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The Long-term Anthropogenic Processes' Effects on Ecological Footprints in Morocco: A STIRPAT Analysis Based on Four Co-integration Approaches

El Asli Hamdi[1]†, Madane Youness[2] and Azeroual Mohamed[1,2]
[1]Laboratory of Economy & Management, Polydisciplinary Faculty of Khouribga, Sultan Moulay Slimane University, Beni Mellal 23000, Morocco
[2]Laboratory MFMDI, SUPMTI, Rabat 10140, Morocco
†Corresponding author: El Asli Hamdi; hamdielasli@gmail.com

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ABSTRACT

Morocco provides a stark example of how a developing country in the southern hemisphere of Africa is struggling with the diverse and devastating impacts of climate change, which are exacerbated by development issues and a lack of studies that allow for understanding the causal effects of environmental degradation, a crucial factor in informing adequate policy responses. An exhaustive STIRPAT analysis, conducted in Morocco from 1970 to 2023, uses four pieces of empirical evidence and four cointegration methods: ARDL, FMOLS, DOLS, and CCR. The increase in ecological footprints of production, consumption, import, and export in Morocco is due to urbanization, technical progress, trade openness, and economic growth, respectively. Anthropogenic processes, attributed to urbanization, economic growth, technological progress, and trade openness, have a positive contribution to environmental alteration and have been found unsustainable in the Moroccan context. Thus, relevant policies are being proposed at the individual, organizational, and governmental levels to reduce their environmental burden, increase bio-capacity regeneration potential, and promote environmental sustainability both in Morocco and beyond.

INTRODUCTION

Identifying comprehensive target variables that account for all aspects of environmental degradation is a challenging task. It is even more challenging in an African emerging country in the southern hemisphere that is struggling with the devastating impacts of climate change, which are exacerbated by development issues and a lack of studies that enable understanding of the causal effects of environmental degradation, a crucial factor in informing adequate policy responses. From this perspective, the ecological footprint (EF) is a synthetic concept that quantifies the anthropogenic impact on the biosphere, resulting in environmental stress (Wackernagel & Rees 1996, Galli 2015, Nautiyal & Goel 2021, Global Footprint Network 2024).

EF helps you understand how humans, driven by economic affluence, energy consumption, and land use for living space and agriculture, affect the environment (Dietz et al. 2007, Rafindadi & Usman 2020). It characterizes the pace and intensity of resource consumption and waste generation relative to the local ecosystem's ability to absorb waste and replenish resources, as represented by the area needed to support the population's needs and offset equivalent consumption and CO_2 emissions (Global Footprint Network 2024).

When attributed to the production of harvests, crops, grazing land, vegetation, fibers, farming and fisheries, woods, medicinal plants, etc., as well as space for urban infrastructure within a country's borders, it is referred to as the ecological footprint of production (EFP) (Global Footprint Network 2024). It specifically tracks the use of productive surface areas, including cropland, grazing land, fishing grounds, built-up land, forest area, pastureland, factories, cities, etc., and CO_2 demand on land (Global Footprint Network 2024).

When materialized within imports, it is referred to as the EF of imports (EFI); within exports, it is called the EF of exports (EFE). This, and the EF, often refers to the apparent EF of consumption (EFC). Sometimes EF is briefly referred to as a footprint, which is the sum of EFP and EFI minus EFE.

In summary, a country's EF represents the total pressure that the population's needs place on ecosystems, including the atmosphere, soil, and subsoil, and, by extension, the demand on biodiversity (Global Footprint Network 2024). It is measured in global hectares (gha), which represent a biologically productive hectare with average bio-productivity, adjusted for the demand on a specific geographical zone each year (Global Footprint Network 2024).

Like many emerging countries, Morocco's EF has impressively grown in the last 50 years as a result of increasing local demand for bio-capacity due to eco-demographic growth and urban expansion, which is putting pressure on the local biosphere by excessive water usage, intensive farming, overgrazing, and deforestation with an overload of anthropogenic CO_2 emissions. This led to anthropogenic incidence on climate change, air pollution, water scarcity, and contribution to global warming (Hamdi & Mohamed 2025).

The country's EFC rose by more than an entire point from 0.91 in 1961 to 1.94 gha per inhabitant in 2023, while BC per capita fell from 1.08 to 0.81 gha per capita for the same period (Dworatzek et al. 2024).

Morocco's economy relied for decades on primary sector where agriculture, mining, fishing and forestry sectors account for 15% of GDP, and employs about 45% of Morocco's active Population (Morocco - Agricultural Sector 2024), with time, the modernization and intensification of agricultural practices have caused soil erosion, salinization and resource attrition, affecting about 5.5 million hectares of land, leading in fine in up and down wards in EF and bio-capacity, respectively (Bouhia 2020).

Morocco is rich in biodiversity, hosting the second-highest concentration of terrestrial biodiversity in the Mare Nostrum (Bouhia 2020). This biodiversity is being threatened by the sabotage of its own homeland, which is caused by the overexploitation of natural resources, deforestation, desertification, air pollution, stream pollution, and soil degradation (Bouhia 2020). As a result, local BC meets only half of Morocco's total EFC; the country met its deficit by relying on 20% net BC imports (Galli 2015).

Although Morocco places its greatest demands on its cropland ecosystem, which provides provisioning services, including agricultural products, crop-based feeds, and fibers, mostly used (45% of total EFC) to produce food, goods, and services (Galli 2015), it remains far from achieving self-sufficiency and meeting local consumption levels, which makes it increasingly reliant on imports to meet its population's nutritional and energy needs. Notably, Morocco is a net importer of all ecosystem services tracked by the EF (Galli et al. 2012, Galli 2015).

The key aspect of innovation and distinction of this study relies on three key aspects:

One key aspect is the exhaustive analysis of the association between various anthropogenic stress factors and four interconnected environmental degradation indicators from the footprint family, imputed to production, consumption, import, and export, respectively, under spanning coverage that outpaces 50 years, from 1970 to 2023.

The second key aspect is that it innovates in the choice of the environmental stress, mainly with ICTs as a proxy of technological progress. Hence, it takes into account trade openness as a control variable, due to Morocco's increasing integration into the global supply chain, and the potential for environmental diffusion stress between countries due to commercial transactions.

The third key aspect is related to the nature of the target key indicators, which reveal complementarities, dualities, and asymmetries between consumption and production, and import and export. This involves the use of four well-known and widely validated co-integration approaches for statistical analysis worldwide.

LITERATURE REVIEW

In the realm of environmental sustainability, STIRPAT (as Stochastic Incidences by Regression on Population, Affluence and Technology) (Aguir et al. 2014) serves as a framework for analysing the interplay between environmental quality, economic affluence, Population dynamics, industrialization, and technological advancements (York et al. 2003). This model allows researchers to quantify how these factors contribute to environmental degradation and sustainability outcomes. The STIRPAT model builds upon the earlier IPAT model by introducing a stochastic element that accounts for uncertainties in data and relationships, pioneered by Ehrlich & Holdren (1971). Then duplicated to a variety of versions, such as the "I(m)PACT(s)" identities (Vélez-Henao et al.

2019, Waggoner & Ausubel 2002, Lin et al. 2009, Vélez-Henao et al. 2019, Hamdi & Mohamed 2024), or the "IP(B)AT" identity (Vélez-Henao et al. 2019, Schulze 2002).

Under the STIRPAT framework, a range of environmental barometers has been examined in numerous studies, in relation to a variety of explanatory variables, including economic growth, human capital, bio-availability, energy use, renewable energy, urbanization, financial inclusion, trade openness, demographics, natural resource attrition, governance and institutional quality.

For example, CO_2 emissions have been used by Bélaïd and Youssef (2016), Bekun et al. (2018), Abbasi et al. (2021), Mirziyoyeva et al. (2022), Raihan & Tuspekova (2022), Zhao et al. (2023), Ullah et al. (2023), Asli et al. (2024), Naz et al. (2024), and Ullah & Lin (2024) to examine factors influencing CO_2 levels, often in relation to economic growth and energy patterns.

Sulfur dioxide (SO_2) emissions have been explored in more recent analyses, notably by Wong et al. (2024) and Xu et al. (2024), while nitrous oxide (N_2O) has been investigated by Seangkiatiyuth et al. (2011), Tian et al. (2018), and Casquero-Vera et al. (2019), focusing on emissions related to agriculture and industrial activity.

Similarly, nitrogen oxides (NO_x) emissions have been examined by Tørseth et al. (2012) and Shaw and Van Heyst (2022), addressing concerns over transportation and industrial emissions.

When it comes to greenhouse gases (GHGs) more broadly, studies by Sarkodie and Strezov (2018), Chen et al. (2021), Tsur (2024), and Ochi and Saidi (2024) provide comprehensive assessments of how black emissions drivers across different national and sectoral contexts.

Lastly, particulate matter (PM) has drawn attention in the works of Griffin (2013) and Yun et al. (2022), often highlighting health implications and links to urbanization and fossil fuel use.

These studies collectively underscore the multifaceted nature of environmental degradation and the broad array of variables influencing ecological and atmospheric quality. However, these barometers have been criticized for lacking thoroughness and inclusiveness (Destek et al. 2018, Altıntaş et al. 2020, Usman et al. 2020, Nathaniel et al. 2020, Ramezani et al. 2022, Sun et al. 2023, Aziz et al. 2022, Ullah et al. 2023, Hamdi & Mohamed 2024) and for being insufficient in measuring decarbonization (Shaw & Van Heyst 2022).

Recently, EF has increasingly been employed as a reliable and multifaceted environmental barometer (Galli et al., 2014) for environmental assessment, monitoring, and policy evaluation (Rafindadi & Usman 2020). Numerous studies have utilized EF as a barometer, such as Hamdi and Mohamed (2024), Padhan & Bhat (2024), Zhou et al. (2024), Farouki and Aissaoui (2024), Mehmood et al. (2023), Li et al. (2023), Xu et al. (2022), Yasmeen et al. (2022), Rafique et al. (2021), Ali et al. (2021), Chen et al. (2021), Okelele et al. (2021), Nathaniel et al. (2020), and Ahmed & Wang (2019), who commonly employed economic growth, demographic tendencies, natural resource rents, and energy patterns such as composition and consumption as central variables that tend to increase environmental pressure.

In national contexts, such as Turkey, Ullah et al. (2023) utilized an ARDL model covering 1970–2018 to prove that economic growth, bio-capacity, urbanization, and natural resources all have a positive impact on EF, implying a linear environmental cost to development.

Similarly, in Pakistan, Ullah & Lin (2024) used an NARDL method analysis from 1990 to 2018, revealing that natural resource rents and economic growth significantly contributed to increasing EF, renewable energy consumption had a mitigating effect.

Interestingly, financial inclusion appears as a recurring variable in more recent literature. In Algeria, for example, Bergougui & Aldawsari (2024) identified inclusive finance as a positive force in managing ecological risks, potentially by enabling green investments and reducing dependency on resource-intensive activities.

In China, Xu et al. (2022) applied FMOLS, DOLS, CCR, and spectral causality techniques over the period of 1990–2017 to conclude that technological advancement and renewable energy use impede EF level in the long run, whereas FDI expedites it.

Back to Morocco, by using ARDL and VAR/VECM cointegration models, it was previously proven that between 1980 and 2022, economic growth, urbanization, and energy use led to an increase in EF, alongside the confirmation of the EKC hypothesis, whereas ensuring advanced education reduced it (Hamdi & Mohamed 2024, Farouki & Aissaoui 2024).

In subnational contexts, for example, financial inclusion, economic growth, urbanization, and natural resource rents were found to significantly increase EF in the ECOWAS, according to estimations using different panel regression methods over 1990-2016 (Ali et al. 2022).

Moreover, in the South Asian context, Mehmood et al. (2023) confirmed this causality-effect link, finding that, from 1990 to 2022, urban and economic growth, as well as human capital and bio-capacity, positively contribute to EF using panel co-integration approaches. Furthermore, it was captured the negative impact of FDI and the mitigating role of green innovation on EF in the context of the BRICS and Next-11, from 1992 to 2018 by Padhan and Bhat (2024).

Nevertheless, the contribution of FDI and trade to EF remains controversial, with conflicting findings: while a 1991-2012 DOLS panel data analysis of the 27 highest emitting countries revealed a negative impact (Uddin et al. 2017), a robust 53-panel regression investigation from 1990 to 2021 in the Belt and Road Initiative regional context found a positive relationship between trade and EF for both imports and exports (Zhou et al. 2024), which is confirmed in the Sub Saharan context, where Okelele et al. (2021) found that EFC per capita decreases with an increase in trade openness and increases with an increase in FDI inflows from 1990 to 2015.

Furthermore, Ahmad et al. (2020) employed the second-generation panel co-integration approach from 1984 to 2016 to find that natural resources and economic growth expand the EF, while technological innovations reduce it, all within the presence of the EKC hypothesis.

In summary, these studies converge on the conclusion that economic growth, urbanization, and natural resource exploitation significantly amplify environmental degradation in developing regions. However, the integration of renewable energy, improvement in institutional quality, and expansion of financial inclusion offer promising pathways toward sustainability. This narrative underscores the urgency of adopting holistic, context-sensitive policies that align economic ambitions with environmental stewardship.

As a continuation, this study aims to provide a plausible clarification of the following problem:

What are the long-term anthropogenic processes' effects, associated with urbanization, economic growth, technological progress, and trade openness on Morocco's EFs of consumption, production, import, and export from 1970 to 2023?

To bring a response to this problem, the following hypothesis is going to be verified:

H: Anthropogenic processes imputed to urbanization, technological progress, economic growth, and trade openness have a positive effect on the EF's four economic varieties.

This hypothesis is split into four sub-hypotheses, following our four econometric models

H_a: Anthropogenic processes have a positive impact on EFP

H_b: Anthropogenic processes have a positive impact on EFC

H_c: Anthropogenic processes have a positive effect on EFE

H_d: Anthropogenic processes have a positive influence on EFI.

MATERIALS AND METHODS

Model Construction

This study relies on STIRPAT, in line with our previous papers (Hamdi et al. 2024, Asli et al. 2024, Hamdi & Mohamed 2024, Hamdi & Mohamed 2025), with this specification:

$$I = a \cdot P^b \cdot A^c \cdot T^d \cdot e$$

Where I is incidence on environment, P is Population dynamics, A denotes affluence, T stands for technology, a, b, c, and d are coefficients that represent the elasticity of each factor, and e is an error term accounting for unobserved factors.

Accordingly, the following functional form is estimated: (EF) = f (URB, GDP, ICT, TRD)

From which are derived the following four specific functional models:

The EFP model: incidence on (EFP) = f (URB, GDP, ICT, TRD)

Table 1: Variables and data presentation.

STIRPAT	Variables	Acronym	Unit	Data source
I	Ecological footprint of production	EFP	Gha/ midyear population	The Global Footprint Network
	of consumption	EFC		
	of import	EFI		
	of export	EFE		
P	Urbanization	URB	Ratio	Urban population (% of total population) - Morocco | Data
A	Gross Domestic Product	GDP	Constant 2015 $	World Bank Open Data
T	Information and Communication Technologies	ICT	Integer	Adoption of communication technologies per 100 people, Morocco
Control variable	Trade openness	TRD	% GDP	World Bank Open Data

The EFC model: incidence on (EFC) = f (URB, GDP, ICT, TRD)

The EFI model: incidence on (EFI) = f (URB, GDP, ICT, TRD)

The EFE model: incidence on (EFE) = f (URB, GDP, ICT, TRD)

Where EF represents ecological footprint, EFC is the ecological footprint of consumption, EFP of production, EFI of import, EFE of export, URB is urbanization, GDP is Gross Domestic Product, ICT stands for the information and communication technologies, and TRD is trade.

Table 1 represents a description of the chosen variables and their corresponding determinants:

N.B: ICTs are closely linked to technological progress, acting as a driver and facilitator of innovation across sectors. ICTs enhance productivity, enable knowledge diffusion, and support the development of new products and services, thus accelerating economic and technological advancement (Vu 2011, Niebel 2017). They drive innovation and efficiency gains in industries, particularly through automation, digitization, and improved communication networks (OECD 2020). Hence, ICT infrastructure is foundational for emerging technologies such as artificial intelligence, the Internet of Things, and big data analytics, which are key components of modern technological progress (Castells 2010, Brynjolfsson & McAfee 2014).

The choice of trade as a control variable is justified by the fact that the EFI and EFE models take into account the exports and imports of goods and services, summed by Trade as %GDP.

Model Demonstration

By taking the functional form of the EFP model as an example, raising it to the natural log, and neglecting the error term, we get the following specifications:

$$LnEFP_t=\beta_0+\beta_1 LnURB_t+\beta_2 LnGDP_t+\beta_3 LnICT_t+\beta_4 LnTRD_t+\mu_t \quad \ldots(1)$$

The ARDL/BTA specification is expressed as:

$$LnEFP_t=\sum_{i=1}^{p}\beta_{0i}LnEFP_{t-i}+\sum_{i=0}^{q}\beta_{1i}LnURB_{t-i}\sum_{i=0}^{q}\beta_{2i}LnGDP_{t-i}\sum_{i=0}^{q}\beta_{3i}LnICT_{t-i}+\sum_{i=0}^{q}\beta_{4i}LnTRD_{t-i}+\delta_0 LnEFP_{t-i}+\delta_1 LnURB_{t-i}+\delta_2 LGDP_{t-i}+\delta_3 LnICT_{t-i}+\delta_4 LnTRD_{t-i}+\varepsilon_t \quad \ldots(2)$$

And at the first difference as:

$$\Delta LnEFP_t=\sum_{i=1}^{p}\beta_{0i}\Delta LnEFP_{t-i}+\sum_{i=0}^{q}\beta_{1i}\Delta LnURB_{t-i}\sum_{i=0}^{q}\beta_{2i}\Delta LnGDP_{t-i}\sum_{i=0}^{q}\beta_{3i}\Delta LnICT_{t-i}+\sum_{i=0}^{q}\beta_{4i}\Delta LnTRD_{t-i}+\delta_0 LnEFP_{t-i}+\delta_1 LnURB_{t-i}+\delta_2 LGDP_{t-i}+\delta_3 LnICT_{t-i}+\delta_4 LnTRD_{t-i}+\varepsilon_t \quad \ldots(3)$$

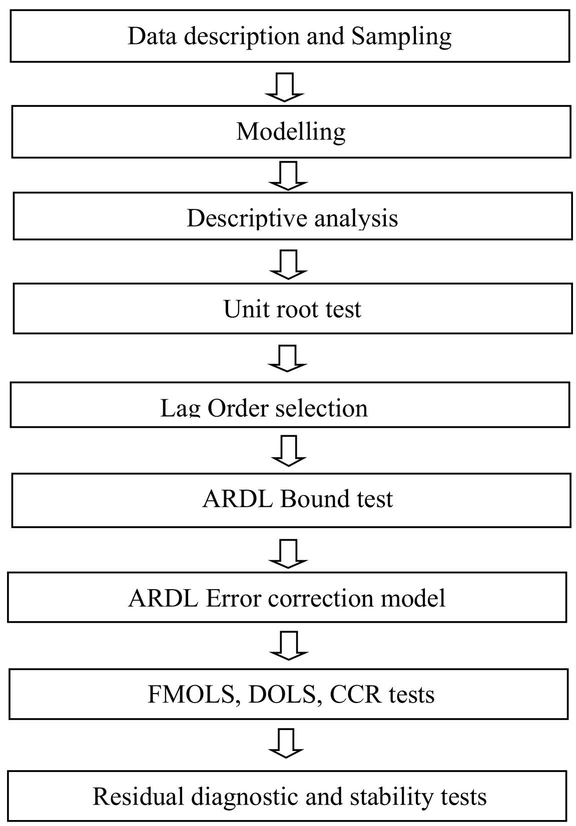
Where t represents the current period, t − i represents the previous period, Δ is the first difference operator, p and q are respectively the lags length for both dependent and independent variables, and the coefficients of the short and long run are shown through *b* and *d*, respectively, while ε_t represents the error term.

Two hypotheses are to be confronted: if there is no co-integration, as stipulates the null hypothesis (H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_d = 0$) vs the alternative one (H_a:$\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq 0$).

If there is co-integration, the error correction model (ECM) representation is specified as:

$$\Delta LnEFP_t=\sum_{i=1}^{p}\beta_{0i}\Delta LnEFP_{t-i}+\sum_{i=0}^{q}\beta_{1i}\Delta LnURB_{t-i}+\sum_{i=0}^{q}\beta_{2i}\Delta LnGDP_{t-i}+\sum_{i=0}^{q}\beta_{3i}\Delta LnFCE_{t-i}+\sum_{i=0}^{q}\beta_{4i}\Delta LnICT_{t-i}+\eta\, ECT_{t-1}+\mu_t \quad \ldots(4)$$

Where ECT represents the error correction term, η is its stochastic coefficient.



Source: Author's own elaboration.

Scheme 1: The study's methodological approach.

The three remaining models are constructed just the same way.

Methodology

This study employs the ARDL approach, supplemented by three other co-integration tools – FMOLS, DOLS, and CCR – to consolidate the reliability of the primary ARDL results. ARDL/ECM is well known for conducting long-run analyses of dynamic relationships between series with different orders of integration (Pesaran & Shin 1998, Pesaran et al. 2001), where the current value of the dependent variable depends on its own past realisations through the distributed lag part (Kripfganz & Schneider 2023). The advantage of this approach lies in identifying co-integrating vectors when there are multiple ones (Nkoro & Uko 2016).

The methodological approach followed in this study is schematized step-by-step in Scheme 1:

Descriptive Analysis

Descriptive analysis is conducted by four techniques: Descriptive statistics, Multiple Correlation Analysis (MCA), Variance inflation factors (VIF), and Pairwise Component Analysis (PCA) (Pearson 1901, Bonett & Wright 2000, Hamdi et al. 2024, Asli et al. 2024, Hamdi & Mohamed 2024, Hamdi & Mohamed 2025).

Unit Root Test

It is essential to verify data stationarity, ensuring statistical properties remain constant over time (Kwiatkowski et al. 1992). The ARDL method depends on the cointegration order of variables (Pesaran et al. 2001). This study employs the ADF test for that purpose (Dickey & Fuller, 1979).

Lag Order Selection

When the auto-regressive model is subject to restrictions of co-integration, there are multiple information criteria for selecting the appropriate lag order (Lütkepohl 1993). They all rely on selecting the lag length with the lowest value (Mallik 2008, Hamdi & Mohamed 2024).

ARDL Bounds Tests

An ARDL bounds test involves performing an F-test on the lagged levels of the independent variable (Nkoro & Uko 2016, Asli et al. 2024), compared with critical values at a 5% level of significance (Narayan 2005, Asli et al. 2024).

Error Correction Model

It can be derived from the ARDL model through a simple linear transformation, which integrates short-run adjustments with long-run equilibrium (Nkoro & Uko 2016, Hamdi & Mohamed 2024). Then it exhibits an associated error correction term (ECT) which measures how quickly the equilibrium is reached in the long run (Engle & Granger 1987, Asli et al. 2024).

FMOLS, DOLS, and CCR Tests

The FMOLS method, developed by Phillips and Perron (1988), is valued for handling endogeneity and serial correlation, especially in small samples (Hamit-Haggar 2012, Asli et al. 2024). DOLS, introduced by Stock and Watson (2003), often yields superior estimates by addressing regressor correlations (Kao, 1999, Asli et al. 2024). As a robustness check, the CCR approach (Pesaran et al. 2001) is also applied, modifying the model to improve chi-square test accuracy (Park 1992, Pattak et al. 2023, Asli et al. 2024).

Residual Diagnostic and Stability Tests

Residual diagnostics are essential for assessing a model's capability and providing directions for potential modifications (Mauricio 2008). The normal distribution of residuals was tested using Bera and Jarque's (1981) method, while heteroscedasticity was checked with Breusch and Pagan's (1979) test, and serial correlation was evaluated using Godfrey's (1978) test. Additionally, the Ramsey (1969) test was used to verify the existence of misspecifications in residuals. The quality of the regression is represented by the CUSUM and CUSUMSQ tests (Brown et al. 1975), and its stability is checked (Doan et al. 1994).

RESULTS

The results from the empirical evidence on the footprint models are presented jointly in a single table, divided into four cases, with each case representing a singular model's results, and each result is commented on underneath its corresponding table.

Descriptive Statistics

Table 2 below provides a statistical description summary of the four model variables.

Results from Table 2 show that the EFC and EFP show symmetrical distributions with moderate variation and pass normality tests, indicating stable and consistent patterns.

In contrast, the EFE is right-skewed and nearly non-normal, suggesting uneven environmental impacts across observations. The EFI, while more symmetric, shows considerable flatness and variability, though it still meets the normality threshold.

Among the explanatory variables, urbanization and trade openness display low variability and approximately

Table 2: Data descriptive statistics.

Parameter	LNEFC	LNEFE	LNEFI	LNEFP	LNURB	LNGDP	LNICT	LNTRD
Mean	17.37984	16.09276	-0.777442	17.30571	3.911890	26.98903	2.256376	4.052313
Median	17.41169	15.97666	-0.834063	17.30516	3.954809	24.64714	1.562475	4.000685
Max	18.10904	16.79392	-0.083382	17.91692	4.172152	37.10619	5.463832	4.616267
Min	16.44590	15.65578	-1.660731	16.70099	3.540292	23.48349	-0.564610	3.602211
Std. Dev.	0.482438	0.320997	0.435008	0.348433	0.183145	5.130629	2.367897	0.220808
Skewness	-0.171867	0.730638	0.031031	-0.054216	-0.456566	1.439369	0.201829	0.380473
Kurtosis	1.922932	2.410983	1.895937	1.884086	2.085151	3.124651	1.341788	2.820291
Jarque-Bera	2.876015	5.585102	2.751314	2.828297	3.759207	18.68102	6.553365	1.375505
Prob	0.237400	0.061265	0.252674	0.243133	0.152651	0.000088	0.037753	0.502705
Sum	938.5112	869.0090	-41.98185	934.5086	211.2420	1457.407	121.8443	218.8249
Sum Sq. Dev.	12.33558	5.461076	10.02931	6.434478	1.777728	1395.138	297.1676	2.584075

Table 3: The EFs models' pair–wise correlations matrices.

The EFP model

	LNEFP	LNURB	LNGDP	LNICT	LNTRD
LNEFP	1.000000				
LNURB	0.966667	1.000000			
LNGDP	0.740718	0.687033	1.000000		
LNICT	0.939598	0.926602	0.728291	1.000000	
LNTRD	0.797232	0.770152	0.715163	0.819587	1.000000

The EFC model

	LNEFC	LNGDP	LNICT	LNURB	LNTRD
LNEFC	1.000000				
LNGDP	0.735419	1.000000			
LNICT	0.951953	0.728291	1.000000		
LNURB	0.983926	0.687033	0.926602	1.000000	
LNTRD	0.811182	0.715163	0.819587	0.770152	1.000000

The EFI model

	LNEFI	LNGDP	LNICT	LNURB	LNTRD
LNEFI	1.000000				
LNGDP	0.767349	1.000000			
LNICT	0.958367	0.728291	1.000000		
LNURB	0.935901	0.687033	0.926602	1.000000	
LNTRD	0.847025	0.715163	0.819587	0.770152	1.000000

The EFE model

	LNEFE	LNGDP	LNICT	LNURB	LNTRD
LNEFE	1.000000				
LNGDP	0.789943	1.000000			
LNICT	0.855346	0.728291	1.000000		
LNURB	0.803808	0.687033	0.926602	1.000000	
LNTRD	0.752038	0.715163	0.819587	0.770152	1.000000

Table 4: Variance inflation factors.

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
LNGDP	1.88E05-	70.57333	2.377818
LNURB	0.030778	2359.634	6.481630
LNICT	0.000269	13.55806	5.700806
LNTRD	0.013504	1111.770	3.797823
C	0.465502	2359.712	NA

normal distributions. GDP and ICT development, however, are highly skewed and non-normal, reflecting structural disparities in economic and digital development.

Overall, most EF indicators are well-behaved statistically, but special attention is needed when modelling variables like GDP, ICT, and EFE due to their distributional characteristics.

Pair-wise Correlation Analysis

Table 3 below illustrates the pair-wise correlation matrices of the four models:

Results from Table 3 suggest consistent correlation patterns. In all cases, environmental impact, whether from production, consumption, imports, or exports, is strongly associated with higher levels of urbanization and ICT development. These two factors exhibit the closest relationships, suggesting they are key structural drivers of ecological pressure. GDP and trade openness also show positive correlations across all models, though slightly weaker. Notably, EFC and EFI demonstrate the strongest overall associations with the explanatory variables, implying that lifestyle and external demand significantly contribute to environmental strain.

In sum, the results point to a shared dynamic: as economies urbanize, digitize, grow, and integrate into global trade, their EFs intensify, especially through consumption and imports. However, these strong correlations require variance inflation factors (VIF) analysis to check any potential multicollinearity concerns. The following Table 4 represents the VIF test outputs

The centered VIF results from Table 4 indicate mild to moderate multicollinearity among explanatory variables. LNGDP and LNTRD show low to acceptable levels (lower than 5), posing no concern. LNURB and especially LNICT exceed the common threshold of 5, signaling moderate multicollinearity. These values suggest, generally, the absence of extreme multicollinearity concerns (since lower

Table 5: ADF Unit Root Test.

At Level		LNEFP	LNEFC	LNEFI	LNEFE	LNURB	LNGDP	LNICT	LNTRD
Constant	t-Statistic	-0.2537	-1.3934	-1.2652	-0.9783	-2.8235	-0.3346	-0.5549	-1.2416
	Prob.	0.9242	0.5784	0.6391	0.7546	0.0619	0.9123	0.8713	0.6497
		n0	n0	n0	n0	*	n0	n0	n0
Constant & Trend	t-Statistic	-8.0492	-6.2846	-3.2571	-2.7545	-2.6791	-1.6683	-1.7760	-2.6892
	Prob.	0.0000	0.0000	0.0848	0.2202	0.2492	0.7514	0.7020	0.2451
		***	***	*	n0	n0	n0	n0	n0
Constant & Trend	t-Statistic	3.4863	4.7905	-2.3395	1.2006	-0.1897	1.1002	0.6494	1.2138
	Prob.	0.9998	1.0000	0.0200	0.9393	0.6131	0.9276	0.8533	0.9407
		n0	n0	**	n0	n0	n0	n0	n0
At First Difference		**d(LNEFP)**	**d(LNEFC)**	**d(LNEFI)**	**d(LNEFE)**	**d(LNURB)**	**d(LNGDP)**	**d(LNICT)**	**d(LNTRD)**
Constant	t-Statistic	-8.6947	-8.4567	-9.5928	-9.8459	-0.4186	-7.2269	-3.1646	-6.2138
	Prob.	0.0000	0.0000	0.0000	0.0000	0.8980	0.0000	0.0279	0.0000
		***	***	***	***	n0	***	**	***
Constant & Trend	t-Statistic	-8.6084	-8.5439	-9.5449	-9.9406	-1.9414	-7.3032	-3.0899	-6.1510
	Prob.	0.0000	0.0000	0.0000	0.0000	0.6187	0.0000	0.1195	0.0000
		***	***	***	***	n0	***	n0	***
Constant & Trend	t-Statistic	-12.9487	-11.8715	-8.8480	-9.6986	-1.2867	-7.1039	-2.3060	-7.3382
	Prob.	0.0000	0.0000	0.0000	0.0000	0.1804	0.0000	0.0217	0.0000
		***	***	***	***	n0	***	**	***

(*) $p < 0.01$, (**) $p < 0.05$, (***) $p < 0.001$.

than 10) that might compromise the precision of coefficient estimates or warrant closer scrutiny.

Unit Root Test

Table 5 summarizes the ADF unit root test results. As shown in the Table 5, the variables are integrated, with some at level I(0), and some others at the first difference I(1), meeting at least one of the stationarity criteria, either with a constant, a constant and a trend, or without at the 5% level. Accordingly, it can be said that the series in question are co-integrated and therefore, their variables can be combined linearly in the long–run, which paves the way for the application of an ARDL bounds, an ECM to define the long-run elasticities, and the three co-integration approaches for results' consolidation.

Lag Order Selection

Table 6 below summarizes the optimal lag selection estimations for the four models:

According to Table 6, with the unanimity of criteria across the four models, the optimal lag is the one with the lowest lag order. For ARDL modelling is 2.

ARDL Bounds Test

Table 7 represents the ARDL bounds test results for the four models. The ARDL bounds test results from Table 7 show that the F-statistics of the EFP, EFC, EFI, and EFE models are significantly higher than both the lower and upper critical value bounds at the 5% level, indicating that the null hypothesis of no co-integration is rejected in

Table 6: Optimal Lag length order selection.

The EFP model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-71.02967	NA	1.44e05-	3.041187	3.232389	3.113998
1	309.9495	670.5234	9.48e12-	-11.19798	10.05077-*	-10.76112
2	357.7008	74.49197*	3.94e12-*	12.10803-*	-10.00481	11.30711-*
3	375.0008	23.52796	5.80e12-	-11.80003	-8.740794	-10.63506
4	388.1802	15.28812	1.09e11-	-11.32721	-7.311959	-9.798178

The EFC model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-59.22253	NA	8.98e06-	2.568901	2.760103	2.641712
1	322.3498	671.5673	5.77e12-	-11.69399	10.54678-*	-11.25713
2	371.0372	75.95233*	2.31e12-*	12.64149-*	-10.53826	11.84057-*
3	392.0068	28.51867	2.94e12-	-12.48027	-9.421036	-11.31530
4	407.9500	18.49411	4.96e12-	-12.11800	-8.102752	-10.58897

The EFI model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-73.02299	NA	1.56e05-	3.120919	3.312122	3.193730
1	316.6852	685.8864	7.24e12-	-11.46741	10.32020-*	-11.03054
2	360.7260	68.70362*	3.49e12-*	12.22904-*	-10.12581	11.42812-*
3	378.1427	23.68678	5.12e12-	-11.92571	-8.866473	-10.76074
4	396.4881	21.28060	7.84e12-	-11.65952	-7.644276	-10.13049

The EFE model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-102.4926	NA	5.07e05-	4.299705	4.490907	4.372515
1	300.2134	708.7625	1.40e11-	-10.80853	-9.661321	-10.37167
2	352.6234	81.75962*	4.82e12-*	11.90494-*	9.801710-*	11.10402-*
3	368.8528	22.07202	7.42e12-	-11.55411	-8.494875	-10.38914
4	384.6882	18.36901	1.26e11-	-11.18753	-7.172278	-9.658497

* indicates lag order selected by the criterion

Table 7: ARDL bounds tests.

The model	F–statistic Value
EFP	10.97171
EFC	17.17399
EFI	4.557081
EFE	5.046055

at 5%, I_0 Bound= 2,86, I_1 Bound=4.01

favour of a long-run co-integration relationship between the variables.

The ARDL Analysis

Table 8 below shows the ARDL and ECM long-run estimations of the four footprint models:

Results from Table 8 show that the endogenous variables progress significantly and proportionally in the same positive direction across the four models. This and the ECT (CointEq(-1)) of each model have a negative and significant value, ranging from 1 to 0, indicating ideal annual adjustment speeds to the long-term equilibrium for the four models.

Residual Diagnostic and Stability Tests

The following Fig. 1 represents the CUSUM and the CUSUMSQ plots of the four models:

As Fig. 1 illustrates, the CUSUM and CUSUMSQ plots for all four models generally fall within the 5% level bounds, with only minor and brief exceptions, indicating their stability.

The EFs Model Normality Tests

Fig. 2 shows the four EF models' Jarque-Bera normality test outputs.

As shown in Fig. 2, the EF models' residuals exhibit a normal distribution at the 5% level.

Residuals Diagnostic and Stability Check Summary

The results of ARDL residual diagnostics and stability tests are regrouped in Table 9:

As shown in Table 9 above, the results indicate that, generally, the EF models exhibit no serial correlation or misspecification in their residuals (except for the EFE), and instead, display normal distributions with homoscedastic data. This suggests that the footprint models are stable, and their residuals do not impact the co-integration modelling process.

The Four Cointegration Methods Result Summary

The Figs. 3,4,5 and 6 graphically represent the four co-

Table 8: The footprint models ARDL long-run estimates.

The EFP model's ARDL estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNURB***	1.416673	0.170776	8.295503	0.0000
LNGDP	0.002467	0.003451	0.714778	0.4786
LNICT**	0.033497	0.013895	2.410765	0.0203
LNTRD	0.010529	0.116341	0.090501	0.9283
C	11.596762	0.738764	15.697522	0.0000
CointEq(-1)	-1.089484	0.148246	-7.349146	0.0000

The EFC model's ARDL estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNURB***	1.924236	0.111154	17.311484	0.0000
LNGDP	0.002582	0.002404	1.073967	0.2886
LNICT***	0.040997	0.009051	4.529376	0.0000
LNTRD***	0.168759	0.065963	2.558373	0.0140
C	9.014011	0.453759	19.865186	0.0000
CointEq(-1)	-1.041008	0.133040	-9.328106	0.0000

The EFI model's ARDL estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNURB	0.618653	0.415879	1.487578	0.1437
LNGDP	0.010629	0.008150	1.304239	0.1986
LNICT***	0.101632	0.035638	2.851763	0.0065
LNTRD	0.099386	0.255452	0.389059	0.6990
C	-4.089530	1.817821	-2.249688	0.0293
CointEq(-1)	-0.438531	0.121079	-3.621856	0.0007

The EFE model's ARDL estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNURB***	1.727166	0.536784	-3.217618	0.0025
LNGDP***	0.038539	0.009025	4.270240	0.0001
LNICT	0.050198	0.039027	1.286234	0.2052
LNTRD	0.104373	0.256254	0.407303	0.6858
C	4.480434	2.188006	2.047725	0.0467
CointEq(-1)	-0.537229	0.113798	-4.720912	0.0000

(*) $p < 0.01$, (**) $p < 0.05$, (***) $p < 0.001$.

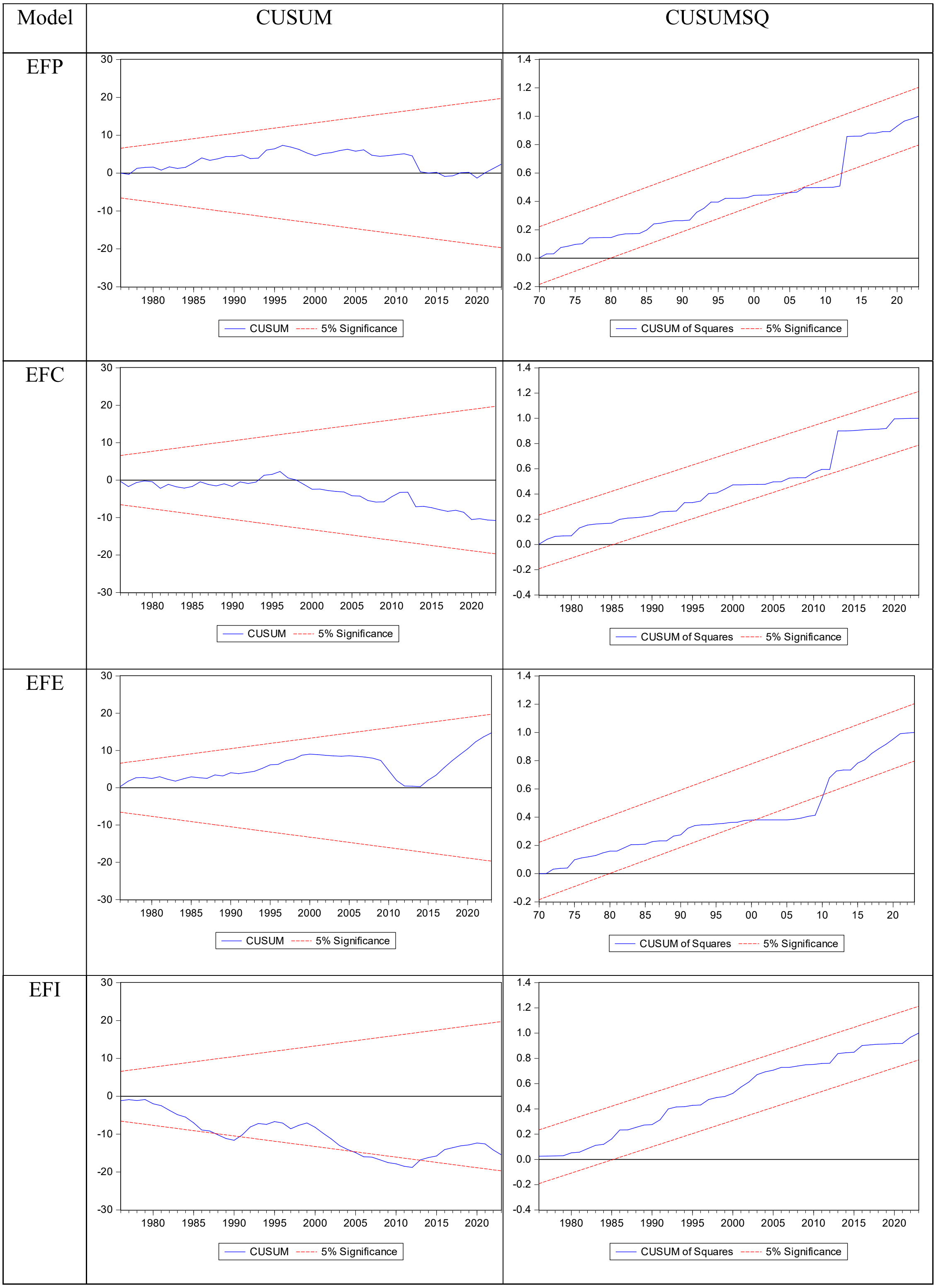
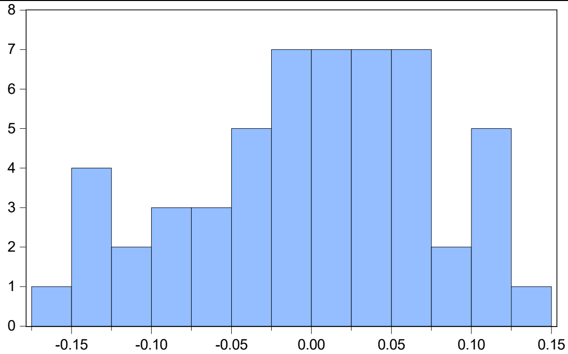
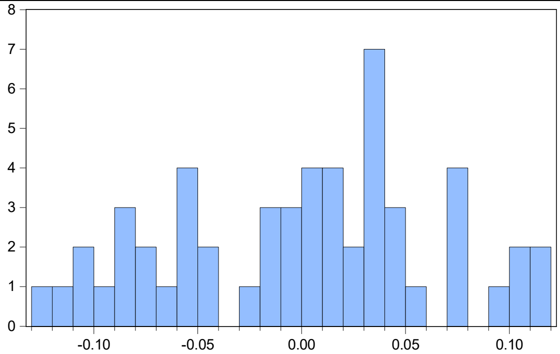


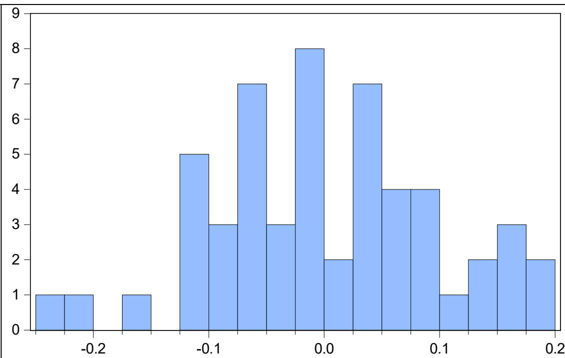
Fig. 1: The EFs models' CUSUM and the CUSUMSQ plots.

<table>
<tr><th>Model</th><th>Jarque-Bera Normality test</th><th>Descriptive statistics</th></tr>
<tr><td>EFP</td><td>
</td><td>Series: Residuals
Sample 1970 2023
Observations 54

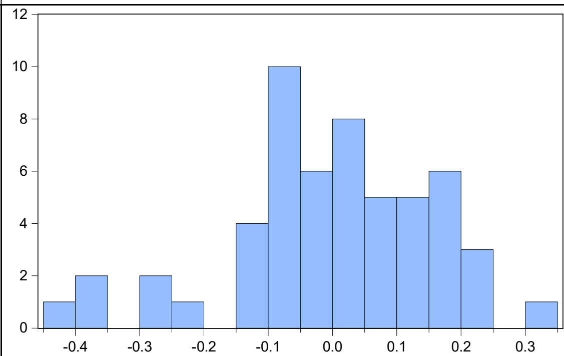
Mean -8.20e-16
Median 0.012828
Maximum 0.138026
Minimum -0.167412
Std. Dev. 0.075367
Skewness -0.343952
Kurtosis 2.366367

Jarque-Bera 1.968082
Probability 0.373797</td></tr>
<tr><td>EFC</td><td>
</td><td>Series: Residuals
Sample 1970 2023
Observations 54

Mean -1.55e-15
Median 0.009354
Maximum 0.115335
Minimum -0.120411
Std. Dev. 0.063489
Skewness -0.116250
Kurtosis 2.154243

Jarque-Bera 1.731063
Probability 0.420828</td></tr>
<tr><td>EFI</td><td>
</td><td>Series: Residuals
Sample 1970 2023
Observations 54

Mean -1.01e-15
Median -0.008537
Maximum 0.186689
Minimum -0.236988
Std. Dev. 0.097692
Skewness -0.060908
Kurtosis 2.622077

Jarque-Bera 0.354747
Probability 0.837467</td></tr>
<tr><td>EFE</td><td>
</td><td>Series: Residuals
Sample 1970 2023
Observations 54

Mean 4.32e-17
Median 0.027228
Maximum 0.313276
Minimum -0.440617
Std. Dev. 0.156916
Skewness -0.607282
Kurtosis 3.401947

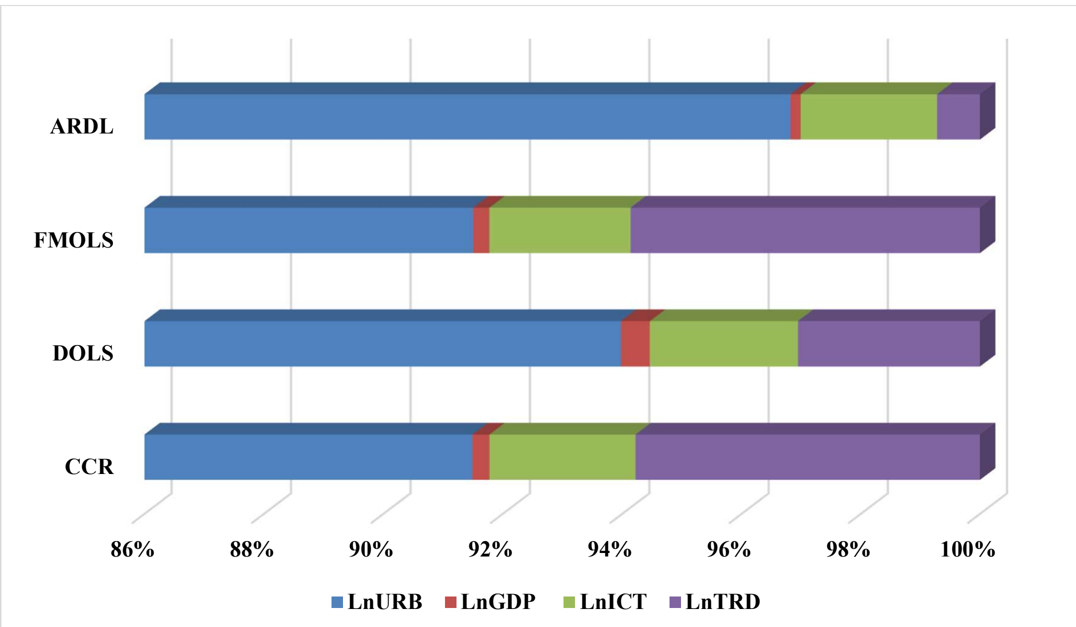
Jarque-Bera 3.682633
Probability 0.158609</td></tr>
</table>

Fig. 2: The Jarque-Bera normality test outputs.

Table 9: The ARDL residual diagnostics and stability tests of the EFs models.

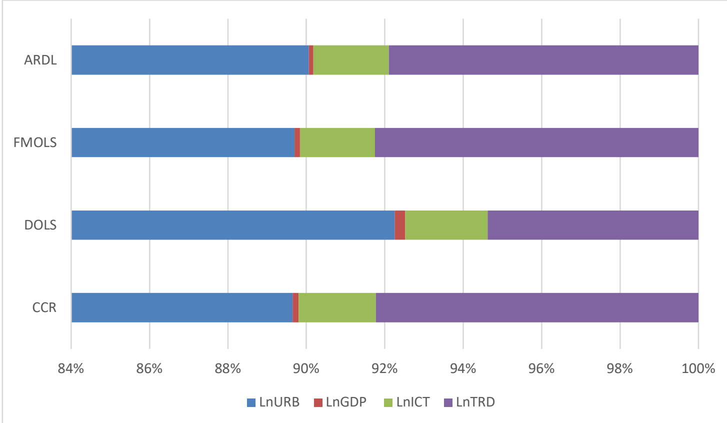
Test & hypothesis	Model	F–Statistic	P–value	Interpretation	Conclusion
Breusch–Godfrey serial Correlation LM (**H_0:** absence of serial correlation)	EFP	0.437579	0.6482	Fail to reject H_0	Absence of serial auto- correlation for the footprint models
	EFC	1.343979	0.2706		
	EFI	11.07573	0.1024		
	EFE	16.95542	0.0912		
Jarque–Bera Normality (**H_0:** Residus are normally distributed)	EFP	1.968082	0.373797	Fail to reject H_0	The four footprints' residuals are normally distributed
	EFC	1.731063	0.420828		
	EFI	0.354747	0.837467		
	EFE	3.682633	0.158609		
Breusch–Pagan–Godfrey Heteroskedasticity (**H_0:** Residus are homoscedastic)	EFP	0.437579	0.6482	Fail to reject H_0	Residus are homoscedastic for the footprint models
	EFC	1.343979	0.2706		
	EFI	2.083177	0.0973		
	EFE	3.656341	0.0910		
Ramsey RESET Functional form (test of specific error) (H_0: No misspecification)	EFP	1.717189	0.1963	Fail to reject H_0	No residus misspecification in the models except for EFI' model
	EFC	0.178952	0.6742		
	EFI	11.07573	0.6001		
	EFE	8.979528	0.0430	Reject H_0	

H_0 is either accepted or rejected at the 5%.



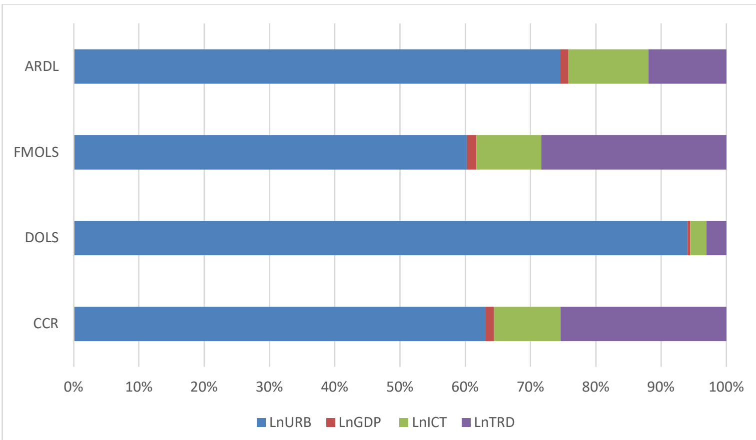
Source: Office outputs based on the authors' own computations

Fig. 3: The EFP model results.



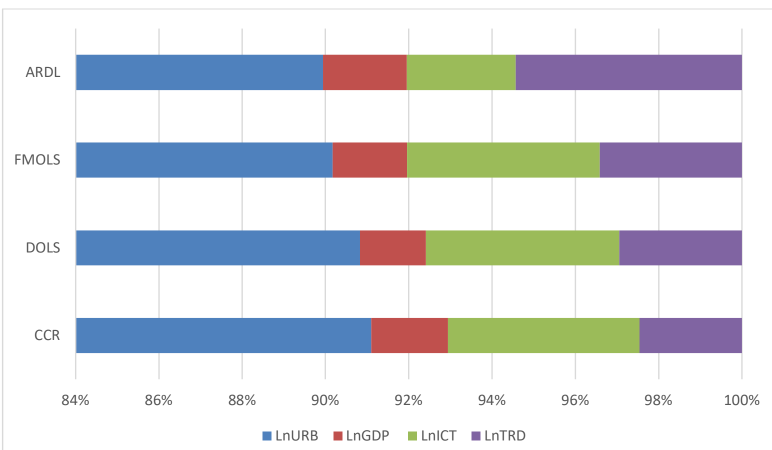
Source: Office outputs based on authors' own computations

Fig. 4: The EFC model results.



Source: Office outputs based on authors' own computations

Fig. 5: The EFI model results.



Source: Office outputs based on the author's own computations

Fig. 6: The EFE model results.

Table 10: Final incidence appreciation on environmental degradation.

MODEL	LnURB	LnGDP	LnICT	LnTRD
EFP	Very high	Very low	Moderate	Moderate
EFC	Very high	Very low	Moderate	high
EFI	So high	Very low	Moderate	Moderate
EFE	So high	Low	Moderate	Moderate
→ Environmental degradation	Very high	Very low	Moderate	Moderate

NB: General appreciation of environmental appreciation is based on the EF's singular appreciations

integration methods' results: Table 10 provides a final incidence appreciation based on the four EF models' results.

DISCUSSION

From the final appreciation in Table 10 above, it can be said that anthropogenic processes associated with urbanization, economic growth, technological progress, and trade openness had a positive impact on EFP, EFC, EFE and EFI in Morocco over five decades (1970–2023).

Based on the previously formulated hypotheses, H_a, H_b, H_c and H_d, are strongly supported.

The findings affirm that urbanization, technological progress, economic growth, and trade openness have significantly contributed to the increase in Morocco's divers EFs. These drivers, while traditionally linked to development and modernization, are shown here to exert unsustainable pressure on the environment, echoing concerns raised in broader literature (Dietz & Rosa 1997, York et al. 2003).

Urbanization, for instance, is typically associated with increased infrastructure demands, resource consumption, and pollution factors that amplify ecological degradation in the absence of green urban planning (Sharma 2011). In Morocco's case, urban sprawl has likely led to habitat loss and increased energy use, worsening ecological impacts.

Technological progress, though often positioned as a solution to environmental challenges, can paradoxically intensify them when it encourages higher consumption and resource exploitation, a phenomenon known as the rebound effect (Polimeni et al. 2008). In Morocco, technology has apparently contributed to increased EFs, suggesting a lack of alignment with sustainable development principles.

Trade openness is another double-edged sword. While it can promote economic diversification and growth, it can also lead to environmental externalities, especially when trade involves ecologically harmful goods or when environmental regulations are weak (Antweiler et al. 2001). The study attributes Morocco's rising ecological impact from imports and exports to these dynamics.

Finally, economic growth in Morocco, while vital for poverty reduction, appears environmentally taxing. This aligns with the (EKC) hypothesis (Hamdi et al. 2025), which posits that environmental degradation first increases with economic growth before eventually declining, though Morocco may still be in the upward phase of this curve (Grossman & Krueger 1995).

The use of four co-integration techniques strengthens the reliability of the results by confirming long-run equilibrium relationships between environmental degradation and its drivers. This methodological rigor allows for more confident policy implications.

Importantly, the conclusion underscores the unsustainability of current trends and advocates for multi-level policy responses. These include individual behavioral changes, organizational reforms, and government-led interventions to boost bio-capacity and mitigate environmental stress. This multi-pronged approach is consistent with global sustainability frameworks, such as the United Nations Sustainable Development Goals (SDGs), particularly Goals 11 (Sustainable Cities), 12 (Responsible Consumption and Production), and 13 (Climate Action).

In sum, the Moroccan context reflects broader trends in the Global South, where the pursuit of development, absent environmental safeguards, risks deepening ecological crises. This study contributes to the growing call for evidence-based, inclusive environmental governance that addresses the root causes of degradation while supporting equitable development.

Policy Implications

The findings underline the urgent need for informed and context-specific policy interventions. Here are some concise and practical sustainable propositions to help undermine and reduce the EF rise and effects, applicable to three individual, organizational, and governmental levels, which can be translated into materialized concrete actions (Table 11).

Study Potential Limitations

This study has three main limitations. Statistically, co-

Table 11: Policy implications' propositions.

Actions level	Policy implications' propositions
Individual	• Biking, walking, or using public transport, for daily commutes, and when possible, opting for electric or hybrid vehicles for personal use (Anbar 2022, Ontario Nature 2024) • Unplugging electronics and appliances regularly when not in use, and switching to LED bulbs and energy star-rated electronics for energy efficiency (Anbar 2022, Blog_Admin 2024) • Incorporating more plant-based meals to reduce emissions from livestock (Ontario Nature 2024, Sarah-Indra 2024) • Practicing waste management by adopting the 3Rs: Reduce, Reuse, Recycle, to minimize waste (Ontario Nature 2024, Blog_Admin 2024) • Composting organic waste. such as agro-food waste (Ontario Nature 2024, Sarah-Indra 2024)
Organizational	• Creating thematic action plans by identifying key areas for improvement (e.g., energy consumption, waste management) and setting clear objectives with specific measures and timelines. • Identifying low-carbon trajectories to set science-based targets for reducing GHG and regularly monitor progress. • Assessing suppliers' carbon footprints and encouraging sustainable practices through incentives and partnerships. • Implementing a collective waste disposal (Hamilton et al 2013).
Governmental	• Setting an achievable, energetic transition as a national objective. • Enacting legislation that enforces sustainable practices across society and the economy, such as renewable energy targets, green incentives, carbon taxation, waste management standards… • Promoting environmental public awareness via official media, school programs and public spending (Hamdi & Azeroual 2023a, 2023b). • Fixing an ultimatum for economic carbon neutralization, with a focus on the intensive emitter sectors such as transport and industry

integration models are effective for long-term analysis but limited to co-integrated series, with challenges in lag selection and model complexity as more variables are added. Cognitively, the study lacks a predictive framework and focuses on traditional STIRPAT factors, omitting emerging variables like energy use, governance, and clean technologies. In terms of scope, the Morocco-specific focus limits the broader applicability and global relevance of the findings.

Plausible Future Prospects

Prospects should continue exploring this study's interactions by extending the spectre of explaining environmental degradation factors, as well as opting for other ecological barometers, and enlarging datasets to include geographical imbalances and panel differential properties.

CONCLUSIONS

This study explored the long-term effects of human-induced processes associated to urban expansion, economic affluence, technological progress and openness to international trade on Morocco's EFs through its four economic varieties: of production (EFP), consumption (EFC), imports (EFI), and exports (EFE) from 1970 to 2023, and how these fluctuations have shaped the trajectory of Morocco's ecological sustainability more than six decades.

To assess these interactions, the study employed four co-integration techniques, namely ARDL, FMOLS, DOLS, and CCR. Each of them was applied to each EF component, enabling a robust and multifaceted understanding of the resultant ecological outcomes.

Findings indicate that urban expansion, along with economic growth, as well as technological progress, besides openness to international trade, have significantly contributed to the intensification of ecological stress in Morocco, that is, the degree of impact varied respectively from high, moderate, subtle, to low across the four EF considered models.

Overall, the study underscores the complex and multifaceted nature of anthropogenic ecological stress in Morocco and highlights the implications of socioeconomic factors in shaping the country's environmental future trajectory through adequate proposed policy implications.

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