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Nexus between Blue Economy, Renewable Energy and Environmental Sustainability in the MENA Region: Evidence from Panel Threshold Regression

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ABSTRACT

This paper attempts to investigate the relationship between blue economic activities, renewable energy and the ecological footprint in the MENA region from 2000 to 2022. The study utilizes the STRIPAT model, thus, the methodology involves multiple econometric techniques such as cointegration tests, quantile via moment, threshold regression and panel Granger causality test. Estimates confirm a significant negative impact of renewable energy consumption and innovations on the ecological footprint, while the effect of the total fisheries production, GDP per capita as well as urban population growth on the ecological footprint is positive and consistent across the study period. The findings reveal the role of extensive economic activities, extensive seas and oceans activities and urbanization as major drivers of environmental damages and the subsequent increase in ecological footprints. Therefore, by promoting sustainable practices and renewable energy utilization, MENA countries can effectively mitigate their ecological footprints and contribute to global climate change mitigation efforts. The study also emphasizes on the significance of sustainable practices and the need for comprehensive policy measures to mitigate the ecological footprint and promote a more environmentally conscious society.

Keywords: Blue Economy, Renewable Energy, Middle East and North Africa, Panel Threshold
JEL Classifications: C21, C24, Q42, Q56

1. INTRODUCTION

The blue economy and renewable energies are closely interrelated and both contribute to environmental sustainability, since the use of renewable energy sources is essential to achieve sustainable development of economic sectors linked to the sea (Wright, 2014; Barr et al., 2021). Renewable energies can contribute to reducing the carbon footprint of maritime sectors (Serri et al., 2017; Fusco et al., 2022)[1]. Blue economy and energy technology trends are intersecting, building potential for future collaboration across sectors (Geerlofs, 2021).

1 Such as wind, solar, hydro and tidal energy, are energy alternatives to fossil fuels.

Renewable energy plays a vital role in the development of the blue economy by providing economic and environmental advantages, reducing carbon emissions and supporting sustainable growth (Kathijotes and Sekhniashvili, 2017). It is suggested by Puspaningtyas (2022) that the utilization of offshore renewable energy facilitates the emergence of new industries and employment opportunities. By incorporating renewable energy into the blue economy, CO_2 emissions can be effectively decreased and stimulate economic expansion. Furthermore, renewable energy is essential for advancing economic prosperity, environmental sustainability, and the responsible utilization of resources within the blue economy.

The blue economy plays a crucial role in fostering global sustainable development through the oceans (Mohan et al., 2020; Elegbede et al., 2023). Its conception rests upon the sustainable exploitation of oceanic resources to stimulate economic expansion, enhance employment opportunities, improve living conditions and safeguard the integrity of the ocean's ecosystem (Schutter et al., 2021). According to Bennett et al. (2019), marine and coastal ecosystems offer an extensive array of goods and services to humanity, encompassing nourishment, raw materials, renewable energy, transportation and tourism. Moreover, they play a fundamental role in confronting the challenges posed by climate change. As highlighted by Ehlers (2016), the blue economy aims to promote economic growth, and improve life and social inclusion without compromising the oceans' environmental sustainability and coastal areas.

As projected by the International Monetary Fund (IMF), global economic growth would increase from an estimated 2.9% in 2019-3.3% in 2020 and 3.4% in 2021 (IMF, 2020). However, the COVID-19 pandemic led to a revision of this projection (OECD and FAO, 2018). Within this context, in the absence of suitable mitigation policies, the International Maritime Organization (IMO) estimates that greenhouse gas emissions associated with the shipping sector could grow by 50-250% by 2050 (IRENA, 2020). Overall, around 80-90% of internationally traded goods, totaling 8.7 gigatonnes, are transported by ship, representing 9.3% of carbon dioxide emissions linked to the transport sector. An IMO greenhouse gas study found that, between 2007 and 2012, shipping was responsible for an average of 2.8% of annual greenhouse gases on a CO_2-equivalent basis (IMO, 2014). In March 2023, a historic agreement was reached at the United Nations for a High Seas Treaty which aims to place 30% of the world's oceans to protect wildlife and ensure equal access to marine genetic resources (IEA, 2023).

The degradation of the environment in the skies and seas has significant economic implications for several economies in the MENA region. Studies indicate that air pollution alone costs an average of 2% of GDP in MENA economies, with the range varying from 0.4% in Qatar to over 3% in Egypt, Lebanon, and Yemen (World Bank, 2022a). Moreover, coastal erosion poses a threat to industries like tourism and fishing, which depend on healthy and clean seas (NOC, 2021). The average annual cost of coastal erosion in Morocco, which is most affected by this issue, is estimated to be 0.6% of GDP, ranging from 0.2% in Algeria to 2.8% in Tunisia. Additionally, the economic impact of marine plastic pollution is significant, with an average cost of around 0.8% of GDP. In countries like Djibouti, Tunisia, and Yemen, this cost exceeds 2% of GDP (World Bank, 2022b).

Recent studies witnessed a surge in the presence of the blue economy in the international arena, linking it to traditional economic activities to foster its efficiency and sustainability and mitigating the greenhouse effect and global warming (Voyer et al., 2020; March et al., 2023). In the related literature, there are studies with different orientations, which include analyzing the impact of the blue economy on aquaculture activities (Campbell et al., 2021; Wiber et al., 2021), maritime transport (Niavis et al., 2017; Tijan et al., 2021), fishing (Fondo and Ogutu, 2021; Sihombing et al., 2022), tourism (March et al., 2019; Rogerson and Rogerson, 2019; Karani and Failler, 2020) and marine biotechnology (Choudhary et al., 2021; Venugopal, 2022).

Following this line of thought, this study aims to investigate the nexus among the blue economy, renewable energy and environmental sustainability within the MENA region from 2000 to 2022. In what follows, Section 2 reviews the related literature that sets out background about the topic. Section 3 provides data and methodology. Section 4 explains the design and construction of the empirical model. Section 5 presents results and discussions. Whilst the final section presents some conclusions.

2. REVIEW OF LITERATURE

The Blue Economy has become a crucial factor in driving the economic development of nations. Many coastal countries are focusing on enhancing the efficient utilization of marine resources, including marine space (Plink et al., 2021). It is mentioned by Joroff that "the concept of using ocean resources in a way that respects the environment can evaluate how both business activity models and new technologies satisfy economic and environmental conditions, contributing to the sustainability of these resources" (Joroff, 2009, p. 171). The European Union (EU) introduced the Intra Maritime Policy (IMP) as part of its 2020 Strategy to promote sustainable and inclusive growth in the blue economy[2]. The principles of the 2020 Strategy emphasize sustainable and environmentally friendly ocean management and economic activities (Sulanke and Rybicki, 2021).

Marine ecosystems offer resources that directly and indirectly contribute to economies and provide ecosystem services for human well-being (Park and Kildow, 2015; Phelan et al., 2020; Roberts et al., 2021). Furthermore, the OECD recognized in "The Ocean Economy in 2030" report that offshore wind power is projected to become the primary source of energy, while commercial shipping is expected to quadruple by 2050 (OECD, 2016). These actions are expected to increase investments in coastal infrastructure, industry and tourism. With an annual economic value estimated at US$2.5 trillion, the 'blue economy' is equivalent to the world's 7th largest economy (World Bank, 2017).

Several previous studies have integrated various perspectives on the blue economy and provided a comprehensive concepts that incorporate sustainability, productivity and development. For example, Martínez-Vázquez et al. (2021) emphasized that maintaining a balance in the capacity and resilience of ocean systems supports a sustainable environment. Whisnant and Vandeweerd (2019) noted that technological advancements, appropriate regulatory policies, tax deductions and research and development (R&D) efforts are pathways to conserve energy and the environment. Kontovas et al. (2022) argued that boosting blue growth while considering ecological, social, and economic sustainability is essential for maximizing societal benefits from ocean resources. Upadhyay and Mishara (2020) confirmed the role of the BE in sustainable and inclusive development.

In recent years, the environment and the global energy sector have received significant attention in the literature, with a particular

2 The IMP selected five key sectors for development: biotechnology, renewable energy, coastal and maritime tourism, aquaculture, and mineral resources, along with emerging subsectors.

emphasis on the geopolitical factors influencing long-term energy production. The International Energy Agency's (IEA) projections on new renewable energy have been scrutinized and criticized in terms of their impact on economic growth, technological advancements, investment opportunities and sustainability of the environment (IEA, 2023). The debate surrounding renewable energy, CO_2 emissions, blue economy has become an intriguing topic in economic literature for both developed and developing countries. Economists, governments and policymakers are actively figuring out methods to ensure a sustainable and healthy environment. Various studies, such as those by (Kumar et al., 2014; Gevorkyan, 2017; Gielen et al., 2017; Koçak and Sarkgüne, 2017; Zoundi (2017); Akbar et al., 2020; Liu et al., 2020 and Khan et al., 2021), have contributed extensive literature on the economic development of renewable energy sources. Another batch of literature focused on oceans amongst (Kaczynski, 2011; De la Vara et al., 2020; Fratila et al., 2021; Roberts et al., 2021) and others. Several studies were country-specific oriented such as the work of (Shahbaz et al., 2013; Kadir and Sibe, 2014; Tang and Tan, 2015; Ahmad et al., 2017; Sulanke and Rybicki, 2021; Hafez et al., 2023) and others.

The future of energy, as suggested by Gielen et al. (2019), lies in technologies associated with renewable energy resources and energy efficiency. They predicted that these technologies will become the leading tool by 2050. (Chontanawat et al., 2008; Chaabouni and Saidi, 2017; Ernst et al., 2018; Bulut and Inglesi-Lotz, 2019; Gielen et al., 2019 and Zheng and Wang, 2021) examined the relationship between energy consumption, economic growth, and environment and found positive connections among these variables. Apergis and Payne (2010) and Kahia et al. (2017) are among the researchers who have advocated for greater investment in renewable energy sources.

Numerous empirical studies have incorporated various variables into the theoretical framework of the energy-sustainability relationship. However, the findings from these analyses have been inconsistent. The majority of existing studies have predominantly focused on linear models. However, due to conflicting results regarding the relationship between the energy, blue economy and the environment, it is necessary to introduce nonlinearity into the empirical methodology. Some researchers have found a positive association, as indicated by studies Chen et al. (2017) and Wang et al. (2019), while others report the opposite Ren et al. (2018) and Wu (2018).

3. DATA AND METHODOLOGY

3.1. Data

The primary aim of this study is to examine the relationship between the blue economy, renewable energy and environmental sustainability. To accomplish this, annual panel data from the Middle East and North Africa (MENA) region, including Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates (UAE) and Yemen, for the period ranging from 2000 to 2022. Analyzing the relationship between the blue economy, renewable energy and environmental sustainability in the MENA region can provide valuable insights into the effectiveness of policies and identify areas for improvement in the region and beyond, this is owed to various motives: (1) The MENA region is strategically located, encompassing countries with access to both the Mediterranean Sea and the Red Sea, that makes it focusing on sustainable economic activities related to oceans, seas and coastal areas. The region's coastline, marine resources and proximity to major international shipping routes provide a unique context for investigating the interplay between the blue economy, renewable energy and environmental sustainability. (2) The MENA region is known for its abundant renewable energy resources, particularly solar and wind energy. It has vast deserts with high solar irradiance and strong winds in coastal areas, making it a prime location for large-scale renewable energy projects. This allows for an examination of how these resources can be harnessed to drive sustainable economic development while reducing dependence on fossil fuels and mitigating climate change. (3) The MENA region faces a range of environmental challenges, including water scarcity, land degradation, pollution and vulnerability to climate change. These challenges pose significant risks to the region's ecosystems, biodiversity, and socio-economic stability. (4) Many countries in the MENA region have traditionally relied on oil and gas exports as a major source of revenue. However, there is a growing recognition of the need to diversify their economies and reduce dependence on finite fossil fuel resources. (5) The region has witnessed various policy initiatives and investments aimed at promoting renewable energy and sustainable development. Governments in the region have implemented renewable energy targets, established regulatory frameworks and launched initiatives to attract investments in the blue economy. Selected variables, descriptions and data sources are presented in Table 1 below.

Initially, it is essential to present the descriptive statistics of the selected variables, this helps in identifying any irregularities within the data series, such as outliers. The depiction of the selected variables is computed through some descriptive measures. Based on the provided descriptive statistics as illustrated in Table 2, the following can be concluded: The mean of the dependent variable (ECF) is 4.1, indicating that, on average, each individual's per capita consumption contributes to an ecological footprint of 4.1 units. With a minimum value of 0.1 and a maximum value of 16.0, this wide range of ECF values, suggests significant variations in ecological footprints across the studied population. The positive skewness (skewness =1.2) indicates that the distribution of ECF is skewed towards higher values, suggesting that a relatively small proportion of individuals may have significantly higher ecological footprints compared to the majority. The high kurtosis (kurtosis =3.3) implies that the distribution has heavy tails and potential outliers, indicating the presence of extreme values in the data. While, the median (p50) ECF value is 2.2, meaning that half of the observations fall below this value. The standard deviation of ECF is 3.8, suggesting a relatively large dispersion of data points around the mean.

Concerning the independent variables, FP has a wide range from 0.981 to 2205.649, suggesting substantial variations in the quantity of fishery resources. RE has a mean of 4.6 of total final energy consumption, indicating differences in the adoption and utilization of renewable energy sources. GDP has a mean of 12118.6 with a minimum value of −8.9 and a maximum value of 73493, reflecting substantial differences in economic development and living standards across the countries studied. UPG ranges from −8.8 to 19.6, while, CE and INOV have means of 111,604.5 and 1040.7 respectively. It's worth noting that all variables show varying degrees of skewness and kurtosis, indicating deviations from a normal distribution and skewed distributions with heavy tails.

The correlation analysis is performed to reveal the relationships between the variables. The correlation matrix of the data is presented in Table 3. The negative correlation between ECF, FP, RE, and INOV suggests that higher levels of fisheries production, renewable energy consumption and patent applications are associated with lower per capita ecological footprints. This could imply that sustainable fisheries practices, increased use of renewable energy and innovation in environmentally friendly technologies contribute to lower ecological footprints. ECF has a positive correlation with GDP and UPG, suggesting that higher GDP per capita and urban population growth are associated with higher ecological footprints. This indicates that economic growth and urbanization may lead to increased consumption and resource usage, resulting in larger ecological footprints. Among independent variables, there is no strong correlation, indicating that multicollinearity may not be a major concern in the regression analysis.

To check the multicollinearity, the variance inflation factor (VIF) is adopted to assess multicollinearity among the independent variables. As indicated in Table 4, the VIF values for all variables are <10, indicating that there is no severe multicollinearity among assigned variables. This suggests that the independent variables are not highly correlated with each other, which strengthens the reliability of the regression analysis. The interpretations and analysis of the selected data provide insights into the characteristics and relationships of the variables, shedding light on potential factors influencing environmental sustainability. Further analysis and modeling can be performed to investigate these relationships in more depth and draw meaningful conclusions.

Table 1: Variable definitions and data sources. Annual data (2000-2022)

Abbreviation	Description	Source
Dependent variable		
ECF	Ecological footprint: per capita consumption	Global hectares: Global Footprint Network (GFN). Available at: https://data.footprintnetwork.org/
Independent variables		
FP	Total fisheries production (metric tons)	Food and agriculture organization (FAO).
RE	Renewable energy consumption (% of total final energy consumption)	IEA, IRENA, UNSD, World Bank, WHO. 2023. Tracking SDG 7: The energy progress report. World Bank, Washington DC.
GDP	GDP per capita (constant 2015 US$)	World Bank national accounts data, and OECD National Accounts data files.
CE	Carbon emissions (CO_2 emissions [kt])	Climate Watch Historical GHG Emissions (1990-2020). 2023. Washington, DC: World Resources Institute. Available at
UPG	Urban population growth (annual %)	World Bank staff estimates based on the United Nations Population Division's World Urbanization Prospects: 2018 Revision.
INOV	Patent applications, (residents plus nonresidents)	World Intellectual Property Organization (WIPO), WIPO Patent Report: Statistics on Worldwide Patent Activity.

Table 2: Summary statistics

Stats	ECF	FP	RE	GDP	CE	UPG	INOV
Mean	4.1	244.469	4.6	12118.6	111604.5	3.0	1040.7
p50	2.2	65.719	1.1	4067.2	55143.2	2.5	281.0
Min	0.1	0.981	0.0	−8.9	373.4	−8.8	1.0
Max	16.0	2205.649	34.6	73493.3	637433.7	19.6	16259.0
SD	3.8	439.021	7.8	16709.3	146105.9	3.0	2534.8
Skewness	1.2	2.2	2.4	2.1	2.2	1.9	4.2
Kurtosis	3.3	7.2	8.4	6.4	7.0	12.0	21.1
N	414	414	414	414	414	414	414

Source: Authors' estimation (statistical work is performed using STATA version 19)

Table 3: Cross-correlation table

	Correlations						
Variables	ECF	FP	RE	GDP	CE	UPG	INOV
ECF	1						
FP	−0.315−**	1					
RE	−0.347−**	0.097*	1				
GDP	0.832**	−0.207−**	−0.308−**	1			
CE	−0.095	0.362**	−0.289−**	0.031	1		
UPG	0.394**	−0.131−**	−0.199−**	0.358**	−0.068	1	
INOV	−0.213−**	0.477**	−0.112−*	−0.059	0.781**	−0.088	1

**Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

Source: Authors' estimation (statistical work is performed using STATA version 19)

For further analysis of the data at hand, Figures 1 and 2 represent averages of ECF, FP, and CE (2000-2022) for countries and the region respectively. Based on the provided data, one can note that Qatar and UAE have the highest ECF values of 13.02 and 10.41 respectively indicating higher consumption patterns and energy demand. This is attributed to factors like industrialization and development. While, Yemen and Iran have the lowest ECF values of 0.82 and 0.11, respectively, suggesting a higher emphasis on environmental conservation. Average values of ECF values show a gradual decrease over the years.

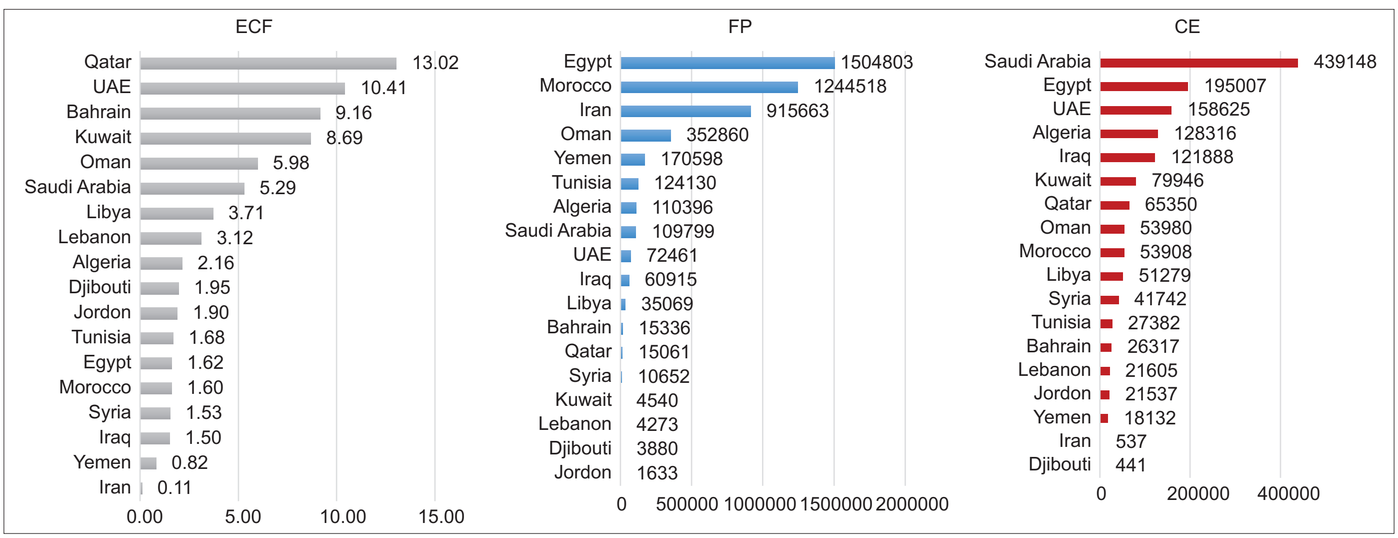
Egypt and Morocco have the highest FP, compared to Djibouti and Jordon as they count the lowest values. Egypt and Morocco are geographically positioned along coastlines with access to large bodies of water, such as the Mediterranean Sea and the Atlantic Ocean, providing favorable conditions for fishing activities and abundant fish populations. On the other hand, Djibouti and Jordan have limited access to large bodies of water and face challenges such as geographical constraints, limited coastline and potentially smaller fish populations. FP average values are increasing over the studied period for the MENA regions as a whole. The increasing average values of FP in the MENA region as a whole over the studied period is due to several factors such as advancements in technology and fishing methods, investments and development of fishing ports and processing facilities, as well as, increased awareness of the economic potential of the fishery industry and population growth.

On the contrary, Saudi Arabia, Egypt and UAE spiked the highest CE values, whereas, Yemen, Iran and Djibouti scored the lowest. Which is aligned with the same patterns and reasons of the ECF. For the entire region, the CE values are continuously rising then showing a gradual decrease over the last years. This decreasing trend implies a potential decline in carbon emissions, indicating progress in addressing environmental concerns.

3.2. Methodology

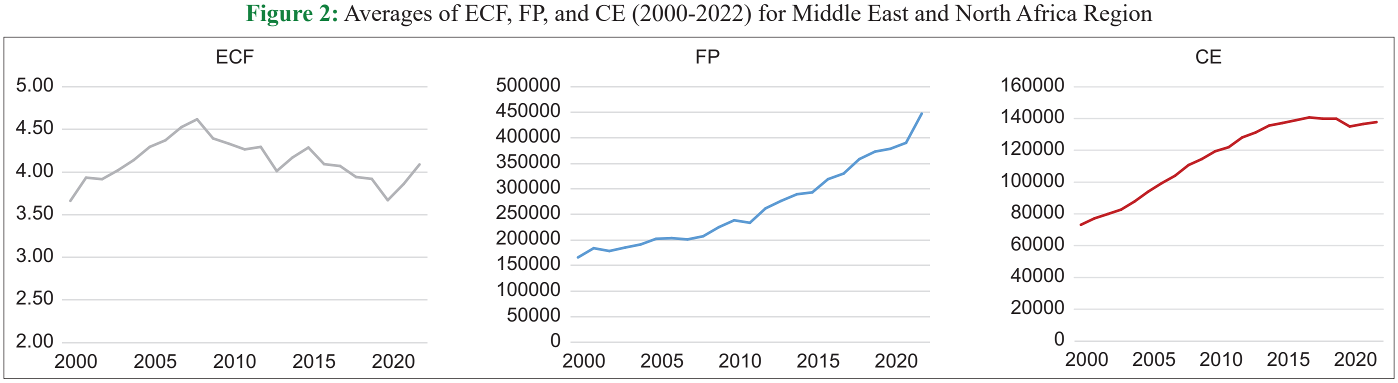
Historically, The IPAT model introduced by Ehrlich and Holdren (1971) was specifically designed to analyze the factors influencing changes in urban eco-efficiency. The model specification includes the following variables: (1). Population (*P*): this variable represents the size of the population and its potential impact on the environment. It accounts for the number of individuals and their consumption patterns, which can contribute to environmental degradation. (2). Affluence (*A*): refers to the level of economic activity and wealth within a given population. It captures the overall standard of living, including income, consumption patterns, and resource use. Higher levels of affluence are generally associated with increased environmental impact. (3). Technology (*T*): represents the level

Figure 1: Averages of ECF, FP, and CE (2000-2022) for countries



Source: Author"s preparation using data sources listed in Table 1

Figure 2: Averages of ECF, FP, and CE (2000-2022) for Middle East and North Africa Region



Source: Author"s preparation using data sources listed in Table 1 of technological development and innovation within a society. It includes factors such as the efficiency of production processes, energy consumption, and resource management. Technological advancements can either mitigate or exacerbate environmental impacts, depending on how they are utilized. represents the environmental impact. This model is explained as follows:

$$I = P \times A \times T \tag{1}$$

Several studies such as Dietz and Rosa (1994), Dietz and Rosa (1997), Waggoner and Ausubel (2002), Chertow (2008) and Sohag et al. (2015) used this model to investigate the interactions between populations, economic growth and technological development. However, it is important to note that the IPAT model also has its drawbacks. Since these statistical associations do not reflect the causal effects among the variables. Therefore, the Stochastic Regression on Population, Affluence and Technology (STIRPAT) model by Dietz and Rosa (1997) was developed as an improvement over the IPAT, to overcome its limitations and allow for empirical hypothesis testing. By incorporating statistical analysis, the model enables researchers to test hypotheses and examine the causal relationships between these variables and changes in urban eco-efficiency. Researchers such as (York et al., 2003; Fan et al., 2006; Wei, 2011; Li et al., 2015; Chu et al., 2016; Ghazali and Ali, 2019; Li et al., 2019; Farazmand et al., 2020; Nasrollahi et al., 2020; Nosheen et al., 2020; Shixiang et al., 2020; Arshed et al., 2021; Montero et al., 2021; Thio et al., 2022; Manocha, 2023) have employed the STIRPAT model to investigate the factors influencing changes in urban eco-efficiency. This model provides a more robust framework for understanding the complex dynamics between population, affluence, technology, and their environmental implications. The STIRPAT model specification is as follows:

$$I_i = \alpha\, P_i^{\beta} A_i^{\gamma} T_i^{\delta}\, \varepsilon_i \tag{2}$$

Where, α is the constant term; β, γ and δ are parameters to be estimated and ε is the error term. A represents affluence measured by GDP per capita, P is population measured by the number of inhabitants, while T denotes technology changes' proxies are industrial activity calculated by the share of the manufacturing industry in total GDP and energy efficiency measured by GDP per unit of energy use. Estimated values of P, A and T vary across countries represented by i. To address the skewness of the distribution and make equations tractable, the log form of STRIPAT is employed, this involves taking the natural logarithm of both sides of the equation as follows:

$$lnI_i = \alpha_0 + \beta \ln\left(P_i\right) + \gamma \ln\left(A_i\right) + \delta \ln\left(T_i\right) + \mu_i \tag{3}$$

Where $lna = \alpha_0$ and $ln\varepsilon_i = \mu_i$, these forms allow measuring the environmental impact for each factor directly. The STIRPAT model has been previously used to examine the impact of explanatory variables on the environment. However, there is no consensus on the significance of these factors. Therefore, this study aims to estimate the following equations to determine their significance. The model analyzes the relationship between ecological footprint and various factors including fishery production, renewable energy, GDP per capita, carbon emissions, urban population and innovation. Thus, the functional form of the equation can be written as follows:

$$\begin{aligned} \ln ECF_{it} &= \alpha_i + \lambda_t + \beta_1 lnFP_{it} + \beta_2 lnRE_{it} + \beta_3 lnGDP_{it} \\ &+ \beta_4 lnCE_{it} + \beta_5 lnUPG_{it} + \beta_6 lnINOV_{it} + \vartheta_{it} \end{aligned} \tag{4}$$

Where the dependent variable in this model is ECF measured in per capita consumption, α_i and λ_t are country and time specific effects respectively, which are used to control for unobservable country heterogeneity and for common time-varying effects that could affect footprints.

4. MODEL CONSTRUCTION

To provide insights into the dynamics of the data structure, the homogeneity or lack thereof within the data is examined. Since panel data is utilized, it is crucial to investigate the presence of cross-sectional dependence. If no cross-sectional dependence is detected, first-generation unit root and cointegration tests are proceeded. Conversely, if cross-sectional dependence is observed, it indicates the need to employ second-generation unit root tests. Subsequently, to investigate the existence of second cross-sectional dependence, the Pesaran scaled-LM and the Pesaran CD tests are employed, as presented by Pesaran (2004). Furthermore, to conduct the second-generation unit root test, the second-generation Cross-Sectionally Augmented IPS (CIPS) and Cross-Sectionally Augmented Dicky-Fuller (CADF) tests are adopted. Upon verifying the stationarity at the first difference, the cointegration test is conducted to determine the presence of a long-run relationship between the variables under study. In this regard, the second-generation cointegration test and Westerlund cointegrations are employed. Upon confirming the existence of a long-run relationship, the study employs appropriate regression approaches to examine the impact of the independent variables on the dependent variable. Multiple regression techniques such as quantile via moment, Driscol Karaay regression and estimations with threshold were employed to validate and reinforce the empirical findings of this study.

4.1. Panel Quantile Regression

Due to the limitations of ordinary least-squares (OLS) regression (Koenker and Bassett Jr 1978; Canay, 2011; You et al., 2015), a panel quantile regression technique was presented to examine the distributional and heterogeneous effect of the different factors across different quantiles. This method is particularly relevant in scenarios where the relationship between the variables of interest exhibits little to no correlation in terms of their conditional means. One notable advantage of quantile regression is its robustness to outliers during the estimation process. This means that extreme observations in the data do not unduly influence the estimation results, making it a reliable tool for analyzing datasets with potential outliers. In this study, a specific variant of quantile regression known as the Method of Moments Quantile Regression (MMQR) developed by Machado and Silva (2019) is employed to address the issue of unobserved heterogeneity. The first GMM estimator uses a fixed grid of quantiles, while the second uses a number of quantiles that diverge along with the sample size. By explicitly revealing the conditional heterogeneity covariance effects of the determinants of ecological footprint, the MMQR methodology allows for individual influences to impact the entire distribution of the dependent variable, rather than just the average values as in the case of Koenker (2004), Geraci and Bottai (2007), Chen and Westgate, (2020). The estimation of the conditional quantiles $Q_Y(\tau|X)$ takes the following form:

$$Y_{it} = \alpha + X_{it}^{'}\beta + (\delta_i + Z_{it}^{'}\gamma)U_{it} \tag{5}$$

Where the probability $P\left\{\delta_i + Z_{it}^{'}\gamma > 0\right\} = 1$ and $(\alpha, \beta^{'}, \delta, \gamma^{'})'$ are parameters to be estimated. (α_i, δ_i), $i = 1,\ldots,n$ designated the individual i fixed effects and Z is a k-vector of identified components of X which are differentiable transformations with elements l given by:

$$Z_l = Z_l(X).\ l = \alpha,\ldots,k \tag{6}$$

X_{it} is independently and identically distributed for any fixed i and is independent across time t. U_{it} is independently and identically distributed across individuals i and through time t and is orthogonal to X_{it} and normalized to satisfy the moment conditions in Machado and Silva (2019), as implied in the following equation:

$$Q_Y(\tau|X) = \left(\alpha_i + \delta iq(\tau)\right) + X'_{it}\beta + Z_{it}^{'}\gamma q(\tau) \tag{7}$$

Whereas $Q_Y(\tau|X)$ indicates the quantile distribution of the dependent variable Y_{it} that is the logarithm of the ecological footprint per capita consumption and is conditional on the independent variable X_{it}. $\alpha_i + \delta iq(\tau)$ is the scalar coefficient which is indicative of the quantile τ fixed effect for individual i.

4.2. Threshold Regression

This study claims that there exists a nonlinear association between blue economy, renewable energy and environmental sustainability. Nevertheless, the distributions of the Conditional Quantile Regression (CQR) approach are defined as conditional on specific covariates, which points to a critical limitation that it cannot fully capture dependence structures (Wenz, 2014; Porter, 2015; Dong et al., 2020; Alejo, 2021). As a result, Firpo et al. (2009) developed the Unconditional Quantile Regression (UQR), a simple regression framework that is similar to a standard regression except that the dependent variable Y is replaced by the re-centered influence function (RIF) of the statistic of interest. They proposed an approximation to the functional form of the RIF conditional expectation, that the parameters correspond to a change in the covariates. In particular, as explained in Fortin et al. (2011), the RIF regression allows for using regression type tools, such as Oaxaca-Blinder type decompositions. However, this is only an approximation to a potentially nonlinear function, as such it may fail to appropriately describe the marginal effects. UQR has the ability to incorporate fixed effects to address selection bias without requiring the redefinition of quantiles (Huber and Ronchetti, 2009). Another notable feature of UQR is defining quantiles before regression. It introduces a new regression model that examines the impact of explanatory variables on quantiles of the unconditional marginal distribution of the dependent variable, as demonstrated by Killewald and Bearak (2014). To analyze the potential nonlinear relationship between the blue economy and the ecological footprint, the baseline-panel regression model is adopted from Hansen (1999):

$$Y_{it} = \alpha_i + \delta q_{it} + \beta_i X_{it} + \varepsilon_{it} \tag{8}$$

Where Y_{it} represents ecological footprint in the country i for period t, while, α_i and ε_{it} represent country-specific fixed effect and random errors respectively. While q_{it} refers to the level of fishery production for each country in the sample during time t. X_{it} represents a k dimensional vector of the control variables. To operate with one threshold, the following form is considered:

$$Y_{it} = \mu_i + \beta'_1 x_{it} I\left(q_{it} \le \gamma\right) + \beta'_2 x_{it} I\left(q_{it} > \gamma\right) + \beta_i X_{it} + \varepsilon_{it} \tag{9}$$

Whereas, γ is is the threshold variable that demarcates the two regimes, I denotes to the indicator function for the two regimes with different regression slopes β'_1 and β'_2. To assess the validity of the threshold model, through comparing it with its corresponding linear values, F statistic is provided:

$$F_1 = \frac{S_0 - S_1}{\hat{\sigma}^2} \tag{10}$$

Where S_0 is the residual sum of squared of errors of the linear model, S_1 is the residual sum of squared errors of the panel threshold estimate model and $\hat{\sigma}^2$ is the residual variance of the panel threshold estimation. The null hypothesis of the non-identification of γ and its associated alternate hypothesis of the existence of at least one threshold are given as follows:

$$H_0 : \beta'_1 = \beta'_2 \text{ and } H_A : \beta'_1 \ne \beta'_2 \tag{11}$$

Referring to (Shao and Shen, 2017; Xie et al., 2017; Wang and Shao, 2019 and Hao et al., 2020), the panel threshold model is constructed with two threshold variables as follows:

$$\begin{aligned} lnECF_{it} &= \alpha + \beta_1 lnx_{it} xI\left(q_{it} \le \gamma\right) + \beta_2 lnx_{it} xI\left(q_{it} > \gamma\right) \\ &+ \sum_{i=1}^{4} X_{it} + \varepsilon_{it} \end{aligned} \tag{12}$$

Where EFP_{it} is the dependent variable, x_{it} is the independent variable, which is uncorrelated with the error term ε_{it}. While q_{it} are threshold variables representing blue economy measured by FP (metric tons) and renewable energy measured by RE (% of total final energy consumption), γ are the threshold values, β_1 and β_2 are the regression slopes of different regimes X_{it} is the vector of the control variables, which are GDP, CE, UPG and INOV, and subscripts $i$and t denote country and the yar, respectively.

4.3. Panel Granger Causality Test

Granger (1969) developed a procedure for analyzing the causal relationships between time series. Suppose and are two stationary series. The model is written as follows:

$$y_{it} = \beta_{0i} + \sum_{0=1}^{p} \beta_{pi} Y_{it-p} + \sum_{q=1}^{Q} \delta_{qi} X_{it-q} + \varepsilon_{it}\ with\ t = 1,\ldots,T \tag{13}$$

This model is used to test whether x causes y. Essentially, if past values of x are significant predictors of the current value of y, even when past values of y have been included in the model.

Then x exerts a causal influence on y. Where, i is the number of countries, T is the times, and t ranges from 1 to T. In addition, $\varepsilon_{it} =\sim N(0,\sigma^2)$ and β_{pi} the coefficients of the autoregressive term, whereas δ_{qi} is the coefficient of the feedback term. Thus, one might easily investigate this causality based on an F test, the null hypothesis is therefore defined as:

$$H_0: \beta_1 = ... = \beta_k = 0 \tag{14}$$

If H_0 is rejected, one can conclude that causality from x to y exists. Then x and y variables can be interchanged to test for causality in the other direction, and it is possible to observe bidirectional causality (feedback). To convert equation 13, the following vector form is explained as follows:

$$\left(1, y_{it-1},\ldots,y_{it-p}\right)^{'} \text{ as } z_{it}, \left(1, X_{it-1},\ldots,X_{it-q}\right)^{'},$$
$$\beta_i\left(\beta_{0i},\ldots,\beta_{pi}\right)^{'}, \delta_i\left(\delta_{0i},\ldots,\delta_{pi}\right)^{'}, y\left(y_{i1},\ldots,y_{iT}\right)^{'}, \varepsilon\left(\varepsilon_{i1},\ldots,\varepsilon_{iT}\right)^{'} \tag{15}$$

The equation is formed as:

$$y_i = Z_i\beta_i + X_i\delta_i + \varepsilon_i \tag{16}$$

Homogeneity of δ_i is assumed, making the above equation as follows:

$$y_i = Z_i\beta_i + X_i\delta + \varepsilon_i \tag{17}$$

The parameter bias is solved by calculating the value of δ as follows:

$$\tilde{\delta} = 2\hat{\delta} - \frac{1}{2}\left(\hat{\delta}_{1/2} + \hat{\delta}_{2/1}\right) = \hat{\delta} + \left((\hat{\delta} - \frac{1}{2}(\hat{\delta}_{1/2} + \hat{\delta}_{2/1})\right) \tag{18}$$

Recently, Panel Granger non-causality testing developed by Juodis et al. (2021) was initiated to analyze the causal relationship between variables in panel data, additionally, it is valid in models with homogeneous or heterogeneous coefficients. It is an extension of the Granger causality test, which is commonly used to assess the causal relationship between variables in time series data. The novelty of their approach lies in the fact that under the null hypothesis, the Granger-causality parameters equal zero and thus they are homogeneous. This allows the use of a pooled fixed effects-type estimator for these parameters only, which guarantees a $\sqrt{NT}$ convergence rate, where N denotes the number of cross-sectional units in the panel. To account for the so-called "Nickell bias" of the pooled estimator, their testing procedure makes use of the Half Panel Jackknife (HPJ) approach of Dhaene and Jochmans (2015). The resulting approach works very well under circumstances that are empirically relevant: moderate time dimension, heterogeneous nuisance parameters and high persistence.

Implementing panel Granger non-causality testing provides a comprehensive approach to assess causal relationships in panel data, considering both the individual and temporal dimensions of the data. The advantages of the Panel Granger non-causality testing are: (1) it accounts for the lagged values of the variables over time, which helps capture the dynamic relationships between the variables. (2) It considers the individual-specific effects, allowing for a more accurate analysis of the causal relationship. (3) Panel Granger non-causality testing addresses endogeneity concerns by incorporating lagged values of the variables, which can help control for potential reverse causality or omitted variable bias. (4) by utilizing the pooled data from different countries across periods, Panel Granger non-causality testing can enhance the statistical analysis, leading to more reliable and robust results.

Table 4: Results of VIF test

Variable	VIF	1/VIF
	7.52	0.132951
CE	5.61	0.178410
INOV	2.97	0.336263
FP	2.38	0.420659
GDP	1.77	0.566011
RE	1.34	0.745789
UPG	1.18	0.849656
Mean VIF	3.25	

Source: Authors' estimation (statistical work is performed using STATA version 19)

5. EMPIRICAL RESULTS AND DISCUSSION

5.1. Diagnostics

Before estimating the model, some standard preliminary tests are undertaken to verify the time-series properties of the selected variables. First, the Pesaran CD (Cross-Sectional Dependence) test and the Pesaran Scaled-LM (Lagrange Multiplier) test are used to examine the presence of cross-sectional dependence in panel data analysis[3]. These tests help determine if there is a correlation between the observations across different cross-sectional units (countries) in the dataset. The Pesaran's CD test assesses whether the residuals from a panel regression model are cross-sectionally correlated. The Pesaran Scaled-LM test examines whether the residuals of the panel regression model exhibit cross-sectional correlation after controlling for the presence of individual-specific effects. A robust test that takes into account the potential heteroscedasticity and serial correlation in the panel data. Results reported in Table 5 show that the null hypothesis of strict cross-sectional independence is rejected for all variables, indicating that the assumption of independence among observations within the same nation is violated. This confirms the presence of cross-sectional dependence, which implies that there are unobserved factors common to the selected countries that affect the dependent variable. In such cases, appropriate methods that account for cross-sectional dependence can be employed to address this issue.

To investigate the homogeneity assumption in panel data analysis, Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) are tested. The former introduced the common correlated effects (CCE) approach, which assumes that there are common unobserved factors that affect all individuals in the panel. The latter proposed a homogeneity test based on the idea that if

3 The approach was first introduced by Koenker and Bassett Jr. (1978) and applied in a number of empirical applications (see, Lamarche 2010; Canay 2011; Galvao Jr 2011, for early contributions).

the relationship between variables is homogeneous, then the coefficients estimated from different subsamples of the panel should be similar. They developed a test statistic called the Blomquist-Westerlund (BW) statistic, which measures the difference in coefficients between different subsamples. It is crucial to conduct the homogeneity test to assess whether the relationships between variables are consistent across individuals and make appropriate adjustments in their analysis if necessary. Table 6 shows the results of the slope homogeneity tests. By comparing the BW statistic to critical values, there is evidence of heterogeneity in the coefficients at a 5% significance level. Therefore, this leads to unbiased and consistent estimates.

Subsequently, the stationary properties of all variables in this study are assessed. To accomplish this, the Augmented Dickey-Fuller (ADF) test is utilized, which is widely recognized for examining time series stationarity. Additionally, the panel unit root test (CADF) proposed by Breitung and Das (2005) is employed. These tests assume a common autoregressive parameter for all individuals in the panel and address cross-sectional dependence by subtracting the cross-sectional averages from the analyzed series. Table 7 presents the outcomes of the panel unit root tests, revealing that it is not possible to reject the null hypothesis of a unit root for all selected variables at the level form. However, when the variables were integrated to the first differences, the null hypothesis of a unit root was entirely rejected at the 1% level. This suggests that it is necessary to utilize variables in first differences for the empirical analysis to avoid biased estimation results arising from spurious relationships. Nonetheless, it is important to note that adopting variables expressed in the first differences would result in the loss of the long-term relationship between the variables. Since the primary interest lies in examining the long-run effects of determinants of the ecological footprints on the environment, using first differences is not a proper option.

Table 5: Results of the cross-sectional dependence tests

Variables	Pesaran's CD	Pesaran Scaled—LM
ECF	4.038***	52.38***
FP	1.78*	39.67***
RE	7.91***	7.481***
GDP	4.568***	56.03***
CE	31.122***	210.2***
UPG	14.495***	144.26***
INOV	25.05***	69.59***

***denotes 1% significance level. **denotes 5% significance level. *denotes 10% significance level

Source: Authors' estimation (statistical work is performed using STATA version 19)

Table 6: Results of slope homogeneity tests

Variables	Δ	Adj Δ
ECF	36.51***	40.49***
FP	2.46**	2.713***
RE	−0.702*	−0.774*
GDP	1.752*	1.93*
CE	3.58***	3.949***
UPG	1.642*	1.89*
INOV	2.14**	5.08***

***denotes 1% significance level. **denotes 5% significance level. *denotes 10% significance level

Source: Authors' estimation (statistical work is performed using STATA version 19)

Therefore, in a subsequent step, the cointegration analysis is conducted to investigate whether a long-run equilibrium depicts the variables in the panel. If a long-run equilibrium is found, regression techniques can be applied to obtain consistent estimates, even in the presence of nonstationary data. To this end, the cointegration tests proposed by Pedroni (2004), Kao (1999), Kao and Chiang (2001) and Westerlund (2007) are employed. Additionally, the Westerlund variance ratio is used to control for cross-sectional dependence. The results of the tests are presented in Table 8. Results consistently indicate that the data is integrated to order one. This aligns with existing literature that has adopted a similar panel quantile regression approach, as observed in studies by (Ike et al., 2020; An et al., 2021; and Aziz et al., 2021).

5.2. Quantile via Moment

As mentioned earlier, this study employs MMQR, since it provides insights into the relationships between the ecological footprint and the independent variables (fishery, renewable energy, GDP per capita, carbon emissions, urban population growth, and innovations) at different quantiles. The coefficients at different quantiles help understand how these independent variables affect the dependent variable across different parts of its distribution. The results of MMQR are provided in Table 9.

Concerning the blue factor, the coefficient estimates of total fisheries production for different quantiles (0.00102, 0.00182, 0.00699, 0.0138, 0.0252) suggest that the effect of the total fisheries production on the ecological footprint is consistent across different quantiles. The positive coefficients of all quantiles suggest that there is a direct impact of the total fisheries production on the ecological footprint. It is worth noting that the magnitude of the impact is increasing at higher levels of fishery production, as the coefficient at the 0.1 percentile is 0.001 compared to 0.9

Table 7: Results of unit root test

Variables	CADF (1st difference)
ECF	−16.216***
FP	−14.046***
RE	−9.913**
GDP	−12.63***
CE	−12.16***
UPG	−16.13***
INOV	−13.66***

***denotes 1% significance level. **denotes 5% significance level. *denotes 10% significance level

Source: Authors' estimation (statistical work is performed using STATA version 19)

Table 8: Cointegration test results

Test	Method	T. statistic	P-value
Pedroni	Modified Phillips–Perron	4.5033	0.0000
	Phillips–Perron	−7.5176	0.0000
	Augmented Dickey–Fuller	−7.0654	0.0000
Kao	Modified Phillips–Perron	−2.3145	0.0045
	Phillips–Perron	−3.2167	0.0022
	Augmented Dickey–Fuller	−3.2216	0.0138
	Unadjusted modified Dickey-Fuller	−2.4528	0.0168
	Unadjusted Dickey-Fuller	−2.0072	0.0446
Westerlund	Variance ratio	−1.8633	0.0650

Source: Authors' estimation (statistical work is performed using STATA version 19)

Table 9: Quantile via moments results

Variables	location	scale	0.1	0.25	0.5	0.75	0.9
Total fisheries production	−0.00653***	−0.00989***	0.00102**	0.00182***	0.00699**	0.0138***	0.0252***
	(0.00101)	(0.00812)	(0.00114)	(0.00829)	(0.00102)	(0.00142)	(0.00224)
Renewable energy consumption	−0.0118***	−0.0142***	0.0121**	0.000187	−0.0124***	−0.0222***	–0.0385c
	(0.00449)	(0.00362)	(0.00534)	(0.00377)	(0.00440)	(0.00614)	(0.00961)
GDP per capita	3.73e−05***	6.56e−06***	4.83e−05***	4.28e−05***	3.70e−05***	3.24e−05***	2.49e-05***
	(2.78e−06)	(2.24e−06)	(3.23e−06)	(2.31e−06)	(2.70e−06)	(3.77e−06)	(5.92e-06)
Carbon emissions	2.35e−07	1.07e−06	−1.57e−06	−6.68e−07	2.85e−07	1.02e−06	2.25e-06
	(8.91e−07)	(7.19e−07)	(1.02e−06)	(7.35e−07)	(8.92e−07)	(1.25e−06)	(1.96e-06)
Urban population growth	−0.0100	0.0179	−0.0402*	−0.0251*	−0.00917	0.00319	0.0238
	(0.0184)	(0.0148)	(0.0209)	(0.0151)	(0.0186)	(0.0260)	(0.0409)
Patent applications, residents plus nonresidents	−0.00252***	−4.39e−05	−0.00178***	−0.00215***	−0.00254***	−0.00285***	-0.00335***
	(4.14e−05)	(3.34e−05)	(4.71e−05)	(3.41e−05)	(4.16e−05)	(5.82e−05)	(9.16e-05)
Constant	1.297***	0.367**	0.523**	1.059***	1.319***	1.656***	1.902***
	(0.177)	(0.162)	(0.227)	(0.112)	(0.176)	(0.303)	(0.401)
Observations	414	414	414	414	414	414	414
Standard errors in parentheses							

***P<0.01, **P<0.05, *P<0.1

Source: Authors' estimation (statistical work is performed using STATA version 19)

percentile which counted as 0.025. This confirms that an increase (decrease) in fishery, increases (decreases) carbon footprint. This result is aligned with (Sieghart et al., 2019; Wang et al., 2019 and Moneer, 2023).

As reported by the World Bank (2023), the MENA region faces a significant threat to its blue economy, which is crucial for the region's economic growth, due to high levels of marine and coastal pollution. The MENA region has the highest per capita plastic footprint, with the average resident releasing over 6 kg of plastic waste into the ocean each year. The Mediterranean Sea, in particular, generates $450 billion annually through its Blue Economy, however, it is currently one of the world's major hotspots for plastic pollution. Despite some progress in raising awareness and managing plastic pollution, it continues to cost MENA countries an average of 0.8% of GDP per year. Plastic pollution has adverse effects on various sectors, including tourism, fisheries, shipping, and the well-being of people in the region. Recognizing the magnitude of the challenge, the governments of Tunisia and Morocco for example developed action plans in 2022 to reduce marine plastic pollution and promote a "circular economy." This circular economy approach aims to minimize waste and pollution by extending the lifespan of plastic products and encouraging material and product sharing. Study conducted by Heger et al. in 2022 reveals that approximately 6.3 k of mismanaged plastic waste enter the Mediterranean waters off the coast of Morocco per kilometer every day, equivalent to nearly 14 pounds over every half a mile. The estimated amount is even higher off the coast of Tunisia, with 9.5 k or 21 pounds per kilometer[4].

On the contrary, the coefficient estimates for renewable energy consumption (−0.0118, 0.0121, 0.000187, −0.0124, −0.0222, −0.0385) indicate a significant impact of renewable energy consumption on the dependent variable at different quantiles. The negative coefficients suggest that an increase in renewable energy consumption is associated with a decrease in the ecological footprint at different quantiles. The positive coefficient at the 0.1 percentile suggests that at lower levels of renewable energy consumption, there is a positive relationship with the ecological footprint. This could be due to factors like challenges in integrating high levels of renewable energy into existing systems, while it has a significant negative impact on 0.5, 0.75 and 0.9 quantiles. That is increasing renewable energy consumption by 1%, median of ecological footprint will decrease by 0.022%. The negative coefficients at higher percentiles suggest that as renewable energy consumption increases, that tends to enhance the environmental conditions.

Recent studies have shed light on the potential negative effects of renewable energy on ecological footprint and environmental sustainability. While renewable energy sources such as wind, solar, and hydropower are often hailed as clean and sustainable alternatives to fossil fuels, these studies suggest that their implementation may not be without drawbacks. One major concern is the impact of large-scale renewable energy projects on wildlife and ecosystems. For instance, wind turbines have been found to pose a significant threat to birds and bats, leading to increased mortality rates. Similarly, the construction of solar farms and hydropower dams can disrupt natural habitats and affect the migration patterns of fish and other aquatic species. Additionally, the production and disposal of renewable energy infrastructure can result in the release of toxic materials and contribute to environmental degradation. These findings emphasize the need for careful planning and consideration of the ecological consequences when implementing renewable energy technologies to ensure a truly sustainable and environmentally friendly energy transition (Hanley and Nevin, 1999; Owen, 2004; Tsoutsos et al., 2005; Patel,

4 Wind energy potential is especially high in North African countries, and it is estimated that wind power potential in this region is 34 times greater than that of northern European countries. Morocco, for example, is estimated to have an offshore wind potential of 200 GW, benefiting from average wind speeds of 7.5-9.5 m per second (m/s) in the south and 9.5-11.0 m/s in the north. Algeria also has tremendous technical wind energy potential estimated at 7,700 GW. To put this in perspective, the total wind capacity in Europe at the end of 2020 was only 216 GW.

Table 10: Estimation 0f a model with a unitary threshold

Model	Threshold	95% CI	
		Lower	Upper
Th-1	492.8652	490.8233	497.5745

CI: Confidence interval. Threshold estimator (CI=95%), with 1000 bootstrap estimates
Source: Authors' estimation (statistical work is performed using STATA version 19)

Table 11: Test for the unitary threshold model

Threshold	RSS	MSE	F. stat	Probability	Crit 10	Crit 5	Crit 1
Single	1.587	0.008	57.951	0.048	54.759	59.681	64.316

CI: Confidence interval, RSS: The residual sum of squares, MSE: Mean squared error. Threshold estimator (CI=95%), with 1000 bootstrap estimates
Source: Authors' estimation (statistical work is performed using STATA version 19)

2009; Solangi et al., 2011; Zound, 2017; Majeed and Luni, 2019; Gareiou et al., 2021; Edenhofer et al., 2022, Enserink et al., 2022; Olabi and Abdelkareem, 2022; Sarwar et al., 2022).

With respect to the other independent variables, the consistently positive coefficients for GDP per capita across different percentiles indicate a positive and significant relationship between economic prosperity (higher GDP per capita) and ecological footprint. That is increasing GDP by 1%, median of ecological footprint will increase by 3.70%. While GDP growth is often associated with positive economic outcomes, it can also contribute to an increase in the ecological footprint, this can be attributed to several reasons: resource intensive economic activities; increased energy demand; expanding infrastructure; increased waste generation; overconsumption and unsustainable production. This not only affects the ecological balance but can also have far-reaching consequences for ecosystems, biodiversity, and natural habitats. It is important to note that the relationship between GDP and the ecological footprint is complex and can be influenced by various factors, including policy choices, technological advancements, and societal values. While economic growth can contribute to negative environmental impacts, it is crucial to implement sustainable development strategies, promote resource efficiency, and adopt environmentally conscious policies to mitigate these negative effects and ensure a more sustainable future.

The relatively small and fluctuating coefficient estimates for carbon emissions suggest a weak relationship between carbon emissions and the ecological footprint. This could be due to complex interactions between carbon emissions and other factors, such as policy interventions, technological advancements or varying levels of environmental awareness and regulations across different percentiles. While the coefficient estimates for urban population growth (−0.0100, 0.0179, −0.0402, −0.0251, −0.00917, 0.00319, 0.0238) suggest that urban population growth has a mixed effect on the ecological footprint across different quantiles. The negative coefficients at lower percentiles suggest that at the early stages of urban population growth, there might be challenges related to infrastructure, resource allocation, or environmental sustainability, leading to a negative impact on the ecological footprint. Nevertheless, higher percentiles indicate that as urban population growth becomes more substantial or reaches a certain threshold, the positive effects of increased urbanization, such as market expansion, or technological advancements, start to dominate, resulting in a positive impact on the ecological footprint.

Table 12: Estimation of models with multiple thresholds

Model	Threshold	95% CI	
		Lower	Upper
Th-1	492.8652	490.8233	497.5745
Th-2	506.46653	505.6529	509.8902
Th-3	511.6796	510.1445	512.0635

CI: Confidence interval. Threshold estimator (CI=95%), with 1000 bootstrap estimates
Source: Authors' estimation (statistical work is performed using STATA version 19)

Focusing on innovations, the negative coefficients for patent applications across all percentiles suggest that higher levels of patent applications are associated with a decrease in the ecological footprint. This could be due to factors such as increased competition, market saturation or intellectual property rights that arise as patent applications increase, potentially impacting footprint negatively and significantly. An increase in patent application by 1%, median of ecological footprint decreases by 0.00254%.

5.3. Threshold Regression

Based on the literature previously reviewed, it is evident that the blue economy has a substantial impact on the environment. However, previous studies have overlooked the potential presence of non-linear effects within the blue economy. Recognizing the possibility of non-linearity, a panel threshold approach is employed to investigate this phenomenon. To begin, we conducted a test to examine the existence of a single threshold using 1000 bootstraps. The null hypothesis (H: $\delta 1 = \delta 2$) assumes that no threshold exists, while the alternative hypothesis suggests the presence of a single threshold. By rejecting the null hypothesis, testing for the existence of multiple thresholds can be proceeded, thereby leading to a more appropriate model. Table 10 displays the existence of a single threshold for the blue economy at 4920.86 (in log form), with a confidence interval ranging from 490.82 to 4970.57. Table 11 reports the results of the significance level test for a single threshold. The obtained P-value is significant, providing evidence to reject the null hypothesis that no threshold exists. Additionally, the F-statistic surpasses the critical value, favoring non-linearity and indicating the absence of a linear relationship between fishery and carbon footprint. These findings highlight the importance of considering non-linear effects within the blue economy and emphasize the need for a more sophisticated model that accounts for multiple thresholds. By doing so, we can gain a deeper understanding of the relationship between the blue economy, environmental impact and carbon footprint.

Table 13: Test for multiple threshold models

Threshold	RSS	MSE	F. stat	Probability	Crit 10	Crit 5	Crit 1
Single	1.5878	0.0082	57.951	0.048	54.759	59.681	64.316
Double	1.7195	0.0061	49.853	0.276	50.583	52.864	58.036
Triple	1.4903	0.0048	36.693	0.561	51.856	58.845	65.964

CI: Confidence interval, RSS: The residual sum of squares, MSE: Mean squared error. Threshold estimator (CI=95%), with 1000 bootstrap estimates

Table 14: Juodis, Karavias, and Sarafidis Non-Causality test

Variables (X-Y)	X not cause Y	Y not Cause X
FP-ECF	7.38***	−1.32**
RE-ECF	−1.97**	−0.81
GDP-ECF	0.82	1.25
CE-ECF	4.21***	1.21*
UPG-ECF	1.29	−0.68
INOV-ECF	−10.3***	0.28

***Denotes 1% significance level. **denotes 5% significance level. *denotes 10% significance level

The reported values are HPJ Wald test

Source: Authors' estimation (statistical work is performed using STATA version 19)

In recent research, a comprehensive investigation was conducted to explore the potential existence of double and triple thresholds in the intricate relationship between the blue economy and the environment. This statistical significance involved conducting rigorous analyses and statistical tests. Table 12, provides the identification of multiple thresholds within the context of fishery production levels. Specifically, three distinct thresholds were estimated, namely 492.8, 506.4, and 511.6, arranged for Th-1, Th-2 and Th-3 respectively. To further validate and assess the presence of these thresholds, Table 13 shows the estimates of 1000 bootstrapping iterations, which were utilized to approximate the likelihood of double and triple thresholds in the examined relationship.

Notably, the results obtained from this finding indicate that a single threshold is statistically significant, with a P = 0.04. This suggests that a specific threshold level significantly influences the association between the blue economy and the environment. However, intriguingly, the analysis reveals that the presence of double and triple thresholds are statistically insignificant, as indicated by probability values of 0.27 and 0.56, respectively. This suggests that the relationship between the blue economy and the environment is primarily characterized by a singular threshold level, rather than multiple thresholds.

5.4. Panel Granger Non-Causality Test

As explained earlier, the panel non-causality test conducted by Juodis, Karavias and Sarafidis examines the relationship between ECF and several independent variables, namely FP, RE, GDP, CE, UPG and INOV. The test aims to determine whether there is a causal relationship between ECF and each of these variables. Based on the test results as explained in Table 14, with a 95% confidence level, several remarks can be noted. There is evidence of a heterogeneous bidirectional relationship between the ECF and each of FP and CE. This means that changes in ECF may have an impact on these variables, and vice versa.

The statistically significant relationship between FP and ECF as indicated by the coefficients of (7.38*** and −1.3**), shows that FP positively affects ECF, which means that as FP increases, it puts additional pressure on ecosystems, leading to ecological changes and potentially increasing the ecological footprint. While ECF can, in turn, negatively influence fishery production. As the ecological footprint increases, it can lead to depletion of fish stocks, loss of biodiversity and degradation of marine habitats. These negative impacts can reduce the productivity and sustainability of fishery resources, thereby affecting FP in the long run.

There is statistically significant positive bidirectional relationship between CE and ECF with magnitudes of (4.21*** and 1.21*) due to extensive activities associated with human development, industrialization, and the burning of fossil fuels tend to result in higher carbon emissions. Factors such as increased energy consumption, transportation demands, and deforestation can contribute to the release of greenhouse gases into the atmosphere, leading to climate change and environmental degradation.

On the other hand, there is evidence of heterogeneous unidirectional relationship between the ECF and each RE and INNOV. Results indicate a significant inverse relationship between RE and ECF, with a coefficient of (−1.97**). This is attributed to the development and utilization of renewable energy sources, such as solar, wind, hydro, and tidal energy, which can contribute to environmental sustainability and mitigate ECF. Furthermore, the coefficient of INNOV −10.3*** proves negative association with EFP.

Conversely, there is insignificant evidence of a causal relationship between ECF and each of GDP and UPG. This suggests that changes in ECF are unlikely to cause changes in GDP and UPG. Suggesting that changes in ECF are unlikely to have a causal impact on GDP and UPG, and vice versa.

6. CONCLUSION

This paper contributes to the understanding of sustainability and environmental impact by shedding light on the complex interplay between economic, demographic and energy-related factors. The paper examines the relationship between various variables and the ecological footprint in the MENA countries over the period from 2000 to 2022. Through the utilization of the STRIPAT model and a range of econometric techniques. Correlation analysis is conducted to examine the relationships between variables. Multicollinearity is assessed using variance inflation factor (VIF), the results suggest no significant multicollinearity issues among the variables. The examination of cross-sectional dependency using Pesaran's CD and scaled-LM tests confirmed the presence of distinct shocks in the data. This finding underscores the importance of considering individual heterogeneity when analyzing causal relationships within panel data. Additionally, the method of moments quantile regression is employed, since it provides insights into the relationships between the ecological footprint and the independent variables (fishery, renewable energy, GDP per capita, carbon emissions, urban population growth, and innovations) at different quantiles. The coefficients at different quantiles help understand how these independent variables affect the dependent variable across different parts of its distribution.

One significant finding is the consistent and direct impact of total fisheries production on the ecological footprint. The positive coefficients observed across all quantiles suggest that an increase in fisheries production leads to an increase in the ecological footprint. Moreover, the magnitude of this impact becomes more pronounced at higher levels of fishery production. Another noteworthy finding is the significant negative relationship between renewable energy consumption and the ecological footprint. The negative coefficients observed at different quantiles indicate that an increase in renewable energy consumption is associated with a decrease in the ecological footprint. Additionally, the study explores the impact of other independent variables. The relationship between carbon emissions and the ecological footprint is found to be relatively weak, suggesting the presence of complex interactions and other influencing factors. The effects of urban population growth on the ecological footprint vary across different quantiles, with negative impacts observed at lower percentiles and positive impacts at higher percentiles. The study also reveals that higher levels of patent applications are associated with a decrease in the ecological footprint, possibly due to increased competition and market saturation. Furthermore, recognizing the possibility of non-linearity, a panel threshold approach is employed to examine the existence of single and multiple thresholds using 1000 bootstraps. Results suggest that a specific threshold level significantly influences the association between the blue economy and the environment. However, the analysis reveals that the presence of double and triple thresholds are statistically insignificant.

It is important to note that the analysis is based on available data and assumes certain relationships and functional forms. Further research and refinement of the model could provide additional insights. Moreover, the study focuses on a specific set of variables and countries, and generalizing the findings to other contexts could add further contribution. Nevertheless, this work contributes to the existing literature on sustainability and environmental economics and provides a foundation for future research and policy discussions aimed at promoting sustainable development and reducing ecological footprints worldwide. The findings have important implications for policymakers, highlighting the importance of conservation measures, renewable energy adoption, and careful urban planning. Further research can build upon these findings to explore additional variables and complex interactions, ultimately guiding efforts towards achieving environmental sustainability.

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