars and policymakers due to the degradation of most climatic indicators during the last century. A vast amount of literature has concentrated on the role of fossil fuel energy sources as the main factor of increasing greenhouse gas emissions and environmental degradation. Therefore, developing and developed countries have faced challenges in balancing their economic needs and their assistance in mitigating climate change. Furthermore, the global economy, including the top remittance receiving economies, are projected to concentrate more on fossil fuels which could threaten environmental quality. To subjugate nature to their will, humans have developed a wide variety of methods and instruments. Economic growth at the country level reveals significant requirements and prerequisites. Production activities need increasing demand for fossil fuel and enlarging polluting energy combustion. Meanwhile, these activities have generated global warming and enhanced hydrocarbon degradation, driven specifically by high energy intensity. Some studies pointed out that the speed of global temperature has been getting higher and even doubled since the pre-industrial era.

Global warming has garnered widespread attention due to the escalating ecological footprints, which have precipitated considerable adverse effects on human welfare. There is a growing focus on the nexus between sustainable development and environmental degradation. Additionally, the Paris Agreement has emerged as a pivotal framework, offering invaluable suggestions and insights aimed at formulating strategies to curtail carbon dioxide emissions. Furthermore, rapid economic development is frequently cited as the primary catalyst for greenhouse gas emissions. Moutinho et al. (2018) highlighted that GDP per capita serves as a key determinant of carbon emissions. Moreover, energy intensity is recognized as a significant factor influencing carbon dioxide emissions. Consequently, it is imperative for major economic powers to reduce their reliance on environmentally damaging energy sources. Moreover, there is an urgent need to foster the development of alternative energy sources such as geothermal, wind, nuclear, and solar power, to bridge the gap between energy intensity and energy efficiency (Kirikkaleli *et al.*, 2023).

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In many countries, the ecological footprint appears to be influenced by various factors, including real GDP, renewable energy consumption, remittance inflows, financial development, and nanotechnological innovation. As previously mentioned, the complex interplay between remittance inflow and technological innovation has emerged as a critical determinant in shaping the ecological footprint of countries, especially those that are top recipients of remittances.

Therefore, the ecological footprint in global hectares (EFConsTotGHA) is composed of six domains: Built-up land, Carbon, cropland, Fishing Grounds, Forest Products, and Grazing Land. However, in recent literature reviews, most researchers have solely used carbon dioxide emissions as an essential indicator of environmental degradation, neglecting other resources such as Built-up land, cropland, Fishing Grounds, Forest Products, and Grazing Land (Yang and Ali, 2021; Zhang and Jahanger, 2022; Aydin and Sahpaz, 2023). Moreover, the ecological footprint is widely regarded as an indicator of environmental degradation (Ulucak and Bilgili, 2018; Solarin and Bello, 2018; Destek, 2021; Işık *et al.,* 2021).

However, our research has identified the potential interaction between renewable energy, economic growth, financial development, and technological innovations on the ecological footprint, particularly in the context of top remittance-receiving economies such as Indonesia, Bangladesh, Vietnam, Pakistan, Egypt, Arab Republic, Mexico, Philippines, China, and India. Technological innovation stands out as a primary pathway to environmental mitigation and the enhancement of real GDP (Chien *et al.,* 2021; Awosusi *et al.,* 2022; Yuan *et al.,* 2023). Therefore, remittance inflows represent another significant source of environmental degradation worldwide, particularly in the top remittance-receiving economies, while also serving as a catalyst for financial development and patent applications (Yang and Ali, 2021; Mazhar and Hussain, 2022). The ecological footprint is typically expressed in global hectares (gha), a standardized unit that accounts for the relative bio productivity of land and sea areas (Borucke *et al.,* 2013). This standardization enables meaningful comparisons across different regions and time periods. The concept is significant as it provides a tangible measure of human demand against nature's supply, or biocapacity. When a population's ecological footprint exceeds its region's biocapacity, it incurs an ecological deficit. This deficit can only be temporarily sustained by depleting ecological resources, importing biocapacity from other regions, or emitting wastes into global commons such as the atmosphere (Lin *et al.*, 2018). The ecological footprint has been widely applied in sustainability assessments, policymaking, and education, offering a more comprehensive view of environmental impact than single-issue indicators like carbon emissions. However, it has limitations, including challenges in accurately accounting for technological changes and variations in land productivity (van den Bergh & Grazi, 2014). Recent research has focused on refining the methodology, improving data quality, and expanding the application of ecological footprint analysis. For example, Galli et al. (2020) explored the use of ecological footprint in assessing progress towards the UN Sustainable Development Goals.

This paper aims to investigate the impact of financial development, renewable energy, and technological innovation on ecological footprint in ten top remittance-receiving economies from 1990 to 2022. It contributed to the environmental literature in three ways: First, it provides valuable insights into the complex relationships between economic growth, financial development, renewable energy, technological innovation, and ecological sustainability. Second, it employs the Panel Quantile Autoregressive Distributed Lag (PQARDL) model, which can capture heterogeneous effects across different quantiles of the ecological footprint distribution. This approach provides a more detailed view of the short- and long-term impacts of variables such as financial development, renewable energy, and technological innovation. Third, the study adds empirical evidence to the Environmental Kuznets Curve (EKC) literature, by identifying an N-shaped relationship between income growth and environmental degradation in some quantiles, emphasizing the complex dynamics at play in environmental outcomes related to economic factors. Moreover, the research highlights the positive impact of renewable energy on ecological sustainability and underscores the necessity for balanced financial development aligned with environmental goals.

This study employs the Panel Quantile Autoregressive Distributed Lag (PQARDL) approach to investigate the complex interplay between remittance inflows, technological innovation, renewable energy adoption, and financial development on ecological footprints in top remittance-receiving economies. Unlike previous studies that often focus solely on linear relationships or single aspects of environmental degradation, our research offers a comprehensive analysis by incorporating multiple dimensions of ecological impact, including six distinct indicators. Furthermore, the use of quantile regression allows us to capture heterogeneous effects across different levels of ecological footprints, providing unique insights into how economic growth and related factors influence environmental outcomes in varying contexts. This methodological advancement positions our study as a significant contribution to the existing literature, addressing critical gaps in understanding the nuanced relationships between economic dynamics and environmental sustainability. Importantly, the ecological footprint inherently includes the impact of air pollution, as both are closely linked through shared sources such as energy consumption and industrial activities. Progiou *et al.* (2023) highlight those policies aimed at reducing global warming, including the promotion of renewable energy and energy efficiency, can significantly lower air pollutants like particulate matter (PM), nitrogen oxides (NOx), and sulfur dioxide (SO2). These reductions contribute directly to decreasing the ecological footprint by mitigating the environmental and health impacts of air pollution. Recent studies have highlighted the importance of comprehensive approaches to reducing greenhouse gas emissions and their impact on the ecological footprint. Martín-Ortega *et al.* (2024) introduced the MITICA framework, which enhances transparency in climate efforts by providing an integrated approach to GHG mitigation. This framework not only aids in reducing emissions but also contributes to a more accurate assessment of ecological footprints. Furthermore, the intersection of these mitigation strategies with adaptation efforts, particularly through National Adaptation Plans (NAPs), plays a crucial role in addressing both climate resilience and environmental sustainability. These integrated approaches offer potential synergies in reducing ecological footprints while enhancing climate resilience.

In addition, the COVID-19 pandemic has provided a unique opportunity to observe rapid changes in human activity and their immediate effects on environmental pressures. Papadogiannaki et al. (2023) evaluated the impact of COVID-19 on the carbon footprint of two research projects, finding that pandemic-related restrictions and adaptations led to significant reductions in emissions. Their study revealed that measures such as teleworking, virtual participation in events, and digitization of bureaucratic processes could reduce emissions by at least 20% compared to pre-pandemic baselines. These findings highlight the potential for policy-driven behavioral changes to substantially impact ecological footprints, even in the short term.

The remainder of the study is organized as follows: the second section focuses on the literature review, introducing the main factors that may significantly influence the ecological footprint, such as remittance inflows, financial development, and technological innovations. The third section deals with the empirical investigation, employing the Panel quantile ARDL method. Finally, the fourth section discusses the results, interpretations, conclusions, and policy implications.

2. Literature review

2.1. Remittance inflows and ecological footprint

Remittances, defined as the transfer of money by foreign workers to their home countries, have garnered increasing interest in the context of environmental sustainability, particularly concerning their impact on ecological footprints. Several studies have investigated the nexus between remittance inflows and ecological footprint. De and Ratha (2012) provided early insights into this relationship, highlighting the potential influence of remittances on household income, asset accumulation, and human capital in mitigating environmental degradation. Usman and Hammar (2020) examined the dynamic relationship between technological innovations, financial development, renewable energy, and ecological footprint, shedding light on the role of remittance inflows as a significant factor shaping environmental outcomes. Similarly, Usman and Jahanger (2021) explored the influence of remittance inflows on environmental deficit, emphasizing the importance of considering institutional quality alongside the Environmental Kuznets Curve hypothesis.

In addition. Yang *et al.* (2021b) conducted a comprehensive analysis of remittance inflows and their impact on the ecological footprint in BICS countries, considering the mediating effects of technological innovation and financial development. Their findings underscored the significance of these factors in shaping environmental sustainability trajectories. Further contributing to the discourse, Yang et al. (2020) and Yang *et al.* (2021a) investigated the dynamic linkage between globalization, financial development, energy utilization, and environmental sustainability, highlighting the role of remittance inflows as a crucial determinant of ecological footprint outcomes, particularly in GCC countries.

Moreover, studies such as Jiang *et al.* (2021), Ahmad *et al.* (2019), Neog and Yadava (2020), Khan *et al.* (2020), Villanthenkodath and Mahalik (2020), Qingquan *et al.* (2020), and Brown *et al.* (2020) have contributed valuable reflections into various aspects of the relationship between remittance inflows and ecological footprint, further enriching our understanding of this complex phenomenon. In addition, research by Opoku *et al.* (2021) and Sharma *et al.* (2019) has expected the importance of disaggregating emissions and considering the role of economic complexity in analyzing the environmental implications of remittance inflows.

Yang, Jahanger, and Ali (2021) examined the influence of remittance inflows on the ecological footprint in BICS countries, investigating the mediating effects of technological innovation and financial development. Their study shed light on the intricate dynamics shaping environmental outcomes in regions with significant remittance inflows.

Therefore, Zhang, Yang, and Jahanger (2022) explored the role of remittance inflow alongside renewable and non-renewable energy consumption in the environment, focusing on top remittance-receiving countries. The empirical analysis, incorporating ecological footprint indicators, provided valuable reflexes into the environmental implications of remittance inflows on a global scale.

In addition, Yadou, Ntang, and Baida (2024) investigated the nexus between remittances and ecological footprint in Africa, examining the moderating effects of ICTs. Their study inspected the role of technological innovations in influencing the relationship between remittance inflows and environmental sustainability in the African context.

Dash, Gupta, and Singh (2024) provided asymmetric evidence from South Asia regarding the impact of remittances on environmental quality. Their findings underscored the need for micro analysis considering regional disparities in environmental outcomes associated with remittance inflows. Dilanchiev, Sharif, Ayad, and Nuta (2024) conducted a panel data analysis focusing on the interaction between remittances, FDI, renewable energy, and environmental quality in top remittance-receiving countries. Their study contributed to make up the complex linkage between economic factors and environmental sustainability in the context of remittance-receiving economies.

Recent studies have examined the nexus relationships between economic growth, environmental degradation, and policy responses in various contexts. For instance, Koutroumanidis *et al.* (2009) utilized ARIMA models and artificial neural networks to predict fuelwood prices in Greece, providing insights into energy consumption patterns that can influence ecological footprints. Similarly, Tampakis *et al.* (2017) explored citizens' views on electricity use and renewable energy production on a Greek island, highlighting the public's perception of energy savings and the potential for renewable sources to mitigate environmental impacts. Furthermore, Zafeiriou *et al.* (2022) conducted a comprehensive analysis of energy and mineral resource exploitation in Greek peripheries during the delignitization era, emphasizing the need for sustainable practices in energy management to align with ecological conservation efforts. Together, these studies underscore the importance of integrating economic growth strategies with environmental sustainability initiatives to effectively address the challenges posed by climate change and resource depletion.

2.2. Technological innovations and ecological footprint

Technological innovations play a crucial role in shaping ecological footprints, with their impact extending across various sectors and regions, especially in the top remittance receiving economies. Many studies have delved into the nexus between technological innovations and ecological footprint, for example on the multifaceted dynamics involved. Saqib, Ozturk, and Usman (2023) investigated the implications of technological innovations, financial developmen, and renewable energy in reducing ecological footprints levels in emerging economies, spotlight the potential for technological innovations to drive sustainability efforts.

Javed *et al.* (2023) assumed the impact of green technology innovation, environmental taxes, and renewable energy consumption on ecological footprint in Italy. Their study affirmed the importance of policy interventions and technological advancements in achieving environmental sustainability goals. Similarly, Dai *et al.* (2023) tested the relationship between sustainable green electricity, technological innovation, and ecological footprint, emphasizing the moderating role of democratic accountability in shaping this nexus. Their findings accentuated the need for governance structures conducive to fostering green technology adoption.

Hassan (2023) focused on modeling the linkage between coal mining and ecological footprint in South Africa, examining the role of technological innovation in mitigating environmental impacts associated with resource extraction activities. The study draw attention to the importance of sustainable mining practices driven by technological advancements.

Dam, Kaya, and Bekun (2024) investigated how technological innovation affects the ecological footprint in E-7 countries in the context of the Sustainable Development Goals (SDGs). Their findings examined the potential for technological innovations to contribute to achieving sustainable development targets.

Qing *et al.* (2024) examined the role of technological innovations, renewable energy, and natural resources in shaping ecological footprint in the South Asian region during globalization. Their study call attention to the need for integrated approaches that leverage technological innovations to promote environmental sustainability.

Alqaralleh (2024) explored the factors influencing the ecological footprint using an asymmetric quantile regression approach. The study provided insights into the differential impacts of various factors across different segments of the population, calling attention to the importance of considering heterogeneity in addressing environmental challenges.

2.3. Renewable energy, and ecological footprint

Renewable energy has emerged as a pivotal component in addressing environmental concerns, particularly in mitigating ecological footprints associated with energy production and consumption. Several studies have delved into the nexus between renewable energy utilization and ecological footprint. Shahnazi and Shabani (2021) investigated the effects of renewable energy sources on ecological footprints, shedding light on the potential for sustainable energy practices to alleviate environmental burdens. Similarly, Azam et al. (2021) provided insights into the role of renewable energy in curbing ecological footprints, calling attention to the importance of transitioning towards cleaner energy alternatives.

Usman *et al.* (2020c) examined the impact of renewable energy utilization on ecological footprint reduction, drawing attention to the need for innovative energy policies to promote sustainability. Furthermore, Anwar *et al.* (2021) explored the relationship between renewable energy deployment and ecological footprint mitigation, underscoring the significance of renewable energy investments in achieving environmental sustainability goals.

Khan *et al.* (2021) contributed to the discourse by analyzing the linkage between renewable energy adoption and ecological footprint reduction, providing empirical evidence supporting the role of renewable energy in mitigating environmental impacts. Additionally, Usman and Hammar (2020) investigated the dynamic relationship between renewable energy development and ecological footprint outcomes, drawing attention to the potential for renewable energy investments to drive sustainable development.

Li and Wang (2023) conducted a comprehensive study examining the impact of renewable energy on per capita carbon emissions and ecological footprint reduction across 130 countries. Their findings suggested that renewable energy adoption plays a crucial role in reducing environmental burdens, contributing to a more sustainable future.

Saqib, Duran, and Ozturk (2023) unraveled the interrelationship between digitalization, renewable energy, and ecological footprints within the Environmental Kuznets Curve framework, making point in the synergistic effects of these factors on environmental sustainability.

Moreover, Wang, Ge, and Li (2023) investigated the role of improving economic efficiency in reducing ecological footprints, with a focus on financial development, renewable energy, and industrialization. Their study accentuated the importance of holistic approaches in promoting sustainable development.

Further contributing to the discourse, Saqib et al. (2024) explored the synergistic impacts of environmental innovations, financial development, green growth, and ecological footprint reduction through the lens of Sustainable Development Goals (SDGs) policies, providing precious items for countries aiming to reduce their ecological footprints. In addition, Roy (2024) examined the impact of foreign direct investment, renewable and non-renewable energy consumption, and natural resources on ecological footprint from an Indian perspective, shedding light on the complex interplay between economic activities and environmental sustainability.

2.4. Research gap

In the context of the recent research gap, the complex interaction between renewable energy, technological innovation, financial development, and their combined impact on the ecological footprint remains inadequately explored. While studies have investigated the individual effects of these factors on environmental outcomes, there is a lack of comprehensive research that integrates these variables to provide a holistic understanding of their collective influence.

Specifically, while Adebayo *et al.* (2023) examine the role of inward remittances in mitigating carbon emissions and Dilanchiev *et al.* (2024) analyses the interaction between remittances, FDI, renewable energy, and environmental quality, there is a gap in research that considers the joint impact of renewable energy, technological innovation, and financial development on the ecological footprint.

Understanding this complex interaction is crucial for devising effective policy interventions and strategies aimed at promoting sustainable development and mitigating environmental degradation. Moreover, such research can provide insights into how countries can leverage renewable energy and technological advancements to achieve environmentally sustainable economic growth while fostering financial development. Therefore, further empirical studies are needed to elucidate the mechanisms underlying this complex nexus and its implications for environmental policymaking and sustainable development initiatives.

3. Methodological framework and data

3.1. Methodology

This study employed panel data for the top remittance-receiving countries, namely Indonesia, Bangladesh, Vietnam, Pakistan, Egypt, Mexico, Philippines, China, and India, which were available for analysis spanning from 1990 to 2022. Panel quantile regression, introduced by Koenker and Bassett in 1978, served as a tool for comprehending and analyzing the relationship between two variables, utilizing the concept of regression quantiles. The authors elucidate that while traditional regression analysis focuses on modelling the conditional mean of the dependent variable given a set of predictors, regression quantiles enable the modelling of the conditional distribution of the dependent variable, offering a comprehensive insight into the relationship between the variables. In their research, Bera *et al.* (2016) employed a combination of asymmetric Laplace probability density (ALPD), maximum likelihood, maximum entropy, and quantile regression to estimate slope parameters based on the mean and median.

Bildirici (2022) proposed a novel econometric method called "PQARDL," which combines panel dynamic relationships with quantile regression to analyze the impact of refugees and governance on the sustainable environment in 21 Middle Eastern and North African countries. The study finds that refugees have a negative effect on the environment, but good governance can alleviate this impact. The PQARDL method shows that policies promoting good governance could be effective in reducing the environmental impact of refugee populations.

In addition, Cho *et al.* 2015 proposed an extension of the dynamic lagged model theory developed by Pesaran and Shin (1998) by incorporating the concept of quantile cointegration regression. The resulting Dynamic Quantile Autoregressive Distributed Lag QARDL model allows for the estimation of quantile-specific coefficients, which capture the differential impacts of the independent variables at different points of the distribution of the dependent variable. This extension of the Pesaran and Shin (1998) model is particularly useful in analyzing time series data with non-linear and heterogeneous properties. The PQARDL model provides a more comprehensive understanding of the relationships between variables by considering both short-term and long-term effects and accounting for non-stationarity and structural breaks in the data.

Based on the research conducted by Cho *et al.* (2015), a Panel Quantile Autoregressive Distributed Lag (PQARDL) model was employed, which combines the Autoregressive Distributed Lag (ARDL) model proposed by Pesaran and Shin (1995) with the quantile regression approach introduced by Koenker and Bassett (1978) across various quantiles of the cross-sectional conditional distributions. Moreover, the ARDL model enables the computation of both short-term and long-term relationships between variables, whereas the quantile regression approach estimates quantile-specific coefficients, capturing the varying impacts of the independent variables across different points of the distribution of the dependent variable.

Indeed, other panel quantile regression methods have integrated the individual effects of both tracking and ladder of a dependent variable (Koenker, 2004; Canay, 2011). These methods allow for the examination of contingent heterogeneous covariance effects of the determinants of environmental degradation through independent variables with a conditional distribution on a K-vector. The estimation process involves non-linear conditional panel quantile regression as follows:

$$Q_x = [\,\eta(Y_{it}, X_{it}, ß_{0,\zeta})|K_{it}] = 0 \quad (1)$$

In the panel quantile method as proposed by Koenker (2004) and Canay (2011), denoted by Qx, the conditional model is defined where Yit represents the endogenous variables, while Kit represents the conditional K-vector containing the independent variables Xit. The residual function is denoted by β0, ζ, where 0≤ζ<1 represents the quantile index. The conditional nonlinear modulation in the model can be represented by the estimator:

$$E\,[\,\zeta\{\eta(Y_{it}, X_{it}, ß_{0,\zeta})\leq 0\}-\zeta\,|\,K_{it}] = 0 \quad (2)$$

Where $\zeta\{\eta(Y_{it}, X_{it}, ß_{0,\zeta})\leq 0\}$ is the "indicator function". In addition, the indicator function $\zeta\{\eta(Y_{it}, X_{it}, ß_{0,\zeta})\leq 0\}$ and serves as an indicator to determine whether the expression $\eta(Y_{it}, X_{it}, ß_{0,\zeta})$ is less than or equal to zero.

To estimate the residual function $ß_{0,\zeta}$, the unconditional moment method involves to analyzing the moments of the data without conditioning on specific values of the variables. By considering the unconditional moments, the estimation of the residual function in the panel quantile model is:

$$E\,\{K_{it}[\,\zeta\{\eta(Y_{it}, X_{it}, ß_{0,\zeta})\leq 0\}-\zeta]\} = 0 \quad (3)$$

In this research, the Panel Quantile Autoregressive Distributed Lags PQARDL method used by Cho *et al.* (2015). The analysis of the impact of macroeconomic variables on ecological footprint employed the Panel Dynamic Quantile Autoregressive Distributed Lag QARDL model within an Error Correction Model (ECM) framework. This approach allows for the examination of the long-run equilibrium relationship across quantiles of the dependent variable and independent variables while accounting for potential short-term dynamics.

The extended PQARDL model with ECM can be represented as follows:

Table 1
Descriptive statistics of variables

	EFP	FD	GDP	REM	REN	TI	FD*REN	REM*FD	REM*TI
Mean	19.32817	3.585935	7.567538	4.082563	3.327598	8.231695	11.85385	14.31160	30.50115
Median	18.91304	3.488409	7.503851	3.365438	3.543275	8.105609	12.58249	11.43281	27.01038
Maximum	22.43542	5.061405	9.204903	14.58334	4.331807	14.24859	16.80407	45.25590	102.2334
Minimum	17.64210	2.555499	6.238513	0.033429	1.629241	4.127134	5.361216	0.155639	0.359908
Std. Dev.	1.216784	0.594063	0.797237	3.270697	0.732575	1.923511	2.868252	11.74918	23.87053
Skewness	0.980215	0.764857	0.476384	0.761302	-0.820122	0.726025	-0.665989	0.725289	0.874052
Kurtosis	2.998707	2.866193	2.484907	2.834639	2.381706	3.894205	2.599907	2.457460	3.202365
Jarque-Bera	41.79577	25.64248	12.75731	25.50916	33.41549	31.62505	21.03486	26.08394	33.67787
Probability	0.000000	0.000003	0.001697	0.000003	0.000000	0.000000	0.000027	0.000002	0.000000
Sum	5044.652	935.9290	1975.127	1065.549	868.5031	2148.472	3093.856	3735.327	7960.801
Sum Sq. Dev.	384.9468	91.75689	165.2526	2781.340	139.5332	961.9729	2138.986	35891.24	148148.5
Observations	330	330	330	330	330	330	330	330	330

Source: Author calculus from World Development Indicators WDI,2023 database and the World Intellectual Property Organization WIPO:www.wipo.int/pct

$$Y_{it}^{q} = \alpha_q + \beta_\tau Y_{i,t-1} + \sum_{i=1}^{p} \beta_i^q Y_{i,t-\mathrm{i}} + \sum_{i=1}^{q} \gamma_j^q X_{j,t-\mathrm{j}} + \sum_{k=1}^{r} \delta_k^q Z_{\mathrm{k},t-\mathrm{k}} + \varepsilon_{it}^{q} \quad (4)$$

Where Y_{it}^{q} represents the dependent variable ecological footprint for quantile q in all used models. $X_{j,t-\mathrm{j}}$ represents the independent variables GDP, GDP², GDP³, REM, REN and TI, in the first model, GDP, GDP², GDP³, FD*REN, REM, and TI, in the second model, GDP, GDP², GDP³, FD*REN, REM, and TI, in the third model, GDP, GDP², GDP³, REM*FD, REN, and TI, in the fourth model, GDP, GDP², GDP³, REM*TI, REN, and FD, in the fourth model for quantile q, .$Z_{\mathrm{k},t-\mathrm{k}}$ can include any other control variables for quantile q, p, q, and r are the respective lag orders for the variables, α_q is the intercept specific to quantile q., β_i^q, γ_j^q, and δ_k^q are coefficients to be estimated for quantile q., ε_{it}^{q} is the error term specific to quantile q.

Additionally, the model incorporates an Error Correction Model ECM to account for short-term dynamics and deviations from the long-run equilibrium. The ECM component can be added as:

$$\Delta Y_{it}^{q} = \mu_q Y_{it-1}^{q} - \beta_0^q - \sum_{i=1}^{p} \beta_i^q Y_{i,t-\mathrm{i}} - \sum_{i=1}^{q} \gamma_j^q X_{j,t-\mathrm{j}} + \sum_{k=1}^{r} \delta_k^q Z_{\mathrm{k},t-\mathrm{k}} + \eta_{it}^{q} \quad (5)$$

Where ΔY_{it}^{q} represents the first difference of the dependent variable ecological footprint for quantile q., μ_q is the speed of adjustment for quantile q indicating how quickly the dependent variable adjusts to deviations from the long-run equilibrium., Y_{it-1}^{q} is the lagged value of the dependent variable for quantile q, β_0^q represents the intercept specific to quantile q in the long-run equilibrium equation., β_i^q, γ_j^q, and $\delta_k^q$are coefficients to be estimated for quantile q in the main model in the long-run equilibrium equation, p, q, and r are the respective lag orders for the variables in the main model, η_{it}^{q} represents the error term specific to quantile q in the ECM component.

The ECM component helps capture the short-term dynamics and adjustments in the dependent variable following deviations from the long-run equilibrium relationship. It measures the speed at which the ecological footprint corrects any imbalances in the relationship with the independent variables and control variables, offering insights into the short-term dynamics of the system.

The concepts of the validity of EKC can be explain by the sign of GDP, GDP², GDP³ are served Allard *et al.* (2018); Lorente & Álvarez-Herranz (2016). An N-shaped pattern involves a low initial value, followed by a rapid increase, and then a decline. In the context of ecological footprint, this might represent a scenario where environmental impact starts low, increases significantly due to unsustainable resource consumption, and then decreases as conservation efforts are implemented. A U-shaped pattern signifies an initial high value, followed by a decrease, and then a subsequent increase. For the ecological footprint, this might represent a situation where resource consumption and environmental impact initially increase with economic development, decrease through conservation, and then increase again due to other factors.

An inverted N-shaped pattern starts with a high value, followed by a decline, and then an increase. In the ecological footprint context, this could imply an initial high environmental impact, a reduction due to sustainability efforts, and then a subsequent increase linked to various factors like population growth or resource-intensive industries.

3.2. Data

This research establishes a connection between various factors, including ecological footprint, remittance inflow, renewable energy, technological innovation, real GDP, and financial development, using the Dynamic Panel Quantile Autoregressive Distributed Lag (PQARDL) model. The study specifically focuses on the top remittance-receiving economies, namely Indonesia, Bangladesh, Vietnam, Pakistan, Egypt, Mexico, Philippines, China, and India (see Figure 1).

The PQARDL regression analysis investigates the relationship between environmental degradation and various factors, including remittance inflow, gross domestic product (GDP), financial development, technological innovation, and renewable energy consumption in the top remittance-receiving economies. The analysis spans the period from 1990 to 2022. Real GDP per capita constant 2015 US$ represents the GDP variables, while the ecological footprint (EFP) comprises six domains: built-up land, carbon, cropland, fishing grounds, forest products, and grazing land. Remittance inflow is measured as

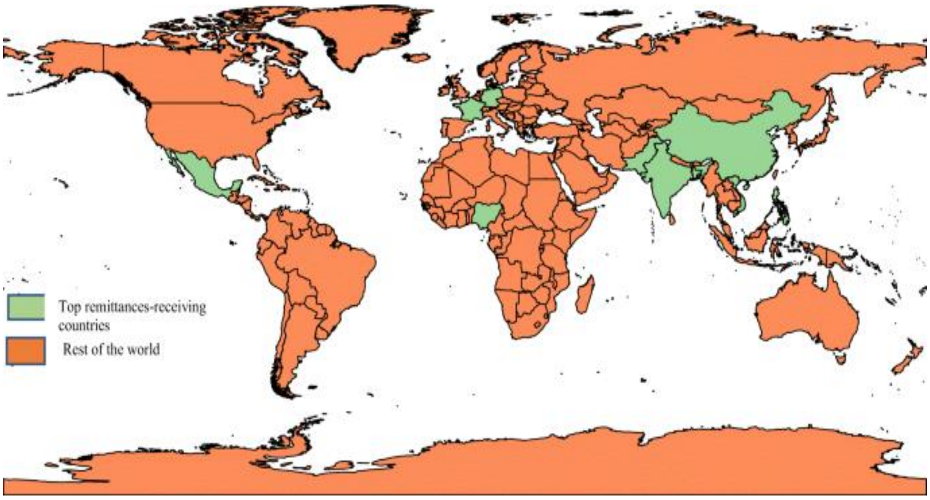

Fig 1. Top remittance-receiving economies (Zhang, et al. (2022))

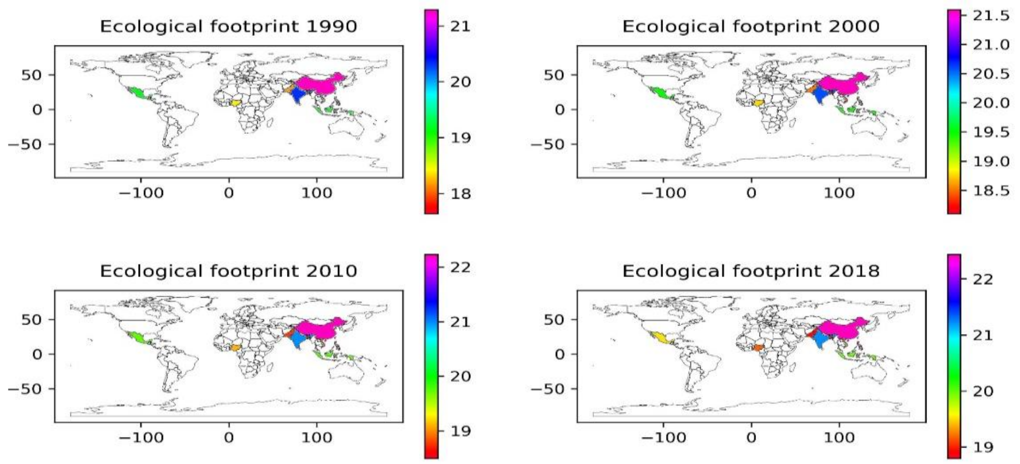

Figure 2 Evolution of EFP

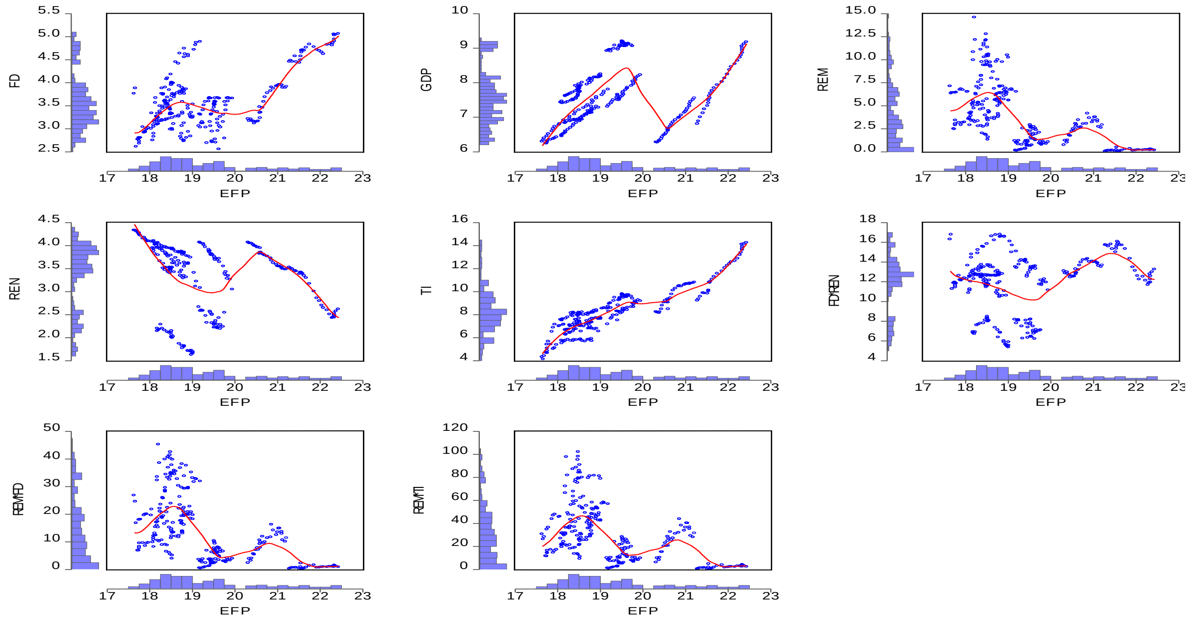

Fig. 3. Scatter Kernel Fit, Panel Stack cross section Multiples Graphs- First vs. All

personal remittances received % of GDP, financial development (FD) is indicated by domestic credit to the private sector by banks % of GDP, technological innovation (TI) includes both resident and non-resident patent applications, and renewable energy consumption (REN) is expressed as the percentage share of renewable energy in total final energy consumption. The intricate relationship between financial development, renewable energy, remittance inflows, and technological innovation is denoted by (FD*REN), (REM*FD), and (REM*TI). All variables used in the analysis were sourced from the World Bank database (WDI 2023), except for the ecological footprint (EFP), which was obtained from the World Intellectual Property Organization (WIPO). Additionally, a logarithmic transformation has been applied to all the data. Refer to Table 1 for details.

The provided data illustrates the trajectory of the Ecological Footprint (EFP) in some of the top remittance-receiving economies over a specific period. Let's take Indonesia as an example. The EFP in Indonesia has exhibited a gradual increase over time, starting at 19.18 in the initial period and steadily rising to reach 19.89 in the final period. This indicates that Indonesia's overall ecological impact has been increasing during this timeframe. A similar pattern is observed in other countries, such as Bangladesh, Vietnam, Pakistan, Egypt, Nigeria, Mexico, the Philippines, China, and India, although with variations in the rate and extent of change. These fluctuations in EFP could be influenced by various factors, including economic growth, technological advancements, energy consumption patterns, and policy measures. Further analysis is necessary to discern the underlying drivers and their implications for sustainable development in these nations. See Figure 2.

4. Results and discussions

4.1. Cross-dependency test results

The utilization of cross-sectional unit root testing relies on implementing the Breusch and Pagan (1980) LM test and the Pesaran (2004) "Cross Dependence" (CD) test. This test utilizes a statistic whose formula is grounded on the correlations between the residuals of each model equation. The estimator of

Table 2
Cross-dependency test

Variables	Breusch-Pagan LM		Pesaran scaled LM		Bias-corrected scaled LM		Pesaran CD	
	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value
EFP	857.3***	.000	96.7***	.000	96.6***	.000	29.0***	.000
FD	285.5***	.000	29.4***	.000	29.2***	.000	6.79***	.000
GDP	965.6***	.000	109.5***	.000	109.4***	.000	31.0***	.000
REM	250.2***	.000	25.2***	.000	25.0***	.000	9.31***	.000
REN	811.8***	.000	91.4***	.000	91.2***	.000	28.3***	.000
TI	542.9***	.000	59.7***	.000	59.5***	.000	22.4***	.000

*** significant at 1% level of significance

the correlation follows an asymptotic standard normal distribution. Therefore, the null hypothesis of independence is rejected when the absolute value of the CD statistic is excessively large. Importantly, this statistic does not necessitate any prior assumption of a spatial dependence matrix.

To evaluate the cross-equation error correlations, Breusch and Pagan (1980) proposed a Lagrange multiplier statistic (LM) for estimating the model. Thus, it is crucial to examine the presence of cross-sectional dependence. See Figure 3.

Cross-dependence CD (Table 2) occurs when a common factor influences the dependent variable across different units, thereby violating the assumption of independence among observations, which is essential for classical panel data models. The table below provides evidence of the existence of unobserved common factors that impact the dependent variables.

4.2. Unit root test

The study of non-stationary time series is crucial in current econometric practice, particularly in macroeconomics. Empirical analyses often begin by examining the stationarity of the time series through the application of various unit root tests. In a multivariate context, researchers frequently aim to identify

Table 3
Unit root test

Test	Diff	Component	EFP	FD	GDP	REM	REN	TI
LLC	Level	C&T	(0.86)	(-1.58) *	(-0.06)	(-0.49)	(1.34)	(-2.85) ***
		C	(0.09)	(-1.01)	(-0.46)	(-1.57) *	(0.83)	(-2.75) ***
	Frst difference	C&T	(-2.56) ***	(-5.00) ***	(-2.38) ***	(-7.98) ***	(-3.21) ***	(-7.12) ***
		C	(-4.26) ***	(-7.26) ***	(-2.35) . 009	(-8.24) ***	(-3.92) ***	(-8.34) ***
Breitung	Level	C&T	(-0.81)	(-0.66)	(0.40)	(-0.02)	(1.50)	(-1.11)
	Frst difference	C&T	(-4.67) ***	(-2.68) .002	(-4.76) ***	(-6.14) ***	(-1.24)	(-7.40) ***
IPS	Level	C&T	(-0.22)	(-1.91) **	(0.72)	(0.17)	(1.38)	(-2.49) ***
		C	(3.08)	(0.13)	(5.63) ***	(-1.59) *	(3.32)	(-1.35) *
	Frst difference	C&T	(5.38) ***	(-5.25) ***	(-3.90) ***	(-7.48) ***	(-4.48) ***	(-8.62) ***
		C	(-7.15) ***	(-6.97) ***	(-3.76) ***	(-8.07) ***	(-5.74) ***	(-9.80) ***
ADF-F	Level	C&T	(17.1)	(36.0) ***	(17.5)	(19.5)	(12.3)	(34.8) ***
		C	(6.03)	(22.0)	(5.78)	(28.2) *	(9.92)	(28.8) **
	Frst difference	C&T	(63.2) ***	(65.5) ***	(46.6) ***	(85.4) ***	(54.5) ***	(99.0) ***
		C	(86.1) ***	(83.3) ***	(48.7) ***	(97.0) ***	(69.4) ***	(119.4) ***
PP-F	Level	C&T	(36.4) ***	(17.9)	()9.12	(45.7) ***	(10.5)	(35.4) ***
		C	(6.37)	(10.4)	(3.5)	(30.3) **	(6.43)	(25.9) *
	Frst difference	C&T	(191.9) ***	(94.7) ***	(108.7) ***	(416.0) ***	(95.3) ***	(533.5) ***
		C	(187.9) ***	(116.4) ***	(77.2) ***	(154.2) ***	(118.6) ***	(177.2) ***

LLC: Levin, Lin & Chu test, IPS: Im, Pesaran and Shin W-stat, ADF-F: ADF - Fisher Chi-square, PP-F: PP - Fisher Chi-square, C&T: Individual effects, individual linear trends
C: Individual effects, *: t-stattistic, ***: Significant with 1%, **: Significant with 5%, *: Significant with 10%

long-term equilibrium relationships between variables by conducting cointegration tests. It is worth noting that unit root and cointegration tests performed on panel data offer greater power compared to their counterparts on individual small-sample time series (Quocviet *et al.,* 2021).

The analysis of non-stationary panel data has gained prominence only recently, following the pioneering work of Levin and Lin (1992). In this regard, we present some unit root tests that are commonly used in panel data analysis. The first generation of tests assumes inter-individual independence of residuals, where any correlations between individuals are considered as nuisance parameters.

First-generation unit root tests provide insights into the implications of the inter-individual independence hypothesis. Subsequently, we introduce second-generation tests, which are more recent and aim to relax the independence assumption. These tests treat the correlations between individuals as nuisance parameters and propose new test statistics that incorporate these interdependencies. The first-generation unit root tests, developed based on the assumption of cross-section independence, include Levin and Lin (1992, 1993), Levin, Lin, and Chu (2002), and Harris and Tzavalis (1999). These tests employ the homogeneous specification of the autoregressive root under the alternative hypothesis H1.

Some unit root tests in panel data analysis, such as those developed by Im, Pesaran, and Shin (1995, 2003), Maddala and Wu (1999), Choi (1999), and Hadri (2000), also adopt the homogeneous specification of the autoregressive root. In

Table 4
Westerland cointegration test

Statistics	Value	Z-Vlue	P-Value
Gt	-4.384	-5.571***	0.000
Ga	-18.143	-7. 89***	0.000
Pt	-9.586	-5.38***	0.000
Pa	-14.18	-10.31***	0.000

*** represents 1% significance level.

Table 5
Results of PQARDL analysis model1

Variable	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.
Quantile	**0.1**		**0.2**		**0.3**		**0.4**		**0.5**	
Long run estimate										
FD	0.012584**	0.0721	0.006619	0.2166	0.006885	0.2114	0.005436	0.3951	0.000666	0.9253
GDP	-0.149706**	0.0556	-0.012194	0.7646	-0.005351	0.8993	-0.040829	0.3611	-0.006157	0.8994
GDP^2	0.038550**	0.0548	0.001008	0.9199	0.001013	0.9212	0.010726	0.3277	0.002652	0.8271
GDP^3	-0.002630	0.0432	-2.26E-05	0.9713	-6.96E-05	0.9127	-0.000701	0.3049	-0.000206	0.7879
REM	0.000822	0.3650	-0.000441	0.4795	0.000285	0.6810	0.000646	0.4773	0.001224	0.2373
REN	-0.000388	0.9573	0.008192*	0.1431	0.002041	0.7306	0.001757	0.7397	0.001222	0.8021
TI	0.000935	0.6797	-0.001160	0.4860	-0.002433	0.1479	-0.002446	0.1424	-0.001810	0.2958
Sort run estimate										
Δ FD	0.006611**	0.5797	0.011613	0.2672	0.022874***	0.0164	0.025077***	0.0138	0.02612**	0.0153
Δ GDP	30.82038***	0.0045	9.557164*	0.1117	11.23488**	0.0778	13.39721**	0.0568	6.164198	0.4505
ΔGDP^2	-4.07436***	0.0039	-1.224190*	0.1101	-1.423253*	0.0817	-1.712915**	0.0587	-0.794833	0.4525
ΔGDP^3	0.180387***	0.0030	0.053742*	0.0945	0.061708*	0.0734	0.074344**	0.0519	0.035988	0.4229
Δ REM	-0.004428**	0.0169	-0.002681	0.2805	-0.002503	0.5303	-0.001575	0.7233	0.000304	0.9157
ΔREN	-0.31326***	0.0000	-0.28553***	0.0000	-0.24942***	0.0000	-0.24013***	0.0000	-0.2380***	0.0000
ΔTI	-0.007904	0.5257	-0.008424	0.3551	0.002163	0.8367	0.001425	0.8709	0.005595	0.5133
ECM1	-1.01575***	0.0000	-0.99929***	0.0000	-0.93173***	0.0000	-0.91994***	0.0000	-0.9744***	0.0000
Quantile	**0.6**		**0.7**		**0.8**		**0.9**		**0.95**	
Long run estimate										
FD	0.000230	0.9745	-0.000385	0.9521	-0.000729	0.8962	-0.004760	0.5259	-0.0238***	0.0042
GDP	0.043034	0.4994	0.043275	0.4815	0.114310**	0.0166	0.119323**	0.0319	0.092429*	0.1321
GDP2	-0.011218	0.4931	-0.011853	0.4573	-0.030439**	0.0195	-0.030855**	0.0402	-0.019738	0.2378
GDP3	0.000777	0.4592	0.000855	0.4044	0.002096**	0.0170	0.002133**	0.0321	0.001357	0.2251
REM	0.001186	0.2588	0.001802	0.0578	0.001788**	0.0625	0.002161**	0.0687	0.002300*	0.1406
REN	0.003993	0.4157	0.005003	0.2796	0.004567	0.3268	2.85E-05	0.9969	-0.003293	0.7790
TI	-0.002502*	0.1499	-0.002306*	0.1901	-0.002568	0.2031	-0.001720	0.5168	-0.001946	0.5254
Short run estimate										
Δ FD	0.026203**	0.0169	0.029315***	0.0057	0.033300***	0.0003	0.037860***	0.0000	0.0550***	0.0000
Δ GDP	-2.989736	0.7712	-3.679924	0.6954	-12.68750**	0.0678	-13.03694*	0.1097	-10.85559	0.2454
ΔGDP^2	0.445177	0.7410	0.553440	0.6529	1.775024**	0.0599	1.884179*	0.0853	1.558475	0.2187
ΔGDP^3	-0.020160	0.7286	-0.025830	0.6276	-0.081256**	0.0578	-0.088847*	0.0702	-0.071937	0.2097
Δ REM	-0.000562	0.8492	-0.003498*	0.1568	-0.001264	0.8256	-0.002128	0.4897	0.00753**	0.0271
ΔREN	-0.29556***	0.0000	-0.31818***	0.0000	-0.38336***	0.0000	-0.40786***	0.0000	-0.2572***	0.0000
ΔTI	0.003994	0.6202	0.004967	0.5135	0.009489	0.2853	0.001980	0.7809	0.005602	0.6495
ECM1	-1.00019***	0.0000	-0.9957-***	0.0000	-1.0270****	0.0000	-0.94476***	0.0000	-1.1460***	0.0000

Source: Author's statistical analysis: ***: Significant with 1%. **: Significant with 5%. *: Significant with 10%

addition, Henin, Jolivaldt, and Nguyen (2001) applied the sequential test methodology.

Table 3 indicates that all variables, except for the technological innovation (TI) variable, are stationary in first differences integrated at the first order, while the TI variable is stationary at the level integrated at the zero order.

4.3. Cointegration test

The application of cointegration techniques in panel data facilitates the examination of long-term relationships among integrated variables. One notable advantage of conducting cointegration tests on panel data is the enhanced power of the test, particularly in empirical studies. Prior to executing cointegration tests, it is imperative to ensure that all series are integrated of order one (I1). To meet this prerequisite, Westerlund (2007) developed four novel panel cointegration tests that exhibit sufficient generality to accommodate a high degree of heterogeneity. These tests rely on structural dynamics rather than residual dynamics and, consequently, do not impose any common-factor restrictions. The primary aim is to test the null hypothesis of no cointegration by scrutinizing whether the error-correction term in a conditional panel error-correction model equals zero. Westerlund and Edgerton (2007) conducted a series of unit-root tests, revealing compelling evidence that both series are nonstationary. The hypothesized relationship between the two variables allows for a linear time trend.

Several researchers, including Westerlund and Edgerton (2007), Phillips and Moon (1999), Pedroni (2004), Kao et al. (1999), and Johansen and Juselius (1990), have developed various cointegration tests to address the challenge of determining the long-run relationship between cross-sections. The outcomes of the Westerlund cointegration test, as presented in Table 4, provide clear evidence that the series EFP, GDP, FD, REM, REN, and TI exhibit a long-term cointegration relationship. This is substantiated by the rejection of the null hypothesis H0 of no cointegration at a significance level of 1%.

4.4. PQARDL estimation results model1

The long-term analysis (Table 5, model1) reveals complex relationships between key variables and the ecological footprint in top remittance-receiving economies. In addition, we have approached the three-dimensional graphs that become visible in the Quantile regression graph (model1) (see Fig 4. Quantile regression graph (model1)). The multivariate panel quantile regression analysis graph respects the robustness check under PQARDL Methodology. Therefore, the multivariate Quantile regression graph results are robust and respect to quantile regression (see Fig 4). Financial development shows a positive relationship with environmental degradation across all quantiles, aligning with Jiang and Ma's (2019) global study on financial development and carbon emissions. This suggests that higher levels of financial development may lead to increased environmental degradation, particularly in lower quantiles. However, this contrasts with findings by Shahbaz et al. (2020) in the United Arab Emirates, where financial development was found to potentially reduce environmental degradation under certain conditions. GDP and its square consistently show a negative relationship with environmental degradation, especially significant at lower quantiles. This supports Wang et

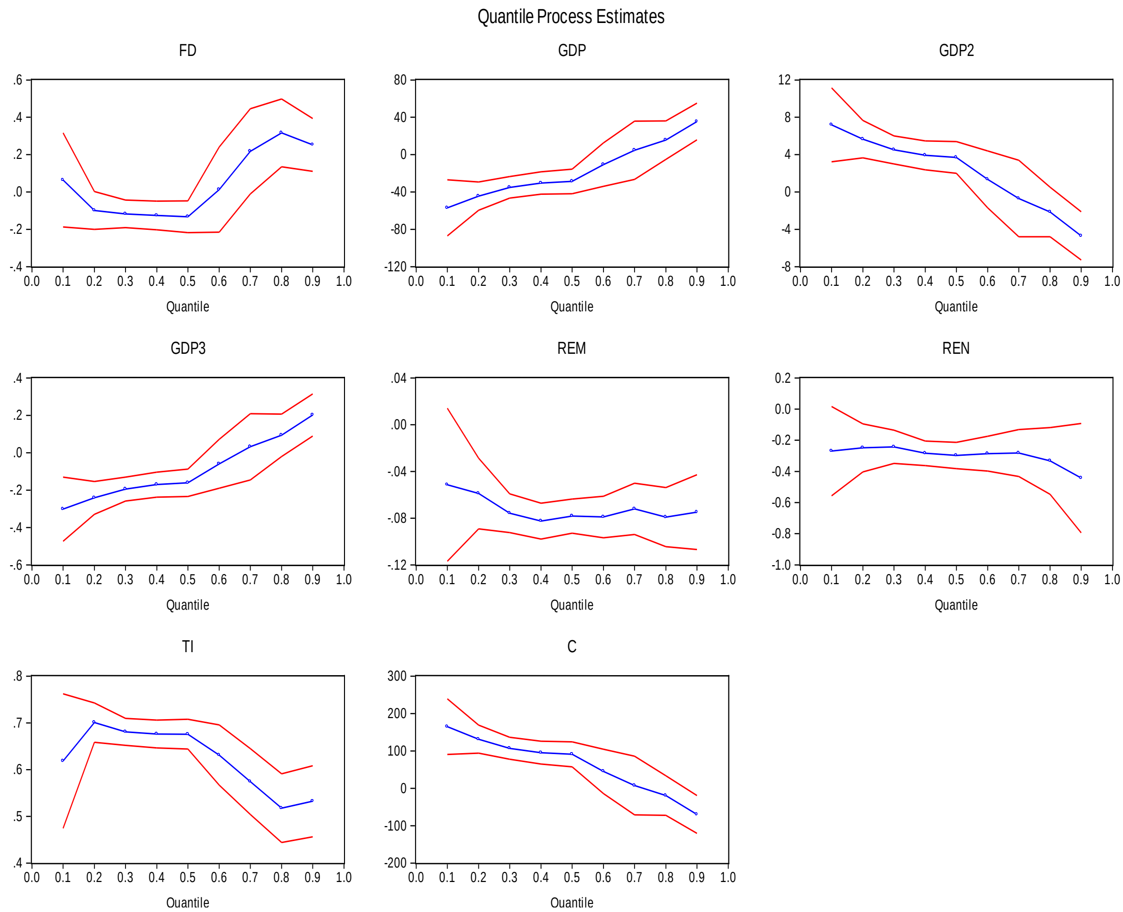

Fig 4. Quantile regression graph (model1)

al.'s (2024) findings but challenges the traditional Environmental Kuznets Curve (EKC) hypothesis. The varying patterns of GDP coefficients across quantiles suggest a more complex relationship between economic growth and environmental degradation than the simple inverted U-shape proposed by the EKC, echoing the nuanced findings of Tsepi et al. (2024) in their decomposition analysis of CO_2 emissions in Greece. Remittance inflow's impact on environmental degradation is inconclusive, with mixed coefficient signs across quantiles. This ambiguity aligns with studies by Aljadani *et al.* (2023) and Yang *et al.* (2020a, 2021), highlighting the complex nature of remittances' environmental impact. The consistent negative relationship between renewable energy consumption and environmental degradation across all quantiles supports Dilanchiev *et al.'s* (2024) findings and underscores the importance of renewable energy in mitigating environmental degradation. Technological innovation's impact is inconclusive, with mixed coefficient signs across quantiles. This contradicts the findings of Martín-Ortega *et al.* (2024), who proposed an integrated approach to greenhouse gas mitigation through technological innovation. The contradiction suggests that the environmental impact of technology in remittance-receiving economies may depend on the specific type and application of technologies, as well as the broader economic and policy context. In the short run, financial development shows a positive relationship with environmental degradation, varying in significance across quantiles. This aligns with Rani *et al.'s* (2023) findings but contrasts with the long-term effects observed in some studies, suggesting a potential time-lag in the environmental benefits of financial development. GDP and remittance inflows show mixed short-term effects, echoing the complexity observed in long-term relationships and aligning with Husnain *et al.'s* (2023) observations on the multifaceted nature of these relationships. Renewable energy consumption consistently exhibits a negative relationship with environmental degradation in the short run, supporting Rani *et al.'s* (2023) findings and reinforcing the importance of renewable energy in both short- and long-term environmental strategies. The inconclusive short-term impact of technological innovation, varying across quantiles, aligns with Husnain *et al.'s* (2023) findings and underscores the need for targeted, context-specific technological policies.

4.5. PQARDL estimation results model2

The analysis of Table 6 and Model 2 reveals complex relationships between financial development, renewable energy, and the ecological footprint. The PQARDL analysis (model 2) shows varying degrees of significance for GDP coefficients across different quantiles, challenging the robustness of GDP's impact on environmental degradation. In addition, we have approached the three-dimensional graphs

Table 6
Results of PQARDL analysis model2

Variable	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.
Quantile	**0.1**		**0.2**				**0.30.4**		**0.5**	
					Long run estimate					
GDP	-0.049628	0.4666	0.046743	0.4366	0.021925	0.6684	0.032568	0.5783	0.036860	0.3845
GDP^2	0.016789	0.3419	-0.008983	0.5811	-0.003078	0.8140	-0.006667	0.6651	-0.008394	0.4305
GDP^3	-0.001279	0.2589	0.000427	0.6910	7.73E-05	0.9258	0.000367	0.7149	0.000520	0.4377
FD*REN	-0.002404*	0.0691	-0.000456	0.7317	0.000262	0.8148	0.001009	0.3892	0.001377	0.2699
REM	-0.000659	0.4994	-0.00108*	0.1705	-0.000301	0.7153	-0.000237	0.7774	0.000627	0.4575
TI	-0.002310	0.4177	-0.00291*	0.1645	-0.002541*	0.0810	-0.003287**	0.0478	-0.0035**	0.0110
					Sort run estimate					
Δ GDP	18.64140*	0.0841	-4.500222	0.7303	-1.341673	0.8798	-0.937346	0.9320	-2.443034	0.7555
ΔGDP^2	-2.47621*2	0.0788	0.548266	0.7510	0.138143	0.9046	0.110308	0.9391	0.334353	0.7395
ΔGDP^3	0.11303*3	0.0636	-0.018412	0.8085	-0.001540	0.9751	-0.001616	0.9795	-0.012631	0.7656
ΔFD*REN	0.002635	0.3977	0.000291	0.9285	0.001571	0.5361	-0.004885	0.6204	-0.006617	0.4944
Δ REM	5.67E-05	0.9816	8.09E-05	0.9774	0.000220	0.9422	-0.000174	0.9577	0.000663	0.8229
ΔTI	-0.002801	0.8499	-0.001830	0.8938	0.004395	0.6209	0.008636	0.3023	0.011391*	0.1483
ECM2	-0.95188***	0.0000	-0.9085***	0.0000	-0.93124***	0.0000	-0.98159***	0.0000	-1.0230***	0.0000
Quantile	**0.6**		**0.7**		**0.8**		**0.9**		**0.95**	
					Long run estimate					
GDP	0.023289	0.5559	0.038117	0.4576	0.038206	0.4262	0.123450	0.2413	0.16692**	0.0045
GDP^2	-0.005300	0.5916	-0.009325	0.4852	-0.010717	0.3865	-0.034483	0.2385	-0.0438**	0.0035
GDP^3	0.000348	0.5736	0.000624	0.4729	0.000825	0.2961	0.002490	0.2126	0.0030***	0.0016
FD*REN	0.001947*	0.1513	0.001430	0.3132	0.00450**	0.0028	0.004298	0.2104	0.00253*	0.1313
REM	0.001805**	0.0435	0.00236**	0.0151	0.000869	0.5572	0.002895	0.3834	0.00338*	0.0729
TI	-0.004324*	0.0029	-0.00352**	0.0294	-0.006703**	0.0069	-0.006744	0.1787	-0.00979**	0.0282
					Short run estimate					
Δ GDP	-1.551920	0.8345	-5.645604	0.5532	-15.36524*	0.1437	-21.50251*	0.1459	-14.23537	0.2968
ΔGDP^2	0.230010	0.8086	0.795142	0.5253	2.101270*	0.1267	3.006214*	0.1372	2.108517	0.2482
ΔGDP^3	-0.008553	0.8303	-0.034369	0.5277	-0.092945*	0.1216	-0.136871*	0.1374	-0.099840	0.2204
ΔFD*REN	-0.010608	0.2807	-0.009008	0.3678	-0.004163	0.6872	-0.006947	0.6043	-0.014145	0.2871
Δ REM	-0.002858	0.2213	-0.001945	0.4564	-0.001101	0.6529	0.002536	0.5900	0.004961*	0.0812
ΔTI	0.014964*	0.0666	0.01500**	0.0546	0.036448**	0.0037	0.026635*	0.1063	0.0408***	0.0000
ECM2	-1.04496***	0.0000	-1.0213***	0.0000	-0.96254***	0.0000	-0.85820***	0.0000	-0.9078***	0.0000

Source: Author's statistical analysis: ***: Significant with 1%. **: Significant with 5%. *: Significant with 10%

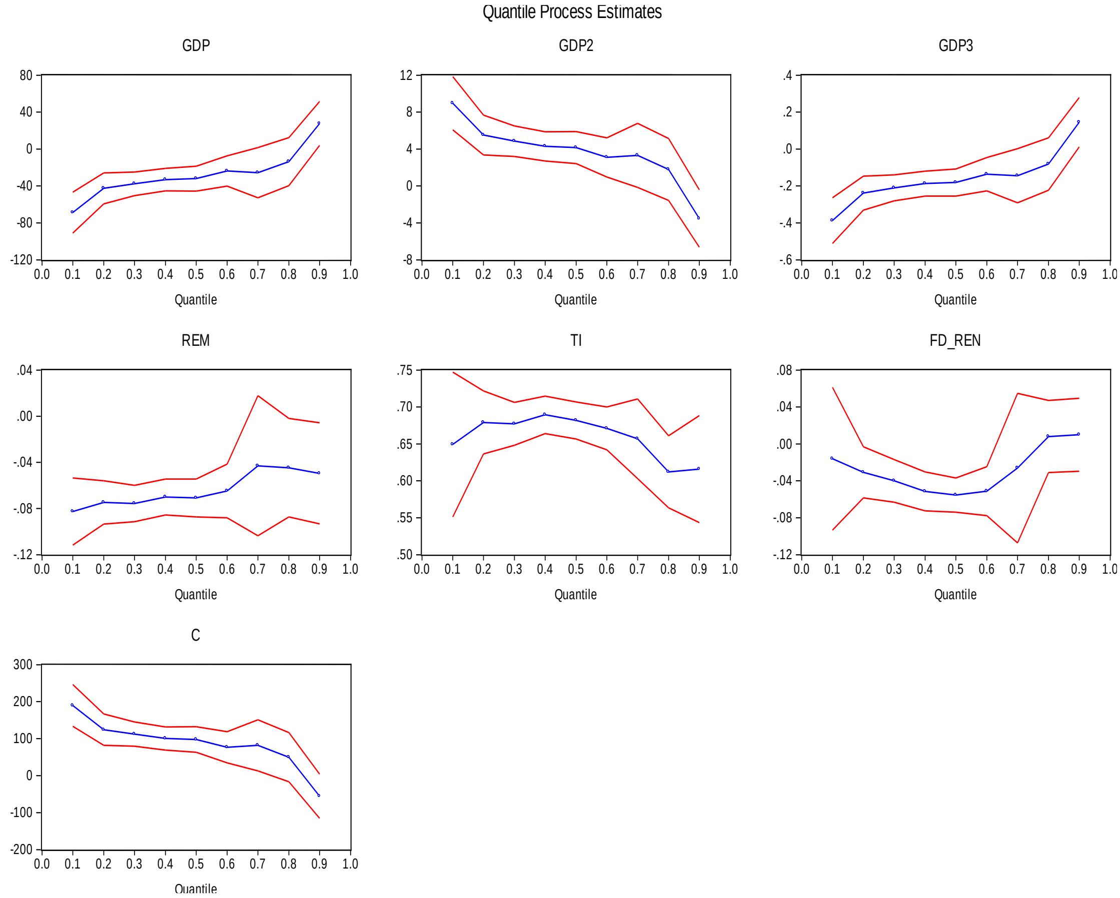

Fig 5. Quantile regression graph (model2)

that become visible in the Quantile regression graph (model1) (see Fig 5. Quantile regression graph (model2)). The multivariate panel quantile regression analysis graph respects the robustness check under PQARDL Methodology. Therefore, the multivariate Quantile regression graph results are robust and respect to quantile regression (see Fig 5). This variability aligns with the findings of Tsepi et al. (2024), who observed complex patterns in CO2 emissions in Greece, suggesting that the relationship between economic growth and environmental degradation is more nuanced than traditional models propose. The interaction between financial development and renewable energy (FD*REN) shows modest significance at the 10th quantile in the long run, echoing Raza et al.'s (2023) findings on the potential synergies between financial development and renewable energy in environmental sustainability. However, the lack of short-term significance for this interaction term contrasts with studies like Shahbaz et al. (2020), who found more immediate impacts in the United Arab Emirates, highlighting the potential for regional variations in these relationships. Remittance inflows show no significant direct effect on environmental degradation in either the long or short term, aligning with Jiang and Ma's (2019) global study. However, this contrasts with the mixed findings reported by Aljadani et al. (2023) and Yang et al. (2020a, 2021) in top remittance-receiving economies, suggesting that the environmental impact of remittances may be highly context-dependent and require more nuanced analysis. The varying significance of technological innovation across quantiles supports Jiang and Ma's (2019) findings on the complex role of technology in environmental quality. This variability challenges the straightforward positive impact proposed by Martín-Ortega et al. (2024), suggesting that the environmental benefits of technological innovation may depend on specific economic and policy contexts. The analysis fails to consistently support the N-shaped Environmental Kuznets Curve (EKC) hypothesis across quantiles. This aligns with recent critiques of the EKC, such as those presented by Stern (2017), who argued for more complex models of the growth-environment relationship. The inconsistent patterns observed in our study contribute to the growing body of literature challenging the universality of the EKC hypothesis. In the short run, the mixed significance of GDP, technological innovation, and the FD*REN interaction term across quantiles aligns with Husnain et al.'s (2023) observations on the multifaceted nature of short-term environmental impacts. This complexity underscores the need for dynamic policy approaches that can adapt to varying short-term effects while working towards long-term sustainability goals. The consistent negative relationship between renewable energy consumption and environmental degradation in both long and short terms, as observed in our study, supports the findings of Dilanchiev et al. (2024) and Rani et al. (2023). This consistency across studies strengthens the case for policies promoting renewable energy adoption as a key strategy for environmental sustainability.

4.6. PQARDL estimation results model3

The analysis of Table 7 and Model 3 reveals complex relationships between remittance inflows, financial development, and the ecological footprint in top remittance-receiving economies. In addition, we have approached the three-dimensional graphs that become visible in the Quantile regression graph (model3) (see Fig 6. Quantile regression graph

Table 7
Results of PQARDL analysis model3

Variable	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.
Quantile	**0.1**		**0.2**				**0.30.4**		**0.5**	
					Long run estimate					
GDP	-0.032227	0.7294	-0.073012	0.4833	-0.028881	0.5031	-0.016712	0.7218	0.018067	0.7443
GDP^2	0.010613	0.6342	0.020585	0.4663	0.008539	0.4143	0.005676	0.6190	-0.004174	0.7653
GDP^3	-0.000899	0.5152	-0.001400	0.4581	-0.000599	0.3504	-0.000421	0.5490	0.000264	0.7653
REM*FD	0.000237	0.4975	-0.000224	0.2781	-8.69E-05	0.6093	0.000122	0.6182	0.000274	0.2948
REN	-0.004763	0.6019	0.001220	0.8103	0.000950	0.8226	0.001379	0.7552	0.003473	0.4253
TI	0.002000	0.6223	-0.002739	0.2838	-0.000972	0.4912	-0.001810	0.2336	-0.00220*	0.1325
					Sort run estimate					
Δ GDP	9.285870	0.5755	17.18485	0.3589	11.95611*	0.0946	8.832306	0.2733	1.405152	0.8855
ΔGDP^2	-1.267091	0.5583	-2.250659	0.3698	-1.530825*	0.0934	-1.147794	0.2659	-0.165286	0.8960
ΔGDP^3	0.060071	0.5208	0.100268	0.3694	0.066904*	0.0812	0.051672	0.2346	0.008594	0.8741
ΔREM*FD	0.000451	0.6545	1.75E-05	0.9798	-0.000439	0.5262	0.000248	0.8112	0.000627	0.4717
Δ REN	-0.277***	0.0000	-0.1918***	0.0012	-0.2368***	0.0000	-0.2652***	0.0009	-0.2654***	0.0002
ΔTI	-0.011089	0.6035	-0.008022	0.4678	-0.005870	0.5718	-0.008872	0.4473	0.003717	0.6727
ECM3	-0.9929***	0.0000	-0.9717***	0.0000	-0.9898***	0.0000	-1.01840***	0.0000	-0.9768***	0.0000
Quantile	**0.6**		**0.7**		**0.8**		**0.9**		**0.95**	
					Long run estimate					
GDP	0.019745	0.6879	0.025497	0.5154	0.063433	0.6685	0.159558***	0.0011	0.097787*	0.1791
GDP^2	-0.005788	0.6376	-0.006983	0.4798	-0.016061	0.7127	-0.04324***	0.0007	-0.02592*	0.1818
GDP^3	0.000423	0.5829	0.000485	0.4371	0.001081	0.7306	0.00301***	0.0004	0.001911*	0.1284
REM*FD	0.00059**	0.0068	0.000605**	0.0091	0.000492*	0.1644	0.001113***	0.0026	0.000503	0.5274
REN	0.005843*	0.1301	0.005051	0.2267	0.002648	0.7833	0.002126	0.7912	0.009146	0.3598
TI	-0.00174*	0.1858	-0.000867	0.5263	-0.001834	0.4792	-0.003040	0.2018	-0.0085**	0.0499
					Short run estimate					
Δ GDP	-0.085036	0.9919	1.840149	0.7826	-5.365266	0.8202	-7.390722	0.5073	-9.997259	0.2313
ΔGDP^2	0.050853	0.9620	-0.199955	0.8146	0.764357	0.8164	1.175949	0.4328	1.515065*	0.1752
ΔGDP^3	-0.001995	0.9647	0.008307	0.8174	-0.034691	0.8202	-0.059117	0.3792	-0.07307*	0.1420
ΔREM*FD	0.000153	0.8556	-0.000691	0.4542	-1.09E-05	0.9969	8.92E-05	0.9427	0.000536	0.6486
Δ REN	-0.2967***	0.0000	-0.32721***	0.0000	-0.32367**	0.0179	-0.36435***	0.0000	-0.2440**	0.0515
ΔTI	0.004722	0.5452	0.003014	0.6224	0.009466	0.4795	0.014917**	0.0587	0.02276**	0.0176
ECM3	-0.9751***	0.0000	-1.03761***	0.0000	-1.01403***	0.0000	-0.92641***	0.0000	-0.9194***	0.0000

Source: Author's statistical analysis: ***: Significant with 1%. **: Significant with 5%. *: Significant with 10%

(model3)). The multivariate panel quantile regression analysis graph respects the robustness check under PQARDL Methodology. Therefore, the multivariate Quantile regression graph results are robust and respect to quantile regression (see Fig 6). The lack of clear and consistent patterns in the coefficients for GDP and its non-linear terms challenges the universal applicability of the Environmental Kuznets Curve (EKC) hypothesis proposed by Grossman & Krueger (1995). This aligns with recent critiques of the EKC, such as those presented by Stern (2017), who argued for more complex models of the growth-environment relationship. The interaction between remittance inflows (REM) and financial development (FD) shows a positive and statistically significant coefficient in the long run, suggesting potential for reducing ecological footprint when these factors are combined. This finding supports Yang's (2008) proposition that remittances can be strategically invested in environmentally sustainable projects. However, it contrasts with the mixed findings reported by Aljadani et al. (2023) and Yang et al. (2020a, 2021) in top remittance-receiving economies, highlighting the need for context-specific analysis of remittance impacts. The positive and statistically significant relationship between renewable energy (REN) and ecological footprint in the long term contradicts the findings of Dilanchiev et al. (2024) and Rani et al. (2023), who found negative relationships. This discrepancy underscores the complexity of renewable energy's impact and suggests that the effectiveness of renewable energy in reducing ecological footprint may depend on specific economic and policy contexts. In the short run, the varying levels of statistical significance and directionality across different quantiles for GDP and other variables align with Husnain et al.'s (2023) observations on the multifaceted nature of short-term environmental impacts. This complexity echoes the findings of Tsepi et al. (2024) in their decomposition analysis of CO2 emissions in Greece, emphasizing the need for dynamic policy approaches. The negative and statistically significant coefficients for technological innovation (TI) in the short run support Al-Mulali et al.'s (2015) findings on the immediate environmental benefits of technological advancements. However, this contrasts with the inconclusive long-term impact found in our study and the integrated approach proposed by Martín-Ortega et al. (2024), suggesting that the environmental benefits of technology may vary over time and across contexts. The lack of consistent evidence for an N-shaped EKC aligns with Cole et al.'s (2006) argument that factors beyond income significantly influence environmental impact. This finding is

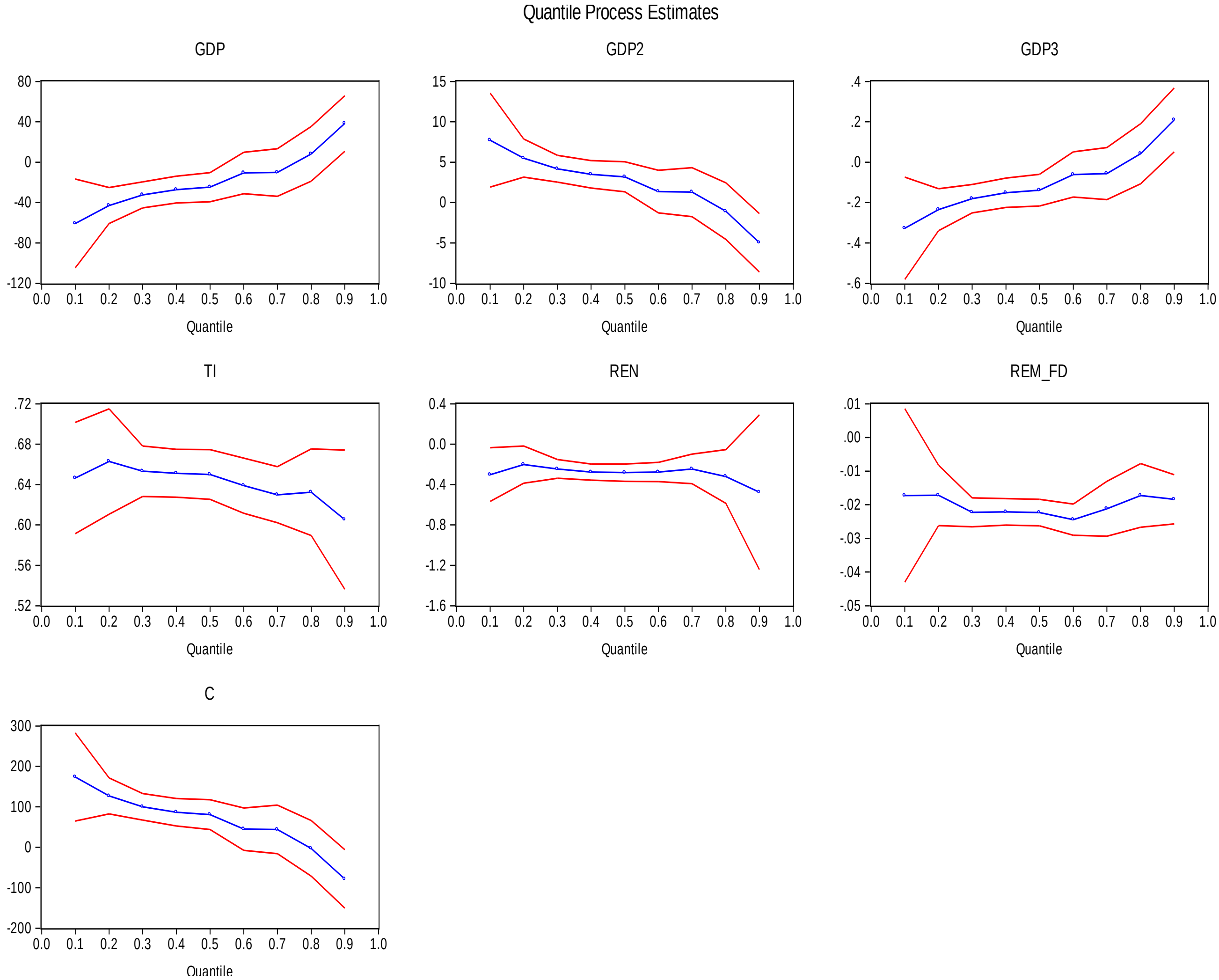

Fig 6. Quantile regression graph (model3)

further supported by recent studies like Shahbaz et al. (2020), who found that financial development could potentially reduce environmental degradation under certain conditions in the United Arab Emirates. These results, when compared with recent literature, highlight the complex and often context-dependent nature of the relationships between economic factors and environmental degradation in remittance-receiving economies. They suggest the need for nuanced, tailored policies that consider both short- and long-term impacts, as well as the specific economic and environmental contexts of these countries. Future research should focus on disentangling these complex relationships and identifying the specific conditions under which remittances, financial development, and technological innovation contribute to or mitigate environmental degradation. Additionally, exploring the potential synergies between these factors, as suggested by the positive REM*FD interaction, could provide valuable insights.

4.7. PQARDL estimation results model4

Table 8 and Model 4 illustrate the complex moderating effect between remittance inflows and technological innovation on the ecological footprint. In addition, we have approached the three-dimensional graphs that become visible in the Quantile regression graph (model4) (see Fig 7. Quantile regression graph (model4)). The multivariate panel quantile regression analysis graph respects the robustness check under PQARDL Methodology. Therefore, the multivariate Quantile regression graph results are robust and respect to quantile regression (see Fig 7). The long-run analysis reveals inconsistent relationships between Gross Domestic Product (GDP) and environmental degradation across different quantiles, challenging the universal applicability of the Environmental Kuznets Curve (EKC) hypothesis. Specifically, while GDP exhibits a negative relationship with environmental degradation, suggesting a potential mitigating effect as economies grow, this relationship is not consistent across quantiles. For instance, the coefficient for GDP is statistically significant and negative in the 10th quantile but turns positive and statistically insignificant in the 90th and 95th quantiles. This inconsistency raises important questions about the applicability of the EKC hypothesis, which posits an inverted U-shaped relationship between economic growth and environmental degradation (Grossman & Krueger, 1995). These findings resonate with critiques from researchers like Stern (2017), who argue that the EKC may not universally apply across all economies or stages of development. The varying impacts of GDP across quantiles echo the findings of Tsepi et al. (2024) in their decomposition analysis of CO2 emissions in Greece, emphasizing the need for a nuanced understanding of economic-environmental interactions. This complexity is further supported by Wang et al.'s (2024) study,

Table 8
Results of PQARDL analysis model4

Variable	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.	Coef	Prob.
Quantile	**0.1**		**0.2**		**0.3**		**0.4**		**0.5**	
Long run estimate										
GDP	-0.1742**	0.0232	-0.035221	0.4420	-0.026622	0.5567	-0.035975	0.4428	-0.017216	0.7544
GDP^2	0.04812**	0.0144	0.008322	0.4636	0.006947	0.5269	0.010091	0.3755	0.005074	0.7115
GDP^3	-0.003***	0.0096	-0.000541	0.4473	-0.000480	0.4790	-0.000697	0.3231	-0.000357	0.6824
REM*TI	-4.60E-05	0.6642	-4.23E-05	0.6507	3.96E-05	0.6441	6.90E-05	0.5292	0.000209*	0.1570
REN	-0.004769	0.5228	0.002697	0.6112	0.001133	0.8191	0.000345	0.9480	0.002456	0.6240
FD	0.003259	0.7373	0.004158	0.4040	0.003022	0.5101	0.001014	0.8459	-0.001841	0.7835
Sort run estimate										
Δ GDP	26.94750*	0.1089	12.13108**	0.0527	13.96765**	0.0241	13.61403**	0.0459	7.838260	0.3720
ΔGDP^2	-3.53541*	0.1113	-1.548259**	0.0530	-1.791439**	0.0243	-1.748624**	0.0461	-1.014733	0.3732
ΔGDP^3	0.15620*	0.1070	0.067174	0.0458	0.077788**	0.0202	0.076084**	0.0393	0.045407	0.3478
ΔREM*TI	-0.00053*	0.0185	-0.000451	0.2714	-0.000238	0.6734	-0.000455	0.3852	-0.000191	0.7343
Δ REN	-0.31232*	0.0001	-0.24403***	0.0000	-0.27485***	0.0000	-0.25298***	0.0000	-0.2868***	0.0000
ΔFD	0.007387	0.4763	0.009951	0.2971	0.017735	0.0556	0.019627	0.0510	0.020037	0.0576
ECM4	-1.1295***	0.0000	-1.00838***	0.0000	-0.94326***	0.0000	-0.91878***	0.0000	-0.9375***	0.0000
Quantile	**0.6**		**0.7**		**0.8**		**0.9**		**0.95**	
Long run estimate										
GDP	0.086247*	0.0824	0.068313*	0.1762	0.091711**	0.0457	0.100737	0.1202	0.143057*	0.0689
GDP^2	-0.021324*	0.0929	-0.017238	0.2049	-0.024556**	0.0507	-0.026016	0.1456	-0.032804	0.1160
GDP^3	0.001371*	0.0949	0.001151	0.2114	0.001715**	0.0471	0.001812	0.1274	0.002145	0.1187
REM*TI	0.000271**	0.0247	0.000257**	0.0080	0.000271**	0.0041	0.000321	0.0308	0.0005***	0.0001
REN	0.000591	0.8874	0.001054	0.7940	0.003533	0.3505	0.002559	0.7571	-0.008548	0.3198
FD	-0.006741	0.3115	-0.004259	0.4401	-0.005650	0.2671	-0.009991	0.2786	-0.0193**	0.0073
Short run estimate										
Δ GDP	-5.881769	0.4618	-5.998566	0.4060	-9.347445*	0.1678	-11.65792*	0.1407	-15.1286*	0.1814
ΔGDP^2	0.803427	0.4453	0.847862	0.3872	1.357016*	0.1435	1.665013*	0.1165	2.133374*	0.1587
ΔGDP^3	-0.034314	0.4511	-0.038531	0.3841	-0.064084*	0.1309	-0.077370*	0.1030	-0.09820*	0.1455
ΔREM*TI	-0.000132	0.7497	-0.000209	0.6029	-0.000282	0.3863	0.000195	0.7509	0.00108**	0.0110
Δ REN	-0.33488***	0.0000	-0.3698***	0.0000	-0.38702***	0.0000	-0.33867***	0.0000	-0.3189***	0.0000
ΔFD	0.019265**	0.0437	0.01870**	0.0435	0.024258**	0.0065	0.031512***	0.0004	0.0425***	0.0001
ECM4	-0.95261***	0.0000	-0.97487***	0.0000	-1.00607***	0.0000	-0.91778***	0.0000	-0.9464***	0.0000

Source: Author's statistical analysis: ***: Significant with 1%. **: Significant with 5%. *: Significant with 10%

which also found non-linear relationships between economic growth and environmental degradation. The interaction term REMTI (Remittance and Technological Innovation) displays mixed results across quantiles in the long run, highlighting the intricate nature of this relationship. The positive influence of REMTI on ecological footprints in certain quantiles suggests that technological innovation, when coupled with remittances, may have varying effects on environmental degradation. This finding contrasts with Yang *et al.* (2021), who reported more consistent effects of remittances and technological innovation on environmental outcomes. Additionally, it aligns with Martín-Ortega *et al.* (2024), who proposed an integrated approach to greenhouse gas mitigation through technological innovation, underscoring the potential for context-specific outcomes. The short-run analysis reveals variability in GDP's impact across quantiles, similar to findings by Husnain *et al.* (2023) regarding the multifaceted nature of short-term environmental impacts. This variability underscores the need for dynamic policy approaches that can adapt to varying short-term effects while working toward long-term sustainability goals. Moreover, the negative and statistically significant coefficient of ΔREMTI in the 10th quantile during the short run aligns with Yang *et al.'s* (2021) findings on the potential mitigating effect of the interaction between remittances and technological innovation on environmental degradation. This supports the notion that advancements in technology related to remittance transfers—such as mobile banking services—can contribute to both economic growth and environmental sustainability in top remittance-receiving economies. However, the inconsistency of REMTI effects across quantiles contrasts with more uniform findings by Aljadani *et al.* (2023) in their study of top remittance-receiving economies. This discrepancy highlights the need for further research into specific conditions under which remittances and technological innovation can effectively contribute to environmental sustainability. The positive repercussions of technological innovation combined with remittance inflows on economic benefits and environmental sustainability align with findings from Shahbaz *et al.* (2020) in the United Arab Emirates. However, mixed significance levels for technological innovation across quantiles suggest that its environmental impact may depend on specific types and applications of technologies, as well as broader economic and policy contexts. Overall, these findings underscore the complexity of relationships among financial development, renewable energy consumption, technological innovation, and their combined effects on ecological footprints in top remittance-receiving economies. They suggest that while certain economic factors can lead to improved environmental

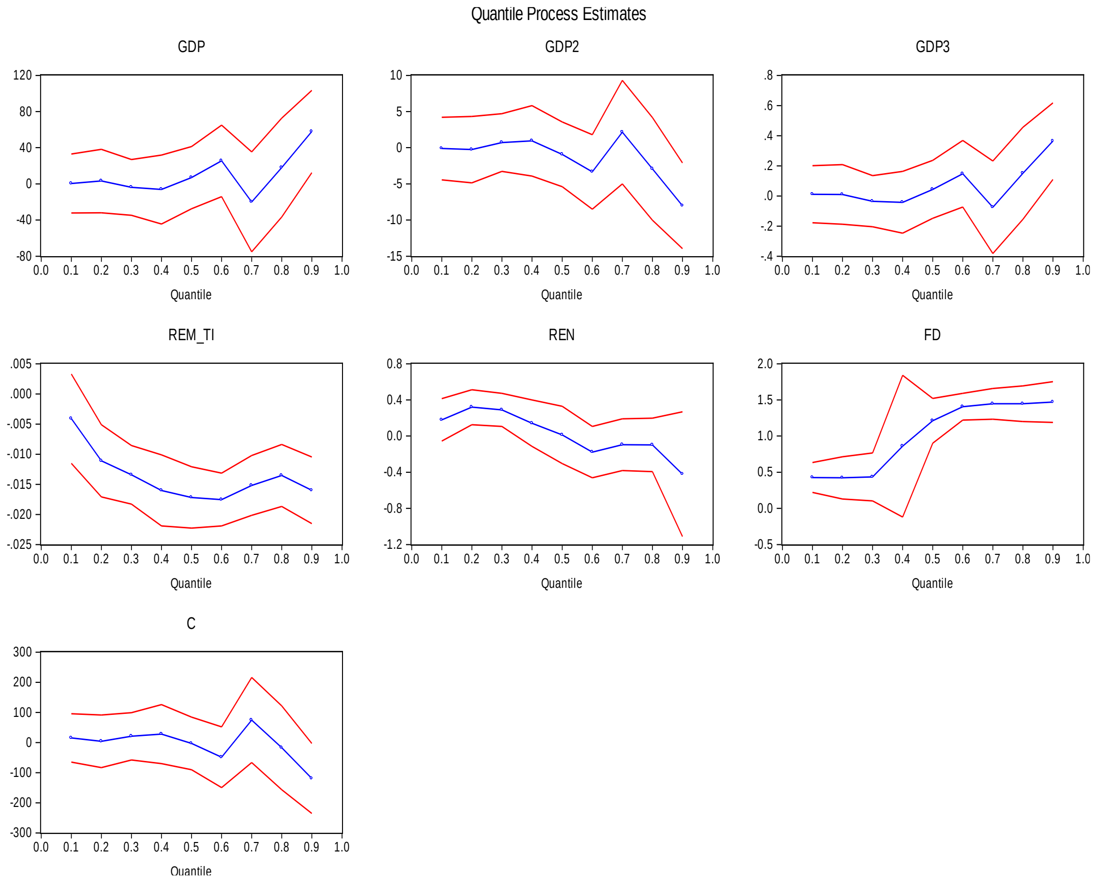

Fig 7. Quantile regression graph (model4)

outcomes under specific conditions, deviations from conventional EKC patterns highlight the need for more nuanced policy frameworks. Future research should focus on disentangling these complex relationships further and identifying specific conditions under which remittances and technological innovations can effectively promote environmental sustainability. Additionally, exploring potential synergies between these factors could provide valuable insights for policymakers aiming to balance economic development with ecological conservation. This revision improves clarity by streamlining sentences, enhancing coherence between ideas, and ensuring a logical flow throughout the discussion while maintaining a comparative analysis with relevant studies.

Our findings on the relationship between economic factors and ecological footprint in remittance-receiving economies align with recent studies on GHG emissions and sustainability efforts in various contexts. Tsepi *et al.* (2024) conducted a decomposition analysis of CO2 emissions in Greece from 1996 to 2020, revealing the complex interplay between economic growth, energy intensity, and emissions. Their findings underscore the importance of considering multiple factors in assessing environmental impact, like our multi-faceted approach to ecological footprint analysis. Moreover, our results on the role of renewable energy in reducing ecological footprint resonate with the findings of Losada-Puente *et al.* (2023), who analyzed energy communities in Spain, Italy, and Greece. Their cross-case analysis highlighted the progress, barriers, and future directions for community-based renewable energy initiatives. These initiatives not only contribute to reducing GHG emissions but also have the potential to significantly impact ecological footprints at local and regional levels. The varying impacts of financial development and technological innovation on ecological footprint across different quantiles in our study suggest that the effectiveness of mitigation strategies may differ based on the level of environmental degradation. This aligns with the MITICA framework proposed by Martín-Ortega *et al.* (2024), which emphasizes the need for tailored and transparent approaches to GHG mitigation. Our findings further support the idea that integrated strategies considering both mitigation and adaptation, as advocated in NAPs, are crucial for comprehensively addressing ecological footprint reduction.

In addition, our study's findings on the relationship between economic factors and ecological footprints in remittance-receiving economies can be contextualized within the broader framework of sudden, large-scale changes in human activity, as observed during the COVID-19 pandemic. Papadogiannaki *et al.* (2023) demonstrated that enforced changes in work patterns and travel behaviors during the pandemic led to significant reductions in carbon footprints. This aligns with our observations on the potential impact of technological innovation and changes in economic activity on ecological footprints. The pandemic-induced shifts, such as increased teleworking and reduced travel, mirror some of the technological and behavioral changes we've examined in our study. For instance, the reduced carbon footprint associated with virtual events and digitized processes during the pandemic parallels our findings on the potential of technological innovation to mitigate environmental pressures. This suggests that policy interventions promoting similar adaptations in remittance-receiving economies could yield substantial reductions in ecological footprints. Moreover, the rapid changes observed during the pandemic underscore the potential for swift policy responses to yield significant environmental benefits. This is particularly relevant to our findings on the varying impacts of financial development and remittances across different quantiles of ecological footprint. It suggests that targeted policies, informed by the lessons of the pandemic, could be especially effective in addressing environmental pressures in countries at different stages of economic development. However, it's important to note that the changes observed during the pandemic were largely the result of enforced restrictions rather than voluntary behavioral shifts. As we consider the long-term implications for policy in remittance-receiving economies, the challenge lies in translating these temporary changes into sustainable, long-term practices that can continue to reduce ecological footprints without compromising economic development.

Overall, these findings highlight the nexus relationships among financial development, renewable energy consumption, technological innovation, and their combined effects on ecological footprints in top remittance-receiving economies. The analysis reveals complex and often contradictory interactions between economic factors and environmental degradation. Financial development shows a positive relationship with environmental degradation across quantiles, suggesting that increased financial activity may lead to ecological harm, particularly in lower economic strata. GDP demonstrates a nuanced relationship with environmental quality, challenging traditional Environmental Kuznets Curve (EKC) hypotheses by showing non-linear and context-dependent effects. Renewable energy consumption consistently emerges as a promising factor in mitigating environmental degradation, exhibiting a negative relationship across both long-term and short-term analyses. In contrast, technological innovation presents a more ambiguous picture, with its environmental impact varying significantly across different quantiles and economic contexts. Remittance inflows further complicate the narrative, showing mixed effects that depend on specific economic and policy environments. These results underscore the need for targeted, context-specific policy approaches that consider the unique characteristics of each remittance-receiving economy.

Finally, the impact of remittance inflows on environmental outcomes in top remittance-receiving economies is complex and multifaceted, as evidenced by the inconclusive results across different quantiles in both long-term and short-term analyses. At the macroeconomic level, remittances can stimulate economic growth and alter economic structures, potentially leading to increased industrialization and consumption, which may have mixed environmental effects. They also contribute to financial development, which the study shows has a positive relationship with environmental degradation. At the microeconomic level, remittances increase household income, affecting consumption patterns and investment decisions. These can lead to both positive outcomes, such as investments in cleaner technologies and education, and negative ones, like increased consumption of energy-intensive goods or investments in polluting small-scale businesses. The mixed coefficients for remittance inflows across quantiles, as noted by Aljadani et al. (2023) and Yang et al. (2020a, 2021), suggest that these macro and micro processes interact differently depending on the level of environmental degradation and other contextual factors.

5. Conclusion and policy implications

This study investigates the impact of remittance inflows, technological innovation, renewable energy adoption, and financial development on the ecological footprint in top remittance-receiving countries, employing a comprehensive approach that incorporates six environmental indicators. Utilizing panel data from 1990 to 2022 and advanced econometric techniques, including the Panel Quantile Autoregressive Distributed Lag (PQARDL) approach, our findings challenge the universal applicability of the Environmental Kuznets Curve (EKC) hypothesis and reveal complex interactions among variables. The study highlights the potential of remittances and technological innovation in reducing ecological footprints when strategically leveraged, aligning with recent research on integrated approaches to greenhouse gas mitigation. The significance of renewable energy in mitigating environmental impacts is underscored, consistent with studies on energy communities and their role in sustainability. Our analysis of short-term dynamics reveals the need for flexible policy approaches, reflecting the complex relationship between economic factors and environmental degradation observed in recent decomposition analyses. The role of financial development in environmental sustainability contributes to ongoing debates, with our findings suggesting the need for careful consideration of financial policies in environmental management, particularly in the context of changing work patterns and travel behaviors as observed during the COVID-19 pandemic. These insights call for holistic policy approaches that balance economic growth with environmental conservation, including the integration of climate mitigation and adaptation strategies, promotion of renewable energy, leveraging of remittances and technological innovation for sustainable development, and implementation of context-specific interventions. Our study also emphasizes the importance of considering rapid policy responses and behavioral changes, as demonstrated during the pandemic, in formulating long-term strategies for reducing ecological footprints. Future research should explore the long-term implications of these complex relationships and the potential for translating pandemic-induced changes into sustainable practices to further inform sustainable development strategies in remittance-receiving economies.

6. Future Work and Research Directions

Future work and research directions could focus on several areas to advance understanding of the complex interplay between economic dynamics and ecological sustainability in remittance-dependent economies. Firstly, exploring the causal mechanisms underlying the observed relationships through rigorous causal inference methods, such as instrumental variable approaches or natural experiments, could provide deeper insights into the pathways through which financial development, renewable energy adoption, and technological innovation influence ecological footprints. Secondly, investigating the role of governance structures and institutional frameworks in moderating the impact of economic variables on environmental outcomes could shed light on the importance of policy interventions in shaping sustainable development trajectories. Additionally, incorporating spatial analysis techniques to account for spatial heterogeneity and spatial spillover effects could enhance the accuracy of modelling ecological footprints. Moreover, considering the role of social factors, such as education levels, cultural norms, and social capital, in shaping environmental behaviors and outcomes could provide a more holistic understanding of sustainable development processes. Lastly, exploring how emerging trends, such as climate change adaptation and mitigation strategies, circular economy initiatives, and green finance mechanisms, intersect with economic dynamics to influence ecological sustainability could offer valuable insights for designing evidence-based policies aimed at promoting sustainable development in remittance-dependent economies.

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Data availability: All data are available upon request.

Contributions: S.T.: Enhance and refine the study's design, streamline data collection processes, and improve the accuracy of calculations to facilitate manuscript preparation.

Competing interests: The author declares no competing interests.

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