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Impacts of Anthropogenic Activities on Morocco's Ecological Footprint: A Long-Run STIRPAT Analysis Using VAR/VECM Modeling

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Abstract: This study assesses the long-term impacts of anthropogenic activities on Morocco's Ecological Footprint (EF), employing a dataset from 1980 to 2022 within the framework of the STIRPAT model and utilizing a model (VAR/VECM) approach. Results indicate that Demographic Growth (DG) and Economic Growth (EG) have contributed to an increase of EF by 13.76% and 119.13% per unit output, respectively. Conversely, Higher Educational (HE) attainment scores is shown to alleviate EF, reducing its output by 50.59%. This analysis underscores the urgent need for policy pathways in Morocco that prioritize ecosystem preservation, foster green growth, and promote Human Capital (HC). Recommendations include enhancing the valorization and expansion of the natural ecosystem, aligning economic and demographic trajectories with the region's Bio-Capacity (BC) regeneration limits, and optimizing EF management through sustainable consumption and production practices.

Keywords: Anthropogenic activities; Ecological footprint; Morocco; STIRPAT; VAR; VECM; Green growth, Bio-capacity; Sustainable development

1. Introduction

The stress placed on the biosphere by resources human's is quantified by a measure called EF, this concept was introduced in mid-nineties by Wackernagel & Rees (1996) for the evaluation of environmental impacts associated with human activities (Nautiyal & Goel, 2021), which represents a conception of the manner that humans are affecting the environment considering production, energy use, management of land for living space, fooding, goods extracting etc. (Dietz et al., 2007; Rafindadi & Usman, 2020). However, few studies around the world have shown interest to the impact of environmental stressors on global biosphere degradation using EF as an indicator such as Zhang et al. (2020), unlike the other popular indicators in the matter, such as CO_2 emissions like Ansari et al. (2019); Naz et al. (2024), or GHG emissions like Sarkodie & Strezov (2018), or even energy consumption like Belloumi & Alshehry (2015), or more than one indicator as Ullah & Lin (2024) did, even less in the Moroccan context excepting one single study of Farouki & Aissaoui, (2024). Morocco, like many countries, has reached critical limits of resources consumption and waste production compared to the bio-capacity potential of regeneration and waste absorption, supposing that any rise in EF reduces the environmental ecosystem quality, this implies that a country become more globalized and technologized, productive and popularized, the more likely it is to experience an ecological overshoot as soon as imaginable. The idea that any rise in EF reduces eventually the ambient ecosystem quality implies that as a country become more globalized and technologized, productive and popularized, the more likely it is to experience an ecological overshoot. Morocco is taking significant steps to reduce its ecological footprint, particularly through investments in clean energies, sustainable agriculture and HC promotion, however, challenges such as water scarcity, waste management, amplified DG correlated to consumption intensification and the climate change effects are posing significant hurdles; which is putting on stake the Moroccan vital ecosystem survival, and subsequently, the harsh issue of the urgent need to conserve the environmental patrimony.

Few studies around the world have shown interest in the impact of environmental stressors on global biosphere degradation using EF as an indicator such as Zhang et al. (2020), unlike the other popular indicators in the matter, such as CO_2 emissions like Ansari et al. (2019); Naz et al. (2024), GHG emissions like Sarkodie & Strezov (2018), or even energy consumption like Belloumi & Alshehry (2015), or more than one indicator as did Ullah & Lin (2024), even less in the Moroccan context excepting one single study of Farouki & Aissaoui (2024). Actually, Morocco, like many countries, has reached critical limits of resource consumption and waste production compared to the bio-capacity potential of regeneration and waste absorption, supposing that any rise in EF reduces the environmental ecosystem quality. This implies that a country such as Morocco when it becomes more globalized, technologized, productive, and popularized, the more likely it is to experience an ecological overshoot as soon as imaginable. The idea that any rise in EF eventually reduces the ambient ecosystem quality implies that as a country becomes more globalized, technologized, productive, and popularized, the more likely it is to experience an ecological overshoot. Therefore, a scientific formulation and a constructive description of the linkage between environmental degradation and anthropogenic activities in the Moroccan context are required to first diagnose the state of ecological gangrene and to assess efficient and targeted policies in order to undermine it. After an in-depth literature review, the research methodology is largely schemed step by step and sufficiently presented method by method, abreast with the variable presentation and the model construction in the 2nd Section , results issued from the empirical evidence are exposed and given an economic interpretation in the 3rd Section, and then discussed and compared with other similar studies outputs in the 4th Section, where also included a critical reflection on the limitations of the study and its potential biases along with future prospects. before it gets concluded with constructive remarks in the 5th and built upon political implications underneath in the 6th section.

2. Literature Review

On one hand, the EKC hypothesis that dissects the long matter-of-debate nexus between environmental degradation and EG (Adhikary & Hajra, 2021) takes the form of an inverted U-shape (Kuznets, 1955), supposing that in the primer phase of an economic cycle, affluence and environmental degradation increase simultaneously, but when a specific level of individual income is reached, the relationship reverses, and further EG leads to a reduction in environmental impact as societies can afford cleaner technologies and stronger environmental regulations (Beyene & Kotosz, 2019). This pattern is more observed in developed economies than in the emerging ones (Dinda, 2004). In the wake of the EKC hypothesis, some researchers founded that demographic and EG are the main causes of human environmental stressors (Dietz & Rosa, 1994; Nautiyal et al., 2019; Varun & Chauhan, 2014; Shree et al., 2021), while others largely considered other endogenous factors such as urban growth, demographic structure, and income distribution (Danish et al., 2019; Liddle, 2011; Yu & Du, 2019). An effective combination of these factors can make possible promoting EG without the environmental resources and ultimately, to ensure human well-being and sustainable development (Farouki & Aissaoui, 2024), in fact many studies have addressed this issue through CO_2 as a target key indicator to asses effective environmental management such as Abbasi et al. (2021); Bekun et al. (2019); Béláïd & Youssef (2017); Mirziyoyeva & Salahodjaev (2022); Raihan & Tuspekova (2022), but as this indicator was subject to waves of massive critics regarding the lack of its exhaustiveness (Altıntaş & Kassouri, 2020; Aziz & Sarwar, 2023; Destek et al., 2018; Nathaniel et al., 2020; Ullah et al., 2023; Usman et al., 2020; Ramezani et al., 2022; Sun et al., 2023). Thus, particular attention has been given to EF as an exhaustive indicator which takes into account a panoply of different ecological stressors (Galli et al., 2013), especially those related to production and consumption from a human behavior perspective. This is why it is substantially more suited to assess comprehension about the linkage of humans with the environment (Rafindadi & Usman, 2020). The following Table 1 highlights some recent works close to the present paper, treating the fluctuations of anthropogenic activities on EFs applied to homologous countries, groups of countries, and regions quasi-identic to Morocco regarding the economic affluence and the demographic structure, in order to define precise references to the hypotheses that guide the study.

In the anthropogenic-environmental-degradation field research, the main adopted theoretical framework is unequivocally STIRPAT pioneered by Ehrlich & Holdren (1971), well known as an analytic practical tool for empirical analysis based on statistical regressions of between human activity variables and environment-dependent indicators, supposing the incidence on natural capital as a commutative product imputed to three categories of environmental stressors: primo (P) for population dynamics and activities, secondo (A) for EG, and tertio (T) for technological progress (York et al., 2003). STIRAPT is the top celebrity among the IPAT family, from which some derived models merit some attention, like the "ImPACT indentity," which identifies “actors with the forces” (Waggoner & Ausubel, 2002). In the same line, some authors proposed the ImPACTs identity (Lin et al., 2009). Some others proposed the "IPBAT identity" Schulze (2002) which was criticized by Diesendorf (2002), who argued that the behavior is already implicit in the IPAT equation as reported (Vélez-Henao et al., 2019).

Table 1. Similar studies of the impacts of anthropogenic activities on ecological footprint

Study Purpose	Coverage	Main Results
"Analyzing the nexus between economy, renewable energy, DG and EF with an empirical evidence using STIRPAT model in Morocco" (Farouki & Aissaoui, 2024)	1980 to 2021	"Long term incidence of individual income, renewable energy consumption, urban growth, trade openness on EF in Morocco in parallel with the confirmation of the EKC hypothesis" (Farouki & Aissaoui, 2024)
"Examining the incidence of, economic factors, HC, energy consumption, and urbanization on CO_2 in Morocco: with an ARDL approach" (Asli et al., 2024)	1970 to 2019	"HC rise leads to a fall-down in carbon emissions, conversely, when EG and energy consumption upsurge, the opposite is resulted" (Asli et al., 2024)
"Examining the cause-effect fluctuations in EF and CO_2 in Pakistan of GDP, renewable energy, natural resources and DG" (Ullah & Lin, 2024)	1990 to 2018	"Natural Ressources and Renewable Energy have an asymmetric impact on environmental quality. While GDP was found to have positive impact with EFP and CO_2" (Ullah & Lin, 2024)
"Investigating the asymmetric impact of patents on green technologies on Algeria's EF" (Bergougui & Aldawsari, 2024)	1990 to 2022	"Upsurge in green technologies (renewable energies and the HC in back up) significantly reduces EF" (Bergougui & Aldawsari, 2024)
"Studying the nexus between renewable energy production, energy consumption and sustainable EG in Turkey using a VECM approach" (Dinç & Akdoğan, 2019)	1980 to 2016	"Causal relationship between renewable energy and EG both in the short and long runs, also a causal relationship running from energy consumption to EG both in the short and long runs, support" (Dinç & Akdoğan, 2019)
"Analyzing the relationship between Renewable energy, urban growth, and EF in MENA" (Nathaniel et al., 2020)	1990 to 2016	"Energy consumption, urbanization, EG, and energy use contribute to environmental degradation" (Nathaniel et al., 2020)
"Weighting the impact of HC on the EF in India through an empirical analysis" (Ali et al., 2022)	1990 to 2016	"Natural resources exploitation, financial inclusion, EG, and urban growth increase the entire panel's EF pressure. While Economic governance institutions, renewable energy consumption, and HC reduce the EF on the ECOWAS economies" (Ali et al., 2022)
"Associating EG and EFs through BC and HC and in South Asia" (Mehmood et al., 2023)	1990 to 2022	"Positive contribution of GDP, HC, BC, and urban growth to EF" (Mehmood et al., 2023)

Source: Authors own collection

In the wake of all these efforts and debates, this study is projected into the Moroccan context with the purpose of clearly responding to the sequential following questioning:

How are human activities, incorporated by EG, DG, and HE, affecting the EF in Morocco?
What is the singular effect of each one of these factors on the EF in Morocco?
And how are these three factors jointly manifesting their impact on the EF in Morocco?

In response to these queries, the following hypothesis has been formulated:

H_0: EG, DG, and HE are affecting the EF in Morocco. From which are to be verified the following sub-hypothesis:
H_{0a}: EG has a negative impact on EF in Morocco.
H_{0b}: DG has a negative incidence on EF in Morocco.
H_{0c}: HE has a negative effect on EF in Morocco.

By bringing constructive demonstrations, the purpose of this study is to measure the incidence of anthropogenic activities on the EF in Morocco.

3. Research Methodology

This study uses a VAR model, which makes able the forecast for future values of multiple data based on their past tendencies. The VAR is estimated after differencing non-stationary series, while the VECM incorporates the co-integrating relationship to model the series in levels. They both exhibit an equilibrium relationship over the long-run. The VECM has an error correction term (ECT) that accounts for short-run deviations from this equilibrium. While a VAR uses only lagged values for the variables as predictors, a VECM also includes the ECT. This study's procedural logarithm is exhaustively schematized in steps in the following Figure 1:

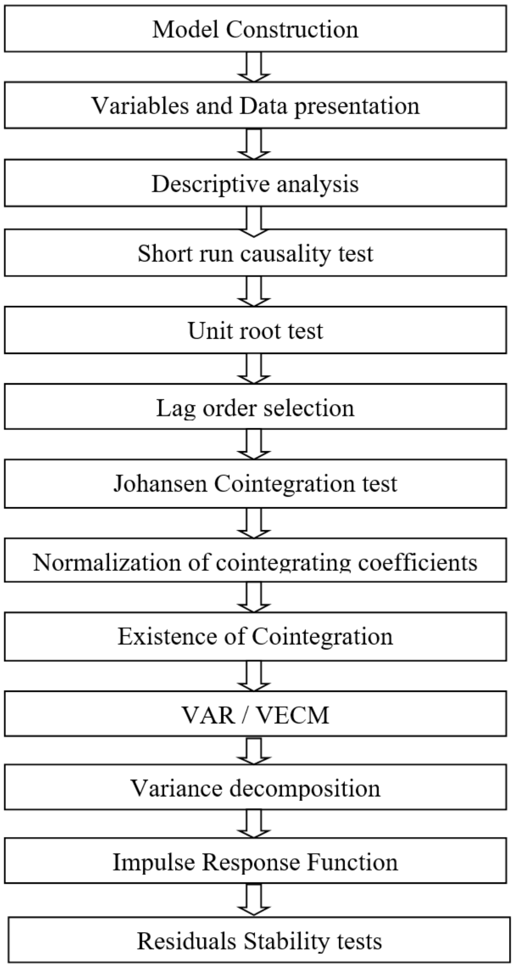

Figure 1. The VAR/VECM approach procedure

3.1 Model Presentation

This study applies the STIRPAT model in line with Abbas et al. (2023); Bargaoui et al. (2014); York et al. (2003) with the following specifications:

$$I = \alpha P_i^b A_i^c C_i^d e_i$$

where, *P* stands for Population quantity, *A* for Affluence and e for Technological progress and vary simultaneously across the observational units through the subscript i, while *b*, *c*, *d* are their respective exponents, the constant θ scales the model, *e* represents the white noise term. Nevertheless, the designation of the technology term is a matter of ceaseless debate, in some papers it is the error term, in some others it is taken for an independent variable (Vélez-Henao et al., 2019). In this paper, Technology is recuperated by HE, because, intuitively, a technological society is a highly educated society, since adopting technology and handling it, especially for production, is necessarily requiring a high level of education and technical knowledge, hence, the relationship between technology and education can be described from an epistemological perspective as “bidirectional, impacting graduates' skills and necessitating educational adaptation to equip students with relevant technology and strategy skills for the modern workplace” (Efthymiou et al., 2022). Accordingly, the following functional form is adopted:

$$EF = f\,(EG, DG, HE)$$

where, *EF* stands for Ecological footprint, *EG* for Economic Growth, *DG* for Demographic Growth and *HE* for Higher Education, with f defined as a linear function.

Table 2 below describes the variables above, their relative data and provide their respective resources:

Table 2. Variables and data presentation

STIRPAT Determinants	Variables	Acronym	Unit of Measure	Data Source
I	Ecological Footprint of consumption per capita	EF	Global hectare	Global Footprint Network
P	Demographic Growth	DG	Unitless	World Development Indicators
A	Economic Growth (GDP per capita)	EG	Constant 2015 USD	World Development Indicators
T	Higher Education enrolments	HE	Number	UNESCO Institute for Statistics (UIS)

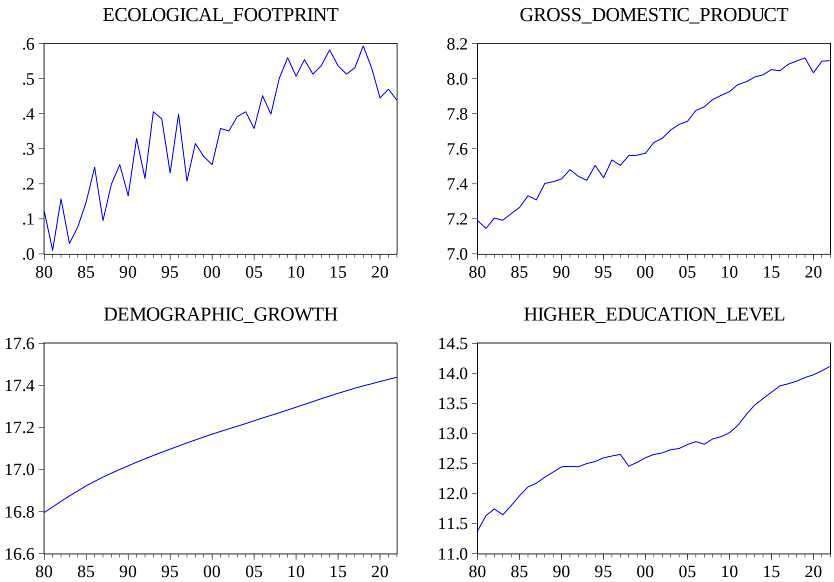

Figure 2. The variables keys' data evolution

Figure 2 provides a graphic description of the variables key's data evolution over the period of study.

3.2 Model Construction

This study is conducted by using a representative sample of 43 annual observations from 1980 to 2022. In which the collected data is expressed in a numeric form, dedicated for second use, and already been published under free common licenses from their original sources, and chosen based on their adequacy for VAR modeling. Hence, the STIRPAT model was applied in the strict sense, in which no control variables were added for the purpose of getting authentic and credible interpretations.

Based on Figure 2, the time series plots are showing upward trends and tend to show relative stability over time except for ecological footprint, which is manifesting a saw tooth curve over time in a rising trend. It is obvious, in the long of the study coverage, that pressure made on natural resources was getting progressively intensive, that the part of each capita of the national production was increasing quasi-expandingly, that DG was sustained at a stable rate, while the portion of highly educated people in Morocco kept increasing significantly. The fallback observed towards the plots' ends concerning EF and DG is essentially due to the fallouts of the Covid-19 conjecture.

By applying the natural log on the functional form, the following specifications are attained:

The initial model:

$$\mathrm{LnEF} = \mathrm{LnEG} + \mathrm{LnDG} + \mathrm{LnHE} + \mathrm{C} \tag{1}$$

The VAR model:

$$\begin{aligned} \mathrm{LnEF_t} &= \beta_0 + \beta_1 \mathrm{LnEF_{t-1}} + \beta_2 \mathrm{LnEG_t} + \beta_3 \mathrm{LnDG_t} + \beta_4 \mathrm{LnHE_t} + \\ & \sum_{i=1}^{3} \lambda_1 \mathrm{LnEF_{t-1}} + \sum_{i=1}^{3} \lambda_2 \mathrm{LnEG_t} + \sum_{i=1}^{3} \lambda_3 \mathrm{LnDG_t} + \sum_{i=1}^{3} \lambda_4 \mathrm{LnHE_t} + \varepsilon_t \end{aligned} \tag{2}$$

where, $\lambda_{0\ldots4}$, $\lambda_{1\ldots4}$ represent the variables coefficients, ε_t the error term, t time periods.

The VECM model:

$$\Delta \mathrm{LnEF}_t = \lambda_0 + \sum_{i=1}^{2} \Delta\lambda_1 \mathrm{LnEF}_{t-1} + \sum_{i=1}^{2} \Delta\lambda_2 \mathrm{LnEG}_t + \sum_{i=1}^{2} \Delta\lambda_3 \mathrm{LnDG}_t + \sum_{i=1}^{2} \Delta\lambda_4 \mathrm{LnHE}_t + \lambda_5 \mathrm{ECT} + \mu_0 \quad (3)$$

where, $\lambda_{0\ldots5}$ represent the short run coefficients, μ_0 the error term, t time periods.

3.3 Methods

The empirical evidence of this study is conducted following the methods explained below:

3.3.1 Descriptive analysis

Descriptive analysis is affected by three techniques: common descriptive statistics, multiple correlation analysis (MCA) introduced by Bonett & Wright (2000), and principal component analysis (PCA) pioneered by Pearson (1901), all in line with El Asli et al. (2024). Descriptive statistics are to be interpreted based on the dispersion indicators (mean, median, and Std Dev), besides Skewness, Kurtoisis, and the Jarque-Bera normality test.

3.3.2 Pairwise Granger causality

The causality test between the variables in the short run is conducted via the direct Granger (1969) Method which was introduced under the following specification:

$$Y_t = \lambda_0 + \sum_{j=1}^{j} \lambda_j\, Y_{t-j} + \sum_{k=1}^{k} \delta_k + X_{t-k} + \varepsilon_t$$

Expressed in the reverse direction:

$$X_t = \theta_0 + \sum_{j=1}^{j} \theta_j\, X_{t-j} + \sum_{k=1}^{k} \phi_k + Y_{t-k} + \mu_t$$

where, X_t and Y_t represent the variables to study the short run causality between; θ_j and λ_j are coefficients endorsing previous periods, λ_0 and θ_0 are constants, t is time and k is the number of lags, ε_t and μ_t are error terms.

The hypotheses to be tested are: H_0: $\delta_k = 0$ against H_a: $\delta_k \neq 0$ / H_0: $\theta_i = 0$ against H_a: $\theta_i \neq 0$.

If $\delta_k \neq 0$ but $\theta_i = 0$ then X_t cause Y_t and if $\theta_i \neq 0$ but $\delta_k = 0$ then Y_t cause X_t.

If both $\delta_k \neq 0$ and $\theta_i \neq 0$, then causality is bi-directional.

3.3.3 Unit root test

ADF for Augmented Dickey & Fuller (1979), tests the possibility that a unit root might be present in an autoregressive (AR) time series when it's not the case we are talking about stationarity or trend-stationarity. It was developed in order to tackle the problem of autocorrelation, which usually arises in time series during empirical analysis. ADF underlies three mathematical versions, implying the existence of the constant and the trend among time series; one version at least must be satisfied fulfilled to judge the realization of stationarity:

$\Delta Y_t = \lambda_1 + Z Y_{t-1} + \theta_i + \mu_t$ (constant only)

$\Delta Y_t = \lambda_1 + \lambda_2 t + Z\, Y_{t-1} + \theta_i + \mu_t$ (trend and constant)

$\Delta Y_t = Z\, Y_{t-1} + \theta_i + \mu_t$ (without trend and constant)

A couple of hypotheses are to be tested through the test: H_0: the variable has unit root / H_a: it doesn't.

3.3.4 Stability check

Stability is checked by undertaking the inverse roots of autoregressive process (AR(p)) (Lütkepohl, 1991).

3.3.5 Lag order selection

Choosing the appropriate lag order length is primordial in VAR models because it enables to reduce the number of unnecessary lags besides the insignificant coefficients, prevent loosing extra degrees of freedom and avoid the multi-collinearity between series.

3.3.6 VAR/VECM approach

This study adopts the VAR/VECM approach, in line with Chamalwa & Bakari (2016) for Nigeria, Georgantopoulos & Tsamis (2011) for Hungary, Musa & Joseph (2014) for Uganda, Azeroual (2016) for Morocco, and Toudas et al. (2017) for Greece based on Engle & Granger (1987) as well as Granger (1986) method.

A VAR (p) model, there can include three terms: a constant (μ_0), a trend (ΦD_t), both, or any of. Its specification can be expressed as:

$$y_t = \mu_0 + \Phi D_t + A_p y_{t-p} + \ldots + A_i y_{t-1} + \varepsilon_t \qquad t = \text{from 1 to T}$$

where, y_t is the representative vector of n stochastic variables, with p as the lag length taken on each variable, A_i is the variables respective coefficients across periods, while ε_t represents the disturbance term.

3.3.7 Johansen co-integration

A VAR can be transferred to VECM using the difference operator (Δ) thanks to Johansen & Juselius (1990) co-integration method, under the condition of the entire data integration in the first order before proceeding to test, the VECM specification is:

$$\Delta y_t = \Pi\, y_{t-k} + \Gamma_1\, \Delta y_{t-1} + \Gamma_2\, \Delta y_{t-2} + \ldots + \Gamma_{k-1}\, \Delta y_{t-(k-1)} + \varepsilon_t \qquad t = \text{from 1 to T}$$

It can also be expressed as:

$$\Delta y_t = \sum_{i=1}^{k-i} \Gamma_i\, \Delta y_{t-i} + \Pi\, y_{t-1} + \mu_0 + \Phi D_t + \varepsilon_t, \qquad t=1,\ldots,T$$

where,

D_t: vector representing the deterministic variables.

$\Pi_i = \sum_{i=1}^{P} A_i$ - I, i=1,..., p-1, where I is the 1st order of integration.

$\Gamma_i = -\sum_{j=i+1}^{p} A_j$, i=1,..., p-1, is the long run matrix impact.

Where the number of cointegrating variables is directly proportional to the number of stationary relationships in the Π-matrix (Chamalwa & Bakari, 2016). If there is no co-integration, all the rows in Π will be zero, while some will be non-zero if there is a stationary combination (Chamalwa & Bakari, 2016). The rank of the matrix Π determines the number of the independent variables as well as the number of the cointegrating variables (Chamalwa & Bakari, 2016). The rank is given by significant eigenvalues found in Π, where each stands for a significant stationary relation (Chamalwa & Bakari, 2016). Hence, if the matrix has a reduced rank, there is a cointegrating relationship among the variables (Chamalwa & Bakari, 2016). Therefore, rank (Π) = 0. It means the absence of stationarity among the variables; as such, it is advisable to difference it first before modelling.

If rank (Π) = p then Π has full rank, therefore all the variables must be cointegrated (Chamalwa & Bakari, 2016).

3.3.8 Likelihood ratio (LR) statistics

The co-integration conducts to two likelihood ratio test statistics: Trace statistics and Max-Eigen statistic proposed by Johansen (1988) and Johansen (1991) in line with Granger (1981).

Trace statistic is expressed as:

$$TR = -T \sum_{i=r+1}^{N} Ln(1-\lambda)$$

where, T is the sample size, λ_i is the ith largest canonical correlation. Two hypotheses are being confronted in Trace test, H_0 of r cointegrating vectors vs H_a of n cointegrating vectors.

Max-Eigen statistic is expressed as:

$$8_{max} = T\, Ln(1-8_{r+1})$$

where, 8_{r+1}, ..., 8_N are the N-r lowest canonical correlations raised to square between X_{t-k} and X_t series, corrected for the effect of the lagged differences of the X_t. Two hypotheses are being confronted in Max-eigen test, H_0 of r cointegrating vectors vs H_a of at least (r+1) cointegrating vectors.

3.3.9 Normalization of the cointegrating vectors

The VAR cointegrating vectors require normalization for plausible economic interpretations, the normalization to unity generates long-run fashion compatible with economic interest (Rossana, 2004).

3.3.10 Error Correction Model (ECM)

ECM is a VECM mechanism by which deviations over the long-run equilibrium are corrected over time, from a period to the following one; in other words, it measures the adjustment speed toward the long-term equilibrium.

The basic form of ECM that can exist between two variables under an OLS approach is:

$$\Delta \boldsymbol{y}_t = \lambda_0 + \sum_{i=1}^{k-i} \lambda_{1i}\, \Delta \boldsymbol{y}_{t-i} + \sum_{i=1}^{k-i} \lambda_{2i}\, \Delta \boldsymbol{x}_{t-i} + \lambda_3 \mathrm{ECT} + \varepsilon_t$$

where, ECT indicates the speed at which disequilibrium between variables is corrected back towards the long-run equilibrium after a shock.

3.3.11 Variance decomposition

Variance decomposition is a partition tool of the total variance in an outcome variable into components of interest based on each component's performance (Zaefarian et al., 2022).

3.3.12 Impulse Response Function (IRF)

IRF in a VAR model, track down the response over time on a standard deviation (shock or innovation) to one or many variables of the model's variables.

3.3.13 Residuals stability

Residual normality in a VAR model is checked via Cholesky orthogonalization of Lütkepohl (1991), serial correlation (Godfrey, 1978), Heteroscedasticity (Breusch & Pagan, 1979).

4. Results

The different test results are detailed, below following the sequence illustrated in scheme 1, and the hierarchy of methods presented in subsection 2.3 above.

Table 3 below summarizes a common statistic description of the model variables:

Table 3. Descriptive statistics

	LNEF	LNEG	LNDG	LNHE
Mean	0.349936	7.665149	17.16267	12.78485
Median	0.385262	7.635713	17.18039	12.64993
Max	0.593327	8.118390	17.43873	14.11684
Min	0.009950	7.145083	16.79503	11.37660
Std. Dev.	0.163452	0.310901	0.184344	0.710913
Skewness	-0.363321	-0.011988	-0.291771	0.218039
Kurtosis	2.047929	1.657456	2.011907	2.370205
Jarque-Bera	2.570053	3.230375	2.359355	1.051361
p-value	0.276643	0.198853	0.307378	0.591153
Sum	15.04725	329.6014	737.9949	549.7483
Sum Sq. Dev.	1.122096	4.059694	1.427271	21.22670
Observational units	43	43	43	43

Results from Table 3 show that the dispersion indicators are generally too close to each other, while Skewness negative values are supposing that (LnEF, LnEG, LnDG) tails are moderately displaced on the left oppositely to LnHE, which seems to be inclined to the right; subsequently, their respective distributions can be described as almost symmetrical. Concerning kurtosis, all variables' plots seem to be platykurtic, having like a flat tail distribution. Finally, Jarque-Bera statistics are supposing that data has normal distribution.

Table 4 below is illustrating the pair wise correlation matrix:

Table 4. Pair-wise correlations matrice

	LNEF	LNEG	LNDG	LNHE
LNEF	1.000000			
LNEG	0.924114	1.000000		
LNDG	0.903823	0.984526	1.000000	
LNHE	0.853813	0.957561	0.964229	1.000000

Results from Table 4 show a vigorous positive correlation between variables in all the possible bi-directions, which is witnessing the solidity of the STIRPAT theoretical framework and the pertinence of the chosen variables for VAR modeling.

Table 5 illustrates principal analysis components through principal component matrix:

Table 5. Principal component matrix

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.795490	3.638686	0.9489	3.795490	0.9489
2	0.156804	0.123066	0.0392	3.952295	0.9881
3	0.033738	0.019771	0.0084	3.986033	0.9965
4	0.013967	---	0.0035	4.000000	1.0000

Results from Table 5 show that the EF 1st direction explains widely 95% of the information detained by the component matrix, while the EG 2nd one explains 4%, while the portions of the 3rd and the 4th directions, which correspond to DG and HE, respectively, are quite neglected. Moreover, the gap between the first direction and the following ones is enormous (more than 90%), which is supposing the autoregressive aspect of the model.

Table 6 below summarizes the ADF stationarity test applied on the four variables under the three main mentioned versions (with constant [WC], with constant and trend [WCT], nor constant or trend [NCT]) at levels and at the 1st difference.

Table 6. ADF unit root test

At Level		LNEF	LNEG	LNDG	LNHE
WC	t-Statistic	-2.1494	-1.1383	-1.8715	-0.6677
	Prob.	***0.2274***	***0.6914***	***0.3419***	***0.8438***
	A	n0	n0	n0	n0
WCT		-1.4330	-1.0677	-1.8902	-1.5858
		0.8351	***0.9223***	***0.6409***	***0.7818***
		n0	n0	n0	n0
NCT		0.6916	6.1913	2.9411	5.6779
		0.8607	***1.0000***	***0.9988***	***1.0000***
		n0	n0	n0	n0
At 1st Difference		**d(LNEF)**	**d(LNEG)**	**d(LNDG)**	**d(LNHE)**
WC		-3.6149	-12.6033	-3.2236	-5.6053
		0.0100	***0.0000***	***0.0263***	***0.0000***
		**	***	**	***
WCT		-4.1573	-12.6279	-3.8775	-5.5183
		0.0117	***0.0000***	***0.0229***	***0.0003***
		**	***	**	***
NCT		-1.9509	-1.3764	-1.6446	-3.9759
		0.0499	***0.1540***	***0.0938***	***0.0002***
		**	n0	*	***

Respective level of significance at a: (*)10%; (**)5%; (***)1% / (no) Not Significant

Results from Table 6 show that all variables become stationary after a first differentiation, this proves that the empirical evidence must be exclusively done with the VAR/VECM approach.

Figure 3 below illustrates the AR(p) graphical representation.

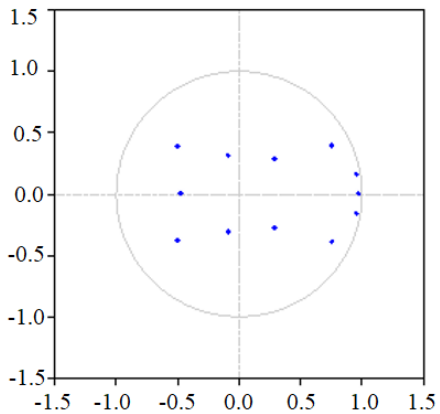

Figure 3. Inverse roots of AR characteristic polynomial
Source: Eviews10 outputs based on Authors computation

Figure 3 shows that all points are dispersedly lying within the unit circle in the complex plan. This implies that the VAR model satisfies the stability condition, that data exhibit a stationary tendency in the long run.

Table 7 below summarizes the optimal lag selection estimations following five tests:

Table 7. Lag length order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	147.4221	NA	9.03e-09	-7.171104	-7.002216	-7.110040
1	413.2930	465.2741	3.41e-14	-19.66465	-18.82021	-19.35933
2	479.5775	102.7411	2.83e-15	-22.17888	-20.65889	-21.62930
3	509.2397	40.04395*	1.53e-15*	-22.86199*	-20.66644*	-22.06815*

* lag order selected by the criterion

As shown in Table 7, on the basis of the rule of thumb (the lowest calculated value), the optimal lag by the unanimity of the five criterions is 3, at which the VAR model is to be set.

Table 8 below summarizes the Pairwise Granger causality test:

Table 8. Granger causality test

H_0: Variable x Does not Granger Cause Toward Variable y	F-Statistic	Prob.
LNEG toward LNEF	17.9470	0.0001
LNEF toward LNEG	3.76845	0.0595
LNDG toward LNEF	23.9704	2.E-05
LNEF toward LNDG	0.18814	0.6669
LNHE toward LNEF	9.30883	0.0041
LNEF toward LNHE	0.53426	0.4692
LNDG toward LNEG	8.29287	0.0064
LNEG toward LNDG	43.1061	9.E-08
LNHE toward LNEG	0.45520	0.5039
LNEG toward LNHE	4.31605	0.0444
LNHE toward LNDG	1.91578	0.1742
LNDG toward LNHE	0.09433	0.7604

Results from Table 8 reveal the existence of two bidirectional causalities running: one between EG and EF and between EG and DG. They also show a unidirectional causality running from DG to ecological footprint, HE to ecological footprint, and EG to HE.

Usually in the co-integration test, the maximum lag length for the VAR model for annual data in Eviews10 is set to 1, with the null hypothesis of the absence of any co-integration.

Table 9 and Table 10 below represent the respective results of the two following tests:

Table 9. Trace test

Number of Co-integrations	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.489435	52.28184	47.85613	0.0181
At most 1	0.263244	24.72009	29.79707	0.1717
At most 2	0.179804	12.19467	15.49471	0.1478
At most 3 *	0.094455	4.067972	3.841466	0.0437

* H_0 rejection at 5%

Table 10. Maximum eigenvalue test

Number of Co-integrations	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.489435	27.56175	27.58434	0.0503
At most 1	0.263244	12.52542	21.13162	0.4967
At most 2	0.179804	8.126700	14.26460	0.3660
At most 3 *	0.094455	4.067972	3.841466	0.0437

* H_0 rejection at 5%

The co-integration trace results from Table 9 show the existence of at most one co-integration equation at 5%, while those from Table 10, which correspond to the Max-Eigenvalue test, indicate that no co-integration equation can exist between the variables. However, when Trace statistics and Max-Eigen statistics produce little contradictions, more importance must be given to Trace statistics as it takes into consideration all of the lowest eigenvalues; subsequently, it has more treatment power than the Max-Eigen statistics (Kasa, 1992; Serletis & King, 1997). Moreover, it is recommended to privilege the trace statistics when the two statistics provide uneven results (Johansen & Juselius, 1990). Thus, it exists at most a unique co-integration equation at 5% in a linear fashion.

The normalization of the revealed co-integration equation, which describes the main long-run dynamics between the explanatory variables and the dependent one, is represented in Table 11 below:

Table 11. The normalized cointegrating coefficients

LnEF	LnEG	LnDG	LnHE
1.000000*	-1.191282*	-0.137644*	0.505900*
	(0.51378)	(1.15828)	(0.09269)

*Normalized cointegrating coefficients/(Std error)

Table 12. VECM parameters estimations

Variables	Co-integrated Equation Values
LNEF (-1)	1
LNEG (-1)	-1.191282 0.51378 [-2.31864]
LNDG (-1)	-0.137644 (1.15828) [-0.11883]
LNHE (-1)	0.505900 (0.09269) [5.45818]
C	4.672998
Error Correction	**D(LNEF)**
CointEq1	-0.348196 (0.10978) [-3.17177]

(Std error)/ [t-statistics]

The inversed Table 11 results of the normalized cointegrating coefficients (inversed in order to have proper interpretations as the long run part of the VECM is not normalized by Eviews10) are 1.191282, 0.137644 and -0.505900 as long run coefficients for EG, DG and HE to ecological footprint, respectively, meaning that whenever economic and DG increase in the correspondent proportions, EF goes with simultaneously, otherwise, whenever higher-education upsurges in the correspondent proportion, EF decreases, suggesting the movement of these variables conjointly to generate a one unit of ecological footprint. As co-integration is proven, an ECM is required.

As shown in Table 12, the ECT from VECM estimates is significantly expressed as:

$$ECT = LnEF(-1) + 1.191282 LnEG(-1) + 0.137644 LnDG(-1) - 0.505900\, LnHE(-1) - 4.672998.$$

This specification reflects the long run adjustment from a previous period deviation to the following, with an estimated speed of 34.81% as suggests the negative and statistically significant CointEq1 coefficient; in other words, 34.81% of the previous error is adjusted in the next, and so on, thus, the convergence from short dynamics toward long-run equilibrium is unequivocally confirmed by the VECM (1) test.

Each coefficient of the co-integration equation is checked in Table 13:

Table 13. VCEM co-integration model coefficients summary

Coint-Coefficient	Value	Std. Error	T-Statistic	Prob.
(1)	-0.348196	0.109780	-3.171768	0.0031
(2)	-0.250562	0.158110	-1.584736	0.1220
(3)	-0.960668	0.355361	-2.703360	0.0105
(4)	-5.367274	3.311009	-1.621039	0.1140
(5)	0.205504	0.145236	1.414963	0.1659
(6)	0.103466	0.051423	2.012053	0.0520

Results from Table 13 show that C1 is negative and significant at 5%, which is definitively confirming the longevity of the VECM co-integration model and its adequacy for economic interpretation.

Table 14 presents the VAR variance decomposition for ten successive periods.

Table 14 results show that the historical trend of EF explains a large part of its own variations, which tend to decrease period over period. Thus, within 10 periods, about 75% of the variance in EF is explained by itself, which is indicative of its exogenous nature. This suggests that we should consider 10 periods for the IRF.

Table 14. Variance decomposition

Period	S.E.	LNEF	LNEG	LNDG	LNHE
1	0.063081	100.0000	0.000000	0.000000	0.000000
2	0.064599	95.39088	2.144422	1.221182	1.243514
3	0.073026	86.91455	7.959742	1.325283	3.800421
4	0.075953	85.87297	7.667727	1.555385	4.903919
5	0.077857	81.91722	11.51414	1.879545	4.689101
6	0.079447	79.55589	12.39112	1.928336	6.124650
7	0.080166	78.73599	12.59060	1.898786	6.774625
8	0.081058	77.61359	12.47848	1.916751	7.991173
9	0.082116	76.44101	12.20092	2.089680	9.268398
10	0.083276	75.50059	11.99747	2.349423	10.15251

Figure 4 establishes the graphic representation of the respective responses to one S.D. (shock or innovation) of EG (represented by LnEG), DG (LnDG), and HE (LnHE) to EF (LnEF) combined in one presentation.

Results from Figure 4 show that a one S.D. (shock or innovation) gradually declines the response of EG from periods 1 to 2, then it rises progressively until the 4th period; this oscillation is regenerated one again until the end of the 6th period; meanwhile, it remains negative from the 4th period until the 10th. That one S.D. (shock or innovation) initially decreases softly DG until the 4th period, and then a stagnation of the response is noticeable for the rest of the interval, remaining negative all along. That one S.D. (shock or innovation) initially increases the response of HE until the 3rd period; this positive response gently declines until the 5th then remains stable, all the way above the horizontal axis. It is concluded that shocks to the EF will have a negative impact on EG, a positive impact on HE, and a negative impact on DG in the short as well as in the long run.

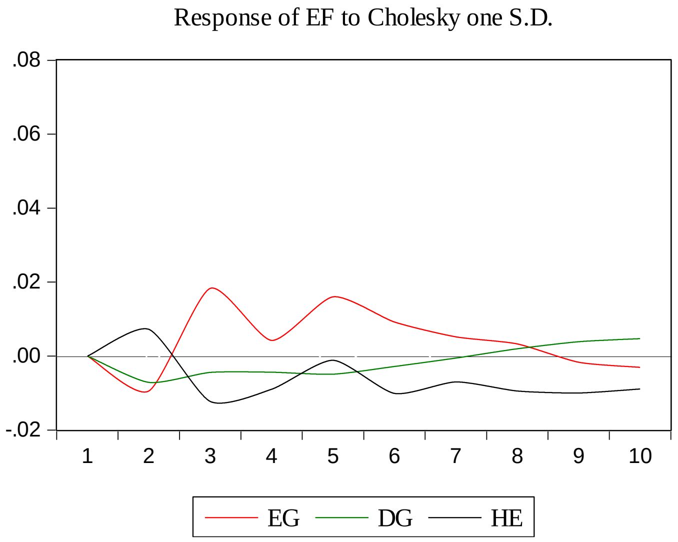

Figure 4. Impulsive response function graphic representation

VAR residuals normality, serial correlation, and heteroscedasticity, respectively, are presented in the following Tables 15, 16, and 17, respectively.

Table 15. Cholesky orthogonalization of Lutkepohl test

H_0: Residuals are Normal				
	Chi-sq	**Df**	**p-value**	**Interpretation**
Skewness	0.192706	1	0.6188	
Kurtosis	2.903381	1	0.9007	No rejection of H_0
Jarque-Bera	0.263129	2	0.8767	

Table 16. Serial correlation test

H_0: No Serial Correlation			
Lags	**LM-Stat**	**Prob**	**Interpretation**
1	24.95343	0.0707	
2	26.02040	0.0537	No rejection of H_0
3	16.36447	0.4278	

Table 17. Heteroscedasticity test

H_0: Residuals are Heteroscedastic		
Chi-sq	**Df**	**Prob.**
231.4145	230	0.4614
Interpretation: Fail to reject H_0		

Results from Table 15 are suggesting that residuals are normally distributed; those from Table 16 show the absence of serial correlation among residuals, which are supposed to be homoscedastic with no cross terms (absence of white noise), as shown in Table 17.

5. Discussions

This paper's findings and dynamics seem to be quite logic and credible because intuitively, a growing economic activity hangs together with more and more consumption, and subsequently, overexploitation of natural resources, idem for DG, which is supposing the increase of population needs in parallel with natural resource attrition, while acquiring HE and professional qualifications by individuals is correlated with good awareness of the dangers of environmental degradation, and consequently, the adoption of ecological behavior and pro-nature gesture as a life style at both dimensions, individually and collectively. Compared to similar studies—for example and not limited to—these results prove once again that EG coupled with energy consumption and urbanization have long-run impacts on EFs in Morocco itself (Farouki & Aissaoui, 2024), in Turkey (Nathaniel et al., 2020), in Pakistan (Ullah & Lin, 2024), and in ECOWAS, a group of African countries neighboring Morocco (Ali et al., 2022). These findings converge with those of Asli et al. (2024); Bergougui & Aldawsari (2024); Dinç & Akdoğan (2019) in terms of HC role in diminishing both CO_2 and EF in Morocco and Algeria, respectively, and from a panel of ECOWAS countries (Ali et al., 2022). Furthermore, these results are supporting recent research outputs in the Indian context proving that HC acquired mainly through HE not only reduces EFs but also acts as a driving force behind environmental policies where HC was found to cause reductions in EFs without feedback effect (Ahmed & Wang, 2019). In the same context but in the opposite direction, while economic and DG pose environmental challenges, some recent studies proved that they present also opportunities for positive impacts through sustainable practices as tested in China by Li et al. (2023). In addition, a recent study highlights a connection in which EG, HC, BC, and urban growth all have a beneficial impact on the EF in five South Asian countries (Mehmood et al., 2023). Hence, encouraging sustainable consumption habits can significantly mitigate the effects of EG and subsequently reduce ecological footprints, for example, by promoting renewable energies, reducing waste, and enhancing recycling efforts (Population Media Center, 2023). In the same line, while many studies support the positive impact of HC on reducing ecological footprints, some research suggests that in certain contexts—particularly in low-income countries—high HC might lead to increased consumption patterns that could elevate EFs due to greater access to resources and technologies (Chen et al., 2021). Furthermore, it was proved that coupling HC promotion with EG serves to augment the adoption of sustainable practices, which enhances BC (Mehmood et al., 2023). However, future prospects are still to be discovered, such as the fluctuations of other factors, including, but not limited to, urbanization, energy intensity, age distribution, the working force, the structure of the economy, clean energies, etc., on the EF in particular and environmental sustainability in general, as for Morocco as for other countries. However, this study, as any other study, manifests some limitations, mainly on three levels:

Econometrically, as the VAR/VECM model excels in capturing multivariate dynamic interactions, revealing short- and long-term behaviors, providing efficient coefficient estimates, and handling perfectly complex analyses, especially in co-integrated time series, it is exclusively suitable for first integrated series I(1) analysis, with controversial divergences on the appropriate lag length order selection. In fact, the more explanatory variables there are, the more numerous coefficients induced, and the more degrees of freedom there are, which makes it relatively complicated to handle, interpret, and fill all the validity conditions.

Epistemologically, as this study doesn't background the findings to predict future fluctuations of the studied variables, it is also restricted to classical STRPAT determinants already well-documented in existing literature in other contexts, in time when other variables such as energy consumption, institutional governance, clean energies, smart environmental gestures, etc. are getting more and more involved in other recent studies.

Limited scope, as this study focuses exclusively on Morocco, which limits its broader applicability and appeal. The findings may not resonate with a wider international audience, reducing the manuscript's overall impact.

6. Conclusion

This research purpose was to examine the way that humans are affecting the vital biosphere in Morocco through the fluctuations of, EG and DG besides the promotion of HC on EF in the last fourth decades, the basic result deduced from empirical evidence is that a solid long run relationship is established between those variables over time, results show that EG is immensely amplifying the environmental stress on the vital ecosystem of Morocco by more than one entire unit of EF output, followed by DG with above a tenth unit, while ensuring HE level to population is diminishing it by a half unit approximatively. In line with these results, H_{0a} and H_{0b} hypotheses, according to which EG and DG are negatively impacting EFs in Morocco, are confirmed, while the H_{0c} hypothesis, according to which HE is negatively impacting EFs in Morocco, is refuted in favor of the positive impact. Results from the Impulsive Response Function (IRF) are confirming this logic sequence; accordingly, the more the economic activity prospers and the population size gets larger, the more stress there is on environmental resources, while the more people get educated and acculturated, the more their EF gets reduced and limited.

7. Policy Implications

In order to undermine the noxious effect of EG and DG and promote HC accumulation, in line with Zafar et al. (2019), it is of the Moroccan government duty to address various policies across these domains, in line with Khan et al. (2024), such as enhancing public awareness through education programs touching upon the benefits of energy conservation and the reduction of energy consumption by inculcating an eco-friendly behavior chart among citizens. Valorising HC and increasing it through public spending on the education sector, public as private (El Asli & Azeroual, 2023a; El Asli & Azeroual, 2023b). Controlling the demographic expansion by providing access to family planning services and providing affordable programs for new couples in order to help manage population growth, besides empowering women with gender approaches and healthcare options, which often lead to smaller, healthier families. Following a sustainable urbanization program by promoting urban planning that emphasizes high-density, innovative practices in sustainable urban planning (Xu, 2024), mixed-use development, this reduces land use, conserves resources, and decreases the need for extensive infrastructure. Integrate parks, green roofs and corridors into urban areas to rise biodiversity, and to improve air quality, and manage stormwater, developing affordable housing that is also energy-efficient, reducing both the EF and the cost burden on low-income families. Adopting economic incentives and policies such as carbon pricing through the implementation of carbon taxes or cap-and-trade systems to make CO_2 more costly and encourage businesses and consumers to reduce their carbon footprint, by fostering renewable energy installations, electric vehicles etc.; regulation of high-impact sectors for industries with high ecological impacts, such as mining, agriculture, and manufacturing. Watch over the quality of institutions (Awad et al., 2024) by enhancing ruling governance (Ali et al., 2022). Accelerate energy transition through industrial decarbonizing and fixing an ultimatum for total carbon neutralization objective, continuing to invest in renewables, keeping reliance on fossil fuels, and incentives for technological innovation related to renewable energy consumption to "encourage structure energy adjustment and reduce carbon footprint" (Su et al., 2022). Act on the determinants of EG in Morocco in order to align it on a green growth model (El Asli et al., 2024). And finally, incite eco-friendly products by promoting the production and consumption of products that have lower environmental impacts through fiscal incitements such as those made from recycled materials, produced locally, or with reduced packaging. The eco-friendly production processes that minimize waste, energy use, and emissions suppose adopting cleaner technologies and sustainable supply chains. The success of Morocco's efforts relies on the continued implementation of these sustainable policies and practices, along with public awareness and international cooperation, especially aligning local growth with sustainable development goals (SDGs), especially SDG 9 for environmental sustainability policies.

Data Availability

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

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