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Temporal dynamics of energy transition and carbon emissions for ecological footprint in Mozambique

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Abstract

Mozambique's sustainability transition is unfolding within a structurally heterogeneous energy–ecology regime, where expanding energy demand, rapid urbanization, and resource-intensive production intersect with entrenched biomass dependence and an emergent fossil-fuel economy. Although the country possesses considerable renewable-energy endowments, the ecological consequences of energy-system transformation remain insufficiently resolved, particularly where energy substitution may reconfigure rather than attenuate environmental pressures. This study interrogates the temporal and structural pathways through which renewable and non-renewable energy consumption, carbon emissions, urbanization, and technological innovation condition ecological footprint in Mozambique over 1985–2015. An Autoregressive Distributed Lag (ARDL) framework characterizes long-run equilibrium relations and short-run disequilibrium adjustments, distinguishing transitional effects from deeper structural pressures. The estimates indicate that fossil-fuel consumption, transport and industrial emissions, and renewable-energy consumption significantly shape ecological footprint in the long run. The negative long-run coefficient on fossil-fuel consumption is interpreted against Mozambique's evolving energy-use configuration, notably the substitution away from

traditional biomass. Conversely, renewable-energy consumption exerts a positive short-run effect, signalling ecological costs during the early transition phase. The error-correction mechanism indicates that approximately 46.8% of disequilibrium is corrected each period. Overall, the findings suggest that the ecological dividend of energy transition is neither automatic nor contemporaneous, but contingent upon the sequencing, composition, and resource intensity of structural change. Policy therefore requires more than fuel substitution: it demands modern energy access, sectoral decarbonization and resource efficiency, and renewable deployment guided by lifecycle ecological appraisal and resource constraints.

Keywords: ARDL model; Energy transition; Ecological footprint; Fossil fuel consumption; Sustainable energy

Graphical Abstracts

Energy, Emissions & Ecological Footprint in Mozambique (1985–2015)

Autoregressive Distributed Lag Analysis (ARDL)



Key Factors



Findings



Policy Recommendations



1. Introduction

The relationship between economic development and environmental sustainability has become increasingly difficult to reconcile, particularly in resource-dependent economies where growth is closely tied to energy use [1]. In principle, development pathways are expected to improve living standards without placing excessive strain on ecological systems. In practice, however, this balance remains difficult to sustain. Many developing countries continue to expand through energy-intensive sectors, often relying on fossil fuels or biomass, with environmental consequences that accumulate gradually over time ([2]; [3]). Mozambique offers a particularly revealing case. Its recent economic trajectory, shaped by energy extraction, infrastructure expansion, and urban growth, has unfolded alongside rising ecological pressure, raising questions about the long-term sustainability of this development path.

Global policy frameworks such as the Paris Agreement and the Sustainable Development Goals (SDGs) call for a decoupling of economic growth from environmental degradation (UNFCCC, 2015). Yet progress toward this goal remains uneven, particularly in regions where structural constraints continue to limit sustainable transitions. Across Sub-Saharan Africa (SSA), economic expansion has been accompanied by increasing ecological demand, reflecting growing pressure on land, energy systems, and natural resources [4]; [2]; [5]. Between 2000 and 2020, the region's ecological footprint expanded significantly (at 65%), outpacing improvements in biocapacity and highlighting the limits of current development models [4]; [2][5]. These trends suggest that, despite policy commitments, the transition toward environmentally sustainable growth remains incomplete.

Mozambique reflects these broader dynamics, though in ways that are shaped by its own structural conditions. The country possesses considerable renewable energy potential, including hydropower capacity estimated at around 23 GW [6]; World [7] and high levels of solar irradiation exceeding 2,200kWh/m² annually [8]. Still, energy use remains heavily dominated by traditional biomass. More than 80% of households rely on charcoal and firewood, a pattern closely linked to deforestation and land degradation [9]. At the same time, Mozambique ranks among the most climate-vulnerable countries globally [7]; [10], experiencing recurrent shocks such as Cyclone Idai in 2019, which exposed the fragility of both environmental systems and development gains [11]. These conditions make sustainability not just a policy goal, but an immediate development concern.

Urbanization and structural transformation add further complexity. Across SSA, urban populations are expected to double by 2050 [12], placing increasing pressure on infrastructure and energy systems. In Mozambique, transport-related emissions already account for a substantial share (35%) of total emissions [13], while industrial expansion continues to depend largely on fossil fuels [14]. Agriculture, which remains central to livelihoods, also contributes to ecological pressure through land expansion, soil degradation, and input-intensive practices. Although emerging initiatives such as solar-powered irrigation in provinces like Nampula demonstrate the potential for integrating renewable energy into productive sectors, these efforts remain uneven and limited in scale [8]. The broader challenge, then, is not simply adopting cleaner energy, but

managing a transition across interconnected systems of production, consumption, and resource use.

The ecological footprint (EFP) framework provides a useful lens to examine these dynamics. By capturing the total ecological demand associated with human activities, including land use, energy consumption, and waste absorption, it offers a more integrated measure of environmental pressure than carbon emissions alone ([1]. This is particularly relevant in contexts like Mozambique, where environmental stress arises from multiple sources operating simultaneously.

Existing research has examined the energy-environment nexus from different perspectives. Cross-country studies suggest that fossil fuel consumption, urbanization, and industrialization tend to increase ecological pressure, while renewable energy adoption can reduce it over time [15]; [3]; [16]). However, much of this evidence is drawn from industrialized or rapidly industrializing economies ([17]; [18]; [19]. In contrast, low-income and resource-dependent countries remain underrepresented. Where Mozambique is concerned, the literature has largely focused on specific sectors such as hydropower development [20]; [21] , liquefied natural gas expansion [22];[23], or renewable technologies [24][25] without fully considering how these elements interact over time.

This creates an important gap. There is limited empirical work that jointly examines fossil fuel use, renewable energy adoption, sectoral emissions, urbanization, and natural resource dependence within a unified analytical framework. Even less attention has been given to the temporal dimension of these relationships. Environmental pressures evolve gradually, shaped by both short-term adjustments and longer-term structural changes. Treating them as static outcomes risks overlooking these dynamics. The problem, therefore, is not simply that Mozambique faces environmental pressure. More importantly, the drivers of this pressure and their interactions over time are not yet well understood. Without this understanding, policy responses risk being fragmented or misaligned, addressing individual sectors without accounting for their combined effects.

This study addresses that problem by examining the determinants of Mozambique's ecological footprint over the period 1985-2015. Specifically, it investigates how energy consumption patterns (renewable and non-renewable), carbon emissions, urbanization, technological innovation, and natural resource rents influence ecological sustainability.

The analysis adopts an Autoregressive Distributed Lag (ARDL) approach, which allows for the estimation of both short-run dynamics and long-run equilibrium relationships within a time-series framework. This study is therefore guided by three key research questions:

1. To what extent do energy consumption patterns and carbon emissions influence ecological footprint in the long run?
2. What short-run adjustment mechanisms characterize the relationship between these variables?
3. How do renewable and non-renewable energy sources differentially influence ecological sustainability in Mozambique?

In doing so, the study makes several contributions. First, it provides empirical evidence from a context that remains relatively underexplored in ecological footprint research. Second, it integrates multiple drivers of environmental pressure within a single econometric framework, allowing for a more comprehensive analysis of sustainability dynamics. Third, by incorporating a temporal perspective, it highlights how environmental outcomes emerge through evolving interactions rather than isolated effects. These contributions are relevant not only for academic debates but also for policy. Mozambique's development trajectory reflects broader challenges faced by resource-dependent economies attempting to balance growth with environmental sustainability. Understanding these dynamics is therefore essential for designing policies that support sustainable energy pathways Mozambique's 2030 Energy Transition Strategy without intensifying ecological pressure. Moreover, this study establishes the importance of the energy-environment relationship, identifies gaps in existing evidence for Mozambique, and addresses these through a dynamic empirical analysis. The remainder of the paper is structured as follows: the next section reviews the relevant literature, followed by the methodological approach, empirical results and discussion, and finally the conclusion and limitations of the study.

2. Literature review

2.1 Energy and ecological footprint dynamics

Sustainable development requires balancing economic growth, environmental protection, and energy security. In many developing economies, this balance remains difficult to achieve. Energy demand is increasing, while environmental pressures continue to grow. The Ecological Footprint (EFP) framework offers a useful way to examine this

relationship. It measures how much biologically productive land and water is required to support human consumption and absorb waste [1]. Because it captures multiple dimensions of environmental pressure, the framework has become widely used in sustainability research.

In Sub-Saharan Africa, ecological footprint levels remain lower than those of industrialized regions. However, recent trends show increasing pressure on ecological systems. Rapid population growth, urban expansion, and dependence on fossil fuels are gradually raising environmental stress across the region [26]; [27]. These dynamics suggest that environmental sustainability challenges may intensify as economies continue to expand. Mozambique reflects many of these regional patterns. Despite possessing large natural resources and considerable bio-capacity (of over 93%), the country faces growing ecological pressure [4]; [7]. One important factor is the structure of the energy system. While hydropower accounts for a large share of electricity production, access to modern energy remains uneven. As a result, many households continue to depend on traditional biomass such as charcoal and firewood.

2.2 Sectoral and structural drivers of environmental pressure

Biomass dependence has important environmental implications. Studies suggest that charcoal production and firewood consumption contribute significantly to deforestation across several African countries [28][29]. In Mozambique, more than 80% of households rely on biomass for cooking and heating [30]. This dependence is often linked to energy poverty, limited electricity access, and weak energy infrastructure [9]. Under these conditions, households rely on locally available resources, which increases pressure on forests and surrounding ecosystems.

However, scholars disagree on the extent to which biomass alone explains deforestation patterns. Some studies emphasize the environmental impact of charcoal production and household energy use [31]; [2]. Others point to commercial agriculture, logging, and land-use changes as equally important drivers of forest loss [32]. These differing perspectives suggest that environmental degradation in resource-rich countries is shaped by multiple interacting factors rather than a single cause. Hydropower development represents another important component of Mozambique's energy system. The country possesses considerable hydropower potential, yet much of this capacity remains underutilized [33]. Expanding hydropower could strengthen regional energy

supply and support economic development. Mozambique already exports electricity to neighboring countries, which highlights the strategic importance of its energy sector [9].

Despite these benefits, hydropower development is not without challenges. Large-scale dam projects can generate environmental and social impacts. These may include ecosystem disruption, biodiversity loss, and displacement of local communities [34]; [35]. Evidence from Latin America shows that rapid hydropower expansion can lead to ecological and social tensions if environmental safeguards are weak ([36]; [37]. Similar concerns have been raised in Mozambique, particularly given the country's vulnerability to climate variability and extreme weather events [38]). Fossil fuel extraction introduces additional environmental pressures. Recent discoveries of natural gas reserves have increased Mozambique's role in global energy markets. While resource extraction may generate economic growth, it can also produce environmental and social costs. Mining and energy projects sometimes displace smallholder farmers and alter local livelihoods , ([39]. Uneven distribution of resource revenues can further deepen inequalities between regions [40]. These challenges reflect broader patterns observed in many resource-dependent economies, where short-term economic gains may conflict with long-term environmental sustainability [41].

Urbanization also shapes environmental outcomes. Across Sub-Saharan Africa, urban populations are expanding rapidly. In Mozambique, cities such as Maputo continue to grow as rural populations migrate in search of economic opportunities. Urban expansion increases demand for transportation, housing, and energy services. Transport alone accounts for a large share of urban emissions (35%) in the country [13]. In addition, informal settlements often lack adequate infrastructure for waste management, sanitation, and energy access, which further increases environmental pressure [42]. Technological innovation may help reduce some of these pressures. New technologies can improve energy efficiency and expand access to renewable energy. In Mozambique, off-grid solar systems have improved electricity access in rural areas [43]. Agricultural technologies such as solar-powered irrigation have also begun to support food production while reducing diesel consumption [44]. Experiences from other countries demonstrate that technological innovation can contribute to environmental improvements when combined with supportive policies [45].

Nevertheless, structural constraints often slow the pace of energy transition in developing economies. Limited financial resources, weak infrastructure, and institutional challenges can restrict the adoption of renewable technologies. In some cases, international financial policies and austerity programs have further constrained investment in green energy systems [46]; [47]. These structural barriers highlight the importance of examining energy transitions within the broader political and economic context.

2.3 Research gap and contribution

Although existing studies provide important insights into Mozambique's energy–environment nexus, the literature remains fragmented across individual energy resources and sectoral development trajectories, particularly hydropower and natural gas ([20]; [21]; [22];[23]. Comparatively limited attention has been given to the joint environmental implications of fossil-fuel consumption, renewable-energy use, urbanization, technological change, sectoral emissions, and natural-resource dependence. This fragmentation is analytically consequential because ecological pressures in economies undergoing structural transformation do not arise from isolated energy sources; they emerge through changing configurations of energy use, production, urban expansion, and resource exploitation. Moreover, much of the empirical literature adopts static, cross-sectional, or narrowly specified approaches, providing limited insight into how these relationships evolve between short-run disturbances and long-run structural adjustment [3]; [15]).

For Mozambique, the resulting evidence base remains particularly thin with respect to the temporal structure of ecological sustainability. The literature provides limited empirical evidence on whether changes in the energy mix generate transitory environmental costs, persistent ecological pressures, or longer-run improvements as the energy system reconfigures. This study addresses this analytical deficit by applying a dynamic ARDL framework to examine the short- and long-run effects of renewable and non-renewable energy consumption, carbon emissions, urbanization, technological innovation, and natural-resource rents on ecological footprint over 1985–2015. Beyond identifying statistical associations, the approach enables the study to distinguish transitional ecological effects from longer-run structural relationships, thereby providing a

more temporally differentiated account of Mozambique's energy transition and its implications for ecological sustainability.

3. Methodology

This study adopts a quantitative research design using an econometric approach to examine the determinants of ecological footprint in Mozambique. The analysis focuses on how energy consumption patterns, carbon emissions, urbanization, technological innovation, and natural resource dependence influence environmental sustainability over time. Specifically, the Autoregressive Distributed Lag (ARDL) estimation approach is utilized to analyze the data and determine the impact of these variables on the ecological footprint.

3.1 Data sources

This study utilizes annual time series data from 1985 to 2015 to examine the relationship between the ecological footprint and various explanatory variables in Mozambique. The ecological footprint (EFP) is used as the dependent variable, as it enables the assessment of environmental impact and the effectiveness of sustainability policies by quantifying resource consumption and waste generation. The EFP data were obtained from the Global Footprint Networks (GFPN) website.

Explanatory variables, including fossil fuel consumption (FFC), urbanization (URB), technological innovation (TEC), renewable energy consumption (REC), natural resources rents (NRS), CO₂ emissions from transport (EST), CO₂ emissions from manufacturing, industry, and construction (EMI), and combustible renewable and waste (CRW), were extracted from the World Bank Development Indicators (WDI). These variables are crucial in influencing the ecological footprint by shaping patterns of resource use, emissions, and overall environmental sustainability. To address multicollinearity issues, all variables were transformed into natural logarithms. This transformation allows for the interpretation of the variables as elasticities. Table 1 provides an operational description and measurements for the environmental variables used in the study.

Table 1. Description and measurement of environmental variables used in the study

Variables	Code	Measurement unit	Source
Ecological footprint	EFP	Global hectare per person	GFPN
Combustible Renewable & Waste	CRW	% of total energy	WDI

CO ₂ emissions from manufacturing, industry & construction	EMI	% of total fuel combustion	WDI
CO ₂ emissions from transport	EST	% of total fuel combustion	WDI
Fossil fuel consumption	FFC	% of total fuel combustion	WDI
Natural resources rents	NRS	% of GDP	WDI
Renewable energy consumption	REC	% of total final energy consumption	WDI
Technological Innovation	TEC	Patent applications, Residents	WDI
Urbanization	URB	Urban population (%)	WDI

Source: Authors' computation (2025)

3.2 Augmented Dickey-Fuller and Philips-Perron unit root tests

The study utilized Augmented Dickey-Fuller (ADF) and Philips- Perron (PP) unit root tests to check the stationarity of the variables, ensuring their suitability for policy decision-making and preventing unit root issues (Dickey & Fuller, 1979) and (Phillips & Perron, 1988).

The ADF and PP unit root test equations are specified as:

$$\Delta z_t = \delta_0 + \delta_1 Z_{t-1} + \sum_{i=1}^k \alpha_i \Delta Z_{t-i} + \mu_t \quad (1)$$

$$\Delta z_t = \delta_0 + \delta_1 t + \delta_2 Z_{t-1} + \sum_{i=1}^k \alpha_i \Delta Z_{t-i} + \mu_t \quad (2)$$

The ADF regression tests the presence of the unit root of Z_t where t and k mean the time and number of lags included in the unit root testing regression. The ΔZ_{t-1} denotes the first difference of the variable with k lags. The term μ_t adjusts the errors of autocorrelation, while α_i , δ_0 , δ_1 , and δ_2 estimated parameters. The null hypothesis of H_0 : $\delta_1 = 0$ has a unit root against the alternative hypothesis H_A : $\delta_1 \neq 0$ are stationary in the equations (1) and (2). The results showed that most of the variables were not stationary at their level, but became stationary after differencing once, indicating integration by order one $I(1)$ [40]; [47].

It is advisable to the optimal lag order of your variables to obtain efficient and unbiased ARDL estimates. The number of lags is determined by information criteria based on the sample size [29]. This is a lag whose estimated model provides the smallest criterion value. The optimal lag is the one that presents the weakest and least information criterion [14].

3.3 Johansen cointegration test

Johansen cointegration is proposed by Johansen and Juselius (1990) for testing the number of cointegration vectors or the rank of Π in the unrestricted vector autoregression model in which the vector variable ($X \times 1$) at a time t is related to the vector of the past variables. The Johansen cointegration equation in the vector autoregression model is specified by:

$$\Delta X_t = \beta_1 + \beta_2 T + \Pi X_{t-1} + \sum_{k=1}^{p-1} \Gamma_k \Delta X_{t-k} + \Phi D_t + \varepsilon_t \quad (3)$$

Where $\Pi = \sum_{k=1}^p A_k = I$ and $\Gamma_k = -\sum_{l=k+1}^p A_l$, X_t is a dimension vector corresponding to the number of the variables which are Π, Γ_k and Φ are parameters matrices to be estimated, D_t is a vector with deterministic elements and ε_t is a random error with a mean of zero and constant variance. The specific interest of testing is the rank of the matrix Π which contains long-run information and the speed of adjustment. The Johansen method estimates the Π matrix from the unrestricted VAR and tests whether we can reject the restriction implied by the reduced rank Π . There are two methods of testing for the reduced rank (Π), the trace test and the maximum eigenvalue specified in equations (4) and (5).

$$\lambda_{trace} = -T \sum_{i=r+1}^q \ln(1 - \lambda_i^2) \quad (4)$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \lambda_{r+1}) \quad (5)$$

Where λ_i is the estimated ordered eigenvalue obtained from the estimated matrix and T is the number of observations after lag adjustment. The trace statistics test the null hypothesis that the number of distinct cointegration vectors is less than or equal to r against a general alternative. The maximum eigenvalue tests the null hypothesis that the number of cointegrating vectors is r against the alternative of $r+1$ cointegrating vector.

3.4 ARDL model

The Autoregressive Distributed Lag model is recognized as an efficient econometric approach for analyzing economic variables that exhibit either $I(0)$ or $I(1)$ stationarity. The model was pioneered and used by Pesaran et al. (2001), and this approach has a variety of flexibilities over the traditional cointegration proposed by Engle and Granger in 1987. This model assesses the explanatory variables' short- and long-run relationships on ecological footprint. The model's ability to generate both short and long-

run elasticities makes it beneficial while employing the ordinary least squares method for cointegration between variables.

Furthermore, the ARDL model offers flexibility in the order of integration of variables and is suitable for explanatory variables that exhibit I (0), I (1), or mutually integrated variables and may be applied to obtain consistent estimates. However, it may not be as effective in cases in which the variables exhibit I (2) stationarity. This study employs ARDL to analyze the long-run relationships and short-run relationships between fossil fuel consumption (FFC), Urbanization (URB), Technological innovation (TEC), Renewable energy consumption (REC), Natural resources rents (NRS), CO₂ emissions from transport (EST), CO₂ Emissions from Manufacturing, Industry and Construction (EMI), combustible renewable and waste (CRW) and Ecological footprint.

The general estimation of the relationship is expressed as follows:

$$Y_t = \alpha_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon_t \quad (6)$$

The relationship in a fitted form can be expressed as follows:

$$\ln EFP_t = f(\ln CRW_t, \ln EMI_t, \ln EST_t, \ln FFC_t, \ln NRS_t, \ln REC_t, \ln TEC_t, \ln URB_t) \quad (7)$$

The model is expressed as follows:

$$EFP_t = \beta_0 + \beta_1 CRW_t + \beta_2 EMI_t + \beta_3 EST_t + \beta_4 FFC_t + \beta_5 NRS_t + \beta_6 REC_t + \beta_7 TEC_t + \beta_8 URB_t + \varepsilon_t \quad (8)$$

Where: β_0 is the Intercept or constant, $\beta_1 - \beta_8$: Coefficient of the explanatory variables (Table 1), Converting equation 7 into the natural logarithm becomes equation 9:

$$\ln EFP_t = \alpha_0 + \beta_1 \ln CRW_t + \beta_2 \ln EMI_t + \beta_3 \ln EST_t + \beta_4 \ln FFC_t + \beta_5 \ln NRS_t + \beta_6 \ln REC_t + \beta_7 \ln TEC_t + \beta_8 \ln URB_t + \varepsilon_t \quad (9)$$

Hence,

$$\begin{aligned} \ln EFP_t = & \beta_0 + \sum_{k=1}^p \beta_1 \Delta \ln EFP_{t-k} + \sum_{k=1}^p \beta_2 \Delta \ln CRW_{t-k} + \sum_{k=1}^p \beta_3 \Delta \ln EMI_{t-k} + \\ & \sum_{k=1}^p \beta_4 \Delta \ln EST_{t-k} + \sum_{k=1}^p \beta_5 \Delta \ln FFC_{t-k} + \sum_{k=1}^p \beta_6 \Delta \ln NRS_{t-k} + \sum_{k=1}^p \beta_7 \Delta \ln REC_{t-k} + \\ & \sum_{k=1}^p \beta_8 \Delta \ln TEC_{t-k} + \sum_{k=1}^p \beta_9 \Delta \ln URB_{t-k} + \lambda_1 \ln EFP_{t-1} + \lambda_2 \ln CRW_{t-1} + \lambda_3 \ln EMI_{t-1} + \\ & \lambda_4 \ln EST_{t-1} + \lambda_5 \ln FFC_{t-1} + \lambda_6 \ln NRS_{t-1} + \lambda_7 \ln REC_{t-1} + \lambda_8 \ln TEC_{t-1} + \lambda_9 \ln URB_{t-1} + \varepsilon_t \end{aligned} \quad (10)$$

In this study, α_0 represents the drift component while Δ indicates the first difference, ε_t means the white noise.

To determine the optimal lag length, the study employs the Akaike information criterion (AIC). After establishing the long-run relationship between variables, the error correction model (ECM) is used to analyze the short-run dynamics. The ECM's general form is given by:

$$\begin{aligned} \Delta \ln EFP_t = & \beta_0 + \sum_{k=1}^p \beta_1 \Delta \ln EFP_{t-k} + \sum_{k=1}^p \beta_2 \Delta \ln EFP_{t-k} + \sum_{k=1}^p \beta_3 \Delta \ln CRW_{t-k} + \\ & \sum_{k=1}^p \beta_4 \Delta \ln EMI_{t-k} + \sum_{k=1}^p \beta_5 \Delta \ln EST_{t-k} + \sum_{k=1}^p \beta_6 \Delta \ln FFC_{t-k} + \\ & \sum_{k=1}^p \beta_7 \Delta \ln NRS_{t-k} + \sum_{k=1}^p \beta_8 \Delta \ln REC_{t-k} + \sum_{k=1}^p \beta_9 \Delta \ln URB_{t-k} + \phi ECM_{t-1} + \varepsilon_t \end{aligned} \quad (11)$$

Where Δ represents the first difference while ϕ is the coefficients of ECM for short-run dynamics. The ECM shows the speed of adjustment in long-run equilibrium after a shock in the short run.

3.4 Bound cointegration test

The bound cointegration test is applicable in cases where several integrated variables of varying orders $I(0)$, $I(1)$ are accessible. The bound cointegration model is specified as:

$$\Delta y_t = \delta_1 Y_{t-1} + \delta_2 X_{t-1} + \sum_{k=1}^p \alpha_i \Delta y_{t-k} + \sum_{l=0}^{q-1} \beta_l \Delta x_{t-l} + \pi_0 + \pi_t + e_t \quad (12)$$

The study hypotheses are formulated as:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0 \quad (13)$$

$$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq \beta_8 \neq 0 \quad (14)$$

The test process involves computing the Fisher statistic (F_c) for various scenarios and thresholds, in addition to simulating critical values (Pesaran et al., 2001). Specifically, the upper bound applies to variables with an order of integration of 1, while the lower bounds pertain to the variables $I(0)$ (Magnus & Eric Fosu, 2006). It is essential to emphasize that the simulated critical values are crucial in this context. If the F-value is greater than the bounded upper value, then there is cointegration but if the F-value is less than the bounded upper value, then there is no cointegration (Atchadé & Nougbodé, 2024).

4 Results and discussion

This study investigates the determinants of the ecological footprint (EFP), examining the interplay between energy consumption (renewables vs. fossil fuels), CO₂ emissions, urbanization, natural resource rents, and technological innovation. The

increasing global concern over environmental sustainability necessitates a deeper understanding of how these factors influence ecological degradation. The results are grounded in economic and ecological theories, including the Environmental Kuznets Curve (EKC) hypothesis, which postulates that environmental degradation initially increases with economic growth but eventually declines as economies adopt cleaner technologies and sustainable practices. This discussion integrates empirical findings with theoretical frameworks and highlights their implications for policy formulation.

4.1 Descriptive statistics

Table 2 presents the descriptive statistics of the ARDL estimation, revealing important trends in the data. The ecological footprint (EFP) varies from 2.5 to 4.66 global hectares per person, with an average of 3.37, indicating significant differences in resource consumption. The high mean of 78.23% for combustible renewables and waste (CRW) and a peak of 93.21% highlight a strong dependence on these energy sources. Emissions from manufacturing and construction (EMI) have an average of 13.82%, ranging from 1.83% to 21.27%, reflecting the varying levels of industrial development. Transportation emissions (EST) account for a significant average of 57.13% of total fuel combustion, emphasizing the environmental impact of the transport sector. Fossil fuel consumption (FFC) averages 7.1%, indicating a continued reliance on non-renewable energy sources, although the minimum of 4.92% suggests some adoption of renewable energy.

Table 2: Descriptive statistics

	EFP	CRW	EMI	EST	FFC	NRS	REC	TEC	URB
Mean	3.37	78.23	13.82	57.13	7.10	10.49	91.04	6.84	28.21
Maximum	4.66	93.21	21.27	74.31	13.02	19.49	96.41	24.46	34.40
Minimum	2.50	69.14	1.83	6.80	4.92	5.94	80.10	1.23	18.33
Std. Dev.	0.67	7.39	5.77	22.69	1.86	2.68	4.56	5.57	4.08

Source: Authors' computation (2025)

Natural resource rents (NRS) contribute a moderate mean of 5.43% to GDP, with a uniform distribution. Renewable energy consumption (REC) averages 8.64%, despite a maximum of 96.41%, indicating potential growth in green energy. Technology innovation (TEC) has a mean of 6.84, ranging from 1.23 to 24.46, reflecting uneven technological development. Urbanization (URB) averages 28.21%, indicating growing urban populations with a uniform distribution. The Jarque-Bera results suggest that the variables are normally distributed.

4.2 Optimal lag length

Before conducting the ARDL bound test, the study employs criteria to determine the lag length to explain the autoregressive length of the time series data. Results can be found in Table 3 below.

Table 3: Optimal lag length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-537.77	NA	19243.6	37.71	38.13	37.84
1	-301.82	309.18	5.73	27.02	31.27	28.35*
2	-95.12	142.55*	0.01*	18.35*	26.42*	20.88

Source: Authors' computation (2025).

The lag selection criteria employed include the Log Likelihood Ratio (LR) statistic, Final Predictor Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quin Information Criterion (HQ), to select the optimal lag order for the Vector Autoregression (VAR) model. According to Table 3, the optimal lag used in the Autoregressive Distributed Lag (ARDL) model is 2. Lag 2 is chosen as the ideal lag because it has many asterisks in the critical value for most criteria, including LR, FPE, SC, and AIC.

4.3 Stationarity and Johansen cointegration test

After determining the optimal lag length, the study conducted the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) unit root tests to check the stationarity of the dataset. These tests are crucial in ensuring that the time series data is stable and suitable for ARDL analysis. The results are presented in Table 4 below.

Table 4. ADF and PP unit root tests

Variable s	ADF		PP		Integratio n Order
	Levels	1 st Differences	Levels	1 st Differences	
EFP	-1.815741	-5.513824***	-1.359101	-11.48508***	I (1)
CRW	-2.371588	-4.432279**	-2.406474	-5.375054***	I (1)
EMI	-2.840201	-5.527721***	-2.840890	-7.963575***	I (1)
EST	-1.546656	-6.224246***	-1.392108	-6.735398***	I (1)
FFC	0.346578	-5.980578***	0.380037	-7.705480***	I (1)
NRS	-2.194274	-3.148956	-2.359694	-5.625934***	I (1)
REC	-0.782272	-6.032296***	-0.606451	-6.032296***	I (1)
TEC	0.155286	-8.760789***	-2.710152	-13.14702***	I (1)
URB	3.692900**	-1.567224	3.913856**	-1.246092	I (0)

Source: Authors' computation (2025). Note: *, **, and *** are significant at 10%, 5% and 1% significance level.

The results in Table 4 revealed that EFP, CRW, EMI, EST, FFC, NRS, REC, and TEC are I (1), exhibiting short-term mean-reverting behavior after first differencing, while URB is I(0), suggesting less long-term trend influence. The mixed integration order justifies using the ARDL model. The non-stationarity of EFP, FFC, and REC underscores their susceptibility to structural changes, requiring the examination of both short-run dynamics and long-run relationships.

The outcome of the cointegration using (Johansen & Joselius, 1990) model/concept is presented in Table 5. The results show that at least two cointegration equations exist in the system of equations.

Table 5. Johansen Cointegration

Hypothesized No. of CE (s)	Eigenvalue	Trace statistic	0.05 Critical value	p-value	Max-eigen statistic	0.05 critical value	p-value
None*	0.9864	494.1728	197.3709	0.0000	124.5980	58.4335	0.0000
At most 1*	0.9629	369.5748	159.5297	0.0000	95.5588	52.3626	0.0000
At most 2*	0.9463	274.0161	125.6154	0.0000	84.8290	46.2314	0.0000
At most 3*	0.8817	189.1871	95.7537	0.0000	61.9128	40.0774	0.0000
At most 4*	0.8115	127.2743	69.8189	0.0000	48.3898	33.8769	0.0000
At most 5*	0.7455	78.8844	47.8561	0.0000	39.6838	27.5843	0.0000
At most 6*	0.5679	39.2001	29.7971	0.0031	24.3397	21.1316	0.0171
At most 7	0.3256	14.8609	15.4947	0.0621	11.4227	14.2646	0.1343
At most 8	0.1118	3.4382	3.8415	0.0637	3.4382	3.8415	0.0637

Source: Authors' computation (2025). Trace statistic and max-eigenvalue test indicate 7 cointegrating eqn(s) at the 0.05 level; * denotes rejection of the hypothesis at the 0.05 level; *MacKinnon-Haug-Michelis (1999) p-values.

4.4 Long run estimation results

The long-run estimation results presented in Table 5 show that fossil fuel consumption, urbanization, technological innovation, renewable energy consumption, natural resources rents, CO₂ emissions from transport (EST), CO₂ emissions from

manufacturing, industry and construction (EMI), combustible renewable and waste had a long-run and short-run statistical effect on ecological footprint.

$$EC = EFP - (-0.012 * CRW - 0.037 * EMI - 0.026 * EST - 0.332 * FFC - 0.053 * NRS - 0.076 * REC + 0.015 * TEC - 0.058 * URB + 17.588)$$

Table 5. Conditional Error Correction Regression (Long run estimates)

Variable	Coefficient	Standard Error	t-Statistic	Probability
lnCRW	-0.0119	0.0149	-0.7666	0.4724
lnEMI	-0.0367**	0.0122	-3.0064	0.0238
lnEST	-0.0256**	0.0090	-2.8329	0.0298
lnFFC	-0.3319**	0.1106	-3.0019	0.0239
lnNRS	-0.0526	0.0276	-1.9064	0.1052
lnREC	-0.0756**	0.0268	-2.8276	0.0301
lnTEC	0.0151	0.0111	1.3539	0.2245
lnURB	-0.0583	0.0483	-1.2071	0.2728
Constant	17.5878***	3.5751	4.9196	0.0027

Source: Authors' computation (2025). Note: *, **, and * are significant at 10%, 5% and 1% significance level.**

Emissions from manufacturing and industry (EMI), transport (EST), fossil fuel consumption (FFC), and renewable energy consumption (REC) significantly affect Mozambique's ecological footprint. There is a negative correlation between emissions and EFP (-0.0367, $P > 0.0238$), meaning that a unit reduction in EMI results in a 3.6% ecological benefit. This finding aligns with previous studies by Ding et al. (2016) and York et al. (2003), who identified emissions and fossil fuel dependency as drivers of global ecological degradation. Transport emissions (EST) also negatively influence the ecological footprint (-0.0256, $P > 0.0092$), suggesting that enhanced transportation efficiency can contribute to sustainability. Sovacool et al. (2020) support this, suggesting a shift to electric vehicles. In consonance with this finding is notable researcher Jorgenson (2014), who emphasized fossil fuel usage while acknowledging green energy's potential to reduce ecological footprints in developing economies. However, sub-Saharan Africa including Mozambique faces challenges in transitioning to electric vehicles due to infrastructure and electricity reliability issues.

Fossil fuel consumption (FFC) has the most significant long-run effect on ecological footprint (-0.3319, $p = 0.0233$). While fossil fuels are widely identified as key drivers of environmental degradation (Nakamya, 2022), the negative coefficient observed appears counterintuitive. In the Mozambican context, this may reflect gradual shifts from biomass to more efficient energy sources, which can reduce pressure on forests and land use. It may also capture improvements in energy efficiency and structural changes in the

economy, where fossil fuels are increasingly used in more productive sectors. However, this result reflects transitional dynamics rather than a long-term environmental benefit, underscoring the complex relationship between energy use and ecological outcomes. The significant negative relationship with renewable energy consumption further supports the potential of renewables to mitigate ecological impacts once the initial challenges of transitioning are overcome. With a coefficient of -0.0756, it suggests that increased renewable energy utilization contributes to reducing the ecological burden, aligning with findings in prior research. [48]), [49]), and [50]), emphasize that renewable energy adoption mitigates environmental decay by supplanting dependence on non-renewable energy sources, major contributors to ecological stress. Given Mozambique's substantial renewable energy potential, particularly in hydro, solar, and wind energy [51], expanding renewable energy infrastructure could be instrumental in addressing ecological challenges while supporting Mozambique's development goals. Integrating renewable energy into food systems like solar irrigation, food processing and storage can also make food systems sustainable and resilient [52].

4.5 Short-run estimation results

The Error Correction Term (ECT) coefficient, denoted as D (EFP (-1)), has a value of -0.468589 and is statistically significant at the 1% level ($p > 0.01$). This coefficient is used to compute the rate of adjustment from short-run fluctuations to long-run equilibrium, and it shows that the yearly rate of adjustment is 46.8%. The estimation results further indicate that the explanatory variables, including fossil fuel consumption (FFC), urbanization (URB), technological innovation (TEC), renewable energy consumption (REC), natural resources rents (NRS), CO₂ emissions from transport (EST), CO₂ emissions from manufacturing, industry and construction (EMI), and combustible renewable and waste (CRW), have significant long-run effects on the ecological footprint (EFP). This underscores the importance of these factors in shaping the environmental sustainability represented by the ecological footprint in the studied context.

Table 6. ARDL error correction model regression (Short run estimates)

Variable	Coefficient	Standard Error	t-Statistic	Probability
D(EFP(-1))	0.1649**	0.0578	2.8548	0.0290
D(CRW)	0.0063***	0.0016	3.9738	0.0073
D(CRW(-1))	0.0099***	0.0019	5.0777	0.0023
D(EMI)	-0.0058***	0.0015	-3.8891	0.0081

D(EMI(-1))	-0.0046**	0.0013	-3.5616	0.0119
D(EST)	-0.0056***	0.0009	-5.8021	0.0011
D(EST(-1))	0.0076***	0.0012	6.4438	0.0007
D(FFC)	0.0189	0.0104	1.8246	0.1179
D(FFC(-1))	0.0993***	0.0124	8.0169	0.0002
D(NRS)	0.0100**	0.0027	3.6993	0.0101
D(NRS(-1))	0.0392***	0.0026	15.1343	0.0000
D(REC)	0.0506***	0.0046	10.9088	0.0000
D(REC(-1))	0.0498***	0.0049	10.0736	0.0000
CointEq(-1)*	-0.4659***	0.0322	-14.4809	0.0000
R-Squared	0.9784			
Durbin-Watson	2.8974			

Source: Authors' computation (2025). Note: *, **, and *** are significant at 10%, 5% and 1% significance level.

In the short run, combustible resources and waste (CRW), fossil fuel consumption (FFC), natural resource extraction (NRS), and renewable energy consumption (REC) significantly impact ecological footprint. Combustible resources and waste (CRW, 0.0063, $P > 0.0073$) and natural resource extraction (NRS, 0.0392, $P > 0.0022$) positively contribute to EFP (Sampene et al., 2023) (Abdi et al., 2024), reflecting the immediate environmental costs of resource exploitation and waste generation. Similar results were reported by Jorgenson and Clark (2012), who highlighted the short-term environmental degradation caused by resource extraction in low-income countries.

Interestingly, a unit increase in renewable energy consumption (REC, 0.0506, $P > 0.0001$) increases the ecological footprint in the short run by 5%. This counterintuitive finding can be attributed to several factors. During the transition to renewable energy, there are often significant infrastructure demands, such as the construction of solar farms, wind turbines, and associated grid improvements. These projects can lead to land use changes, resource extraction, and other environmental impacts that temporarily elevate the ecological footprint (Álvarez-Herránz et al., 2017). Inefficiencies in the initial phases of renewable energy implementation, such as the use of less efficient technologies or maintenance of old energy systems alongside new ones, can contribute to short-term environmental costs (Kabeyi & Olanrewaju, 2022; Raugei et al., 2012). While renewable energy consumption may temporarily increase the ecological footprint, it is essential to recognize this as part of a necessary transition towards more sustainable energy systems. Studies (Bang et al., 2016; Levin et al., 2019) maintain that the long-term benefits of renewable energy far outweigh these short-term costs, emphasizing the importance of a comprehensive approach that considers both immediate and future

ecological impacts. This finding aligns with the work of (Álvarez-Herránz et al., 2017), who noted that while renewable energy projects are essential for long-term sustainability, they can incur immediate ecological costs related to resource use and environmental disruption. Similar observations have been made by authors like (Zhang et al., 2020) highlighted that the life cycle impacts of renewable energy systems, particularly during installation and initial operation phases, can be significant.

Fossil fuel consumption (FFC, 0.0993, $P > 0.0025$) remains a significant short-term driver of ecological degradation, consistent with its long-term impact. A unit increase in FFC degrades the ecology/environment. This finding reinforces the need for Mozambique to prioritize renewable energy adoption and reduce reliance on fossil fuels, particularly given its significant reserves of natural gas. However, this potential is hampered by limited resources for full exploration, instabilities as well as poor infrastructural development.

4.6 ARDL bound cointegration test results

To test whether the environmental variables used in the study have a long-run equilibrium relationship (cointegration). In conducting the cointegration test of environmental variables, this study utilized the ARDL bound F-Bounds Test shown in Table 7.

Table 7. ARDL Bounds Cointegration Test (F-Bounds test)

Test Statistic	Value	Significant	I (0)	I (1)
F-statistic	8.388	10%	1.85	2.85
K	8	5%	2.11	3.15
		2.5%	2.33	3.42
		1%	2.62	3.77

Source: Authors' computation (2025). Note: *, **, and *** are significant at 10%, 5%, and 1% significance level

As reported in Table 7, in the cointegration bound testing, the F-statistic value of 8.388 is greater than the upper limit upper bound critical values I (1) of (3.15) at a 5% significance level. Moreover, the F-statistic value is also greater than the upper limit value of I (1) at the 1% significance level which is 3.77. This indicates that all the environmental variables have a long-run equilibrium relationship or can be said that the variables move together in the long run. This suggests that the null hypothesis of no cointegration can be rejected, providing strong evidence of a long-run cointegrating relationship between the ecological footprint and the explanatory variables.

4.7 Diagnostic test

The diagnostic tests were conducted to check normality, homoskedasticity, and serial correlation, for the error term and outcomes of the study are displayed in Table 8. The results indicate that the dataset is normally distributed, and no issues of homoscedasticity, serial autocorrelation, and specification errors were detected.

Table 8. Post diagnosis results

Classical Assumption	Type of Test	F-Statistic	Probability	Conclusion
Normality	Jarque Bera	0.3827	0.8258	Data normally distributed
Autocorrelation	Breusch-Godfrey Serial Correlation LM	2.8029	0.1734	No Autocorrelation
Heteroskedasticity	Heteroskedasticity (Breusch Pagan- Godfrey)	0.7143	0.7411	No Heteroskedasticity
Regression Specification Error	Ramsey RESET	0.0003	0.9866	No Specification error

Source: Authors' computation (2025).

4.8 CUSUM and CUSUMQ results

The validity of the bounds test models is contingent upon the diagnostic properties of the error terms and the temporal stability of coefficients. Specifically, the residuals must adhere to the assumptions of normality, homoscedasticity, and absence of serial correlation, while the model parameters should exhibit structural consistency over the sample period. To evaluate coefficient stability, the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests, as outlined by Brown et al. (1975), are employed. These tests require the recursively estimated statistics to remain within the 5% critical bounds, demarcated by red lines in Figures 1 and 2. The graphical outputs reveal that the blue trajectories, representing the CUSUM and CUSUMQ statistics, persistently lie within the 5% significance thresholds (red lines) across the observation period. This empirical evidence confirms the stability of the autoregressive distributed lag (ARDL) model, thereby validating its robustness in identifying long-run cointegration relationships. The results affirm that the model satisfies the requisite diagnostic criteria, ensuring its reliability for inferring equilibrium dynamics over time.

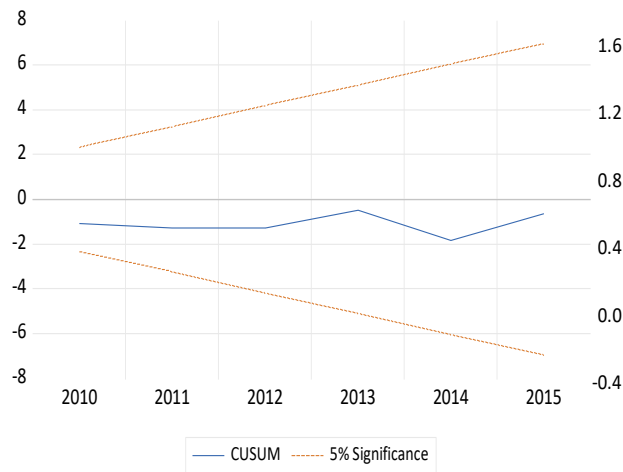


Figure 1. CUSUM

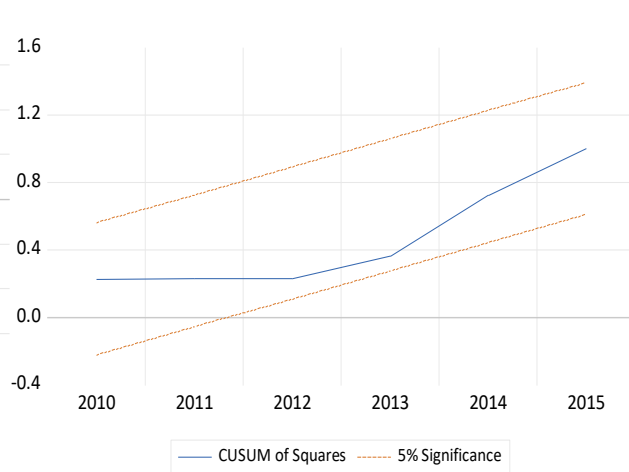


Figure 2. CUSUM of Squares

The study assessed the ARDL model's forecasting accuracy through static analysis of carbon dioxide emissions from 1985-2015, using Theil's inequality coefficient and Symmetric Mean Absolute Percentage Error (MAPE). As shown in Figure 3, the ARDL model had the lowest Root Mean Squared Error (RMSE) and Theil's inequality coefficient among evaluated models. The model achieved an RMSE of 0.013879 for ecological footprint predictions, with a Theil's inequality coefficient of 0.002076, approaching zero and indicating minimal divergence between predictions and actual values. The SMAPE value of 0.330237 suggests a 33.02% average deviation between forecasts and empirical data, affirming the model's reliability for long-term environmental forecasting.

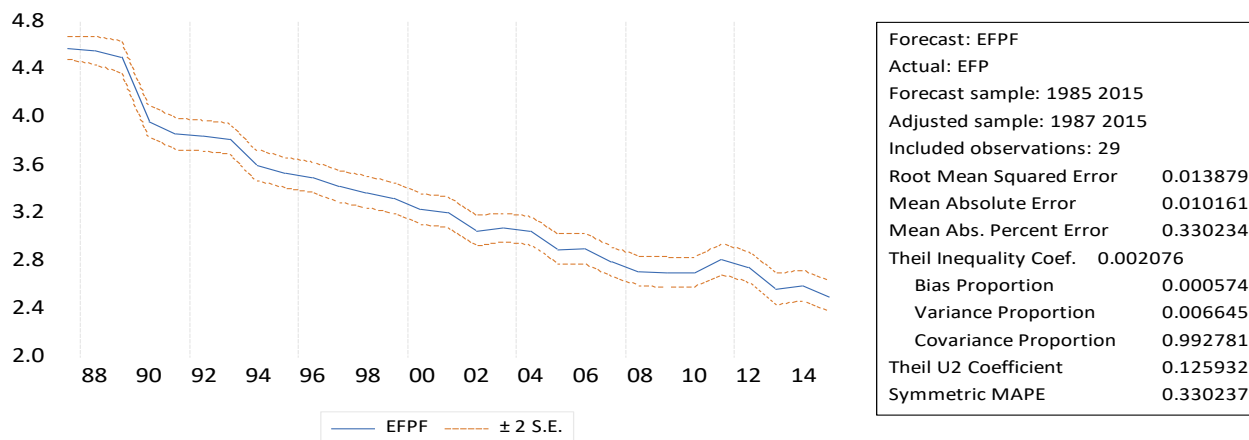


Figure 3. Actual and forecasted EFP from 1985 to 2015

5. Conclusion

This study investigated the temporal and structural dynamics through which energy-system transformation shapes ecological sustainability in Mozambique over 1985–2015. Using an Autoregressive Distributed Lag (ARDL) framework, the analysis distinguished long-run equilibrium relationships from short-run adjustment dynamics among ecological footprint, fossil-fuel consumption, renewable-energy consumption, transport and industrial emissions, urbanization, technological innovation, and natural-resource rents.

The findings demonstrate that Mozambique's energy–ecology nexus is neither linear nor temporally uniform, but conditioned by the composition and stage of energy-system transformation. In the long run, fossil-fuel consumption, transport and industrial emissions, and renewable-energy consumption significantly shape ecological footprint. The negative long-run coefficient associated with fossil-fuel consumption is interpreted within Mozambique's evolving energy-use configuration, particularly the displacement of traditional biomass by commercial energy sources. Renewable-energy consumption, in contrast, is associated with reduced ecological pressure in the long run, reinforcing its potential contribution to sustained environmental improvement.

Short-run dynamics reveal a contrasting transition effect, with renewable-energy consumption associated with increased ecological footprint, suggesting that early-stage energy transformation may generate environmental costs through infrastructure expansion, material requirements, and resource use. The error-correction coefficient indicates that approximately 46.8% of disequilibrium is corrected each period, confirming substantial adjustment toward long-run equilibrium. Environmental pressures therefore reflect the interaction of immediate transition effects with longer-term structural adjustment.

Overall, the evidence suggests that the ecological dividend of energy transition is neither automatic nor contemporaneous; rather, it depends on the sequencing, composition, resource intensity, and institutional governance of structural change. The study contributes context-specific evidence from an underrepresented resource-dependent economy and demonstrates the importance of incorporating temporal and structural heterogeneity into energy–environment analysis. For Mozambique, the policy challenge is therefore not simply to expand renewable energy, but to manage the transition in ways that reduce biomass dependence, lower the ecological intensity of productive sectors, and ensure that short-run transition costs do not undermine longer-run sustainability gains.

5.1 Policy implications

The findings point to the need for Mozambique to govern energy transition as a process of structural reconfiguration rather than as a simple substitution of fossil fuels with renewable energy. The positive short-run ecological effect associated with renewable-energy consumption cautions against treating renewable expansion as environmentally costless. Renewable deployment should therefore be accompanied by lifecycle

environmental appraisal, resource-sensitive infrastructure planning, and safeguards that minimize land, material, and ecosystem pressures during the transition phase. This is particularly important where rapid infrastructure expansion could transfer environmental burdens from energy consumption to land-use change, material extraction, or ecosystem degradation.

Reducing dependence on traditional biomass requires more than discouraging its use; it requires expanding reliable, affordable and spatially accessible modern energy alternatives, particularly for energy-poor rural and peri-urban populations. Energy-access policy should consequently be integrated with electrification, clean-cooking provision, decentralized energy systems, and productive-use applications capable of reducing household and productive reliance on biomass. Such substitution can address the environmental externalities associated with biomass dependence while simultaneously strengthening energy security and productive capacity.

The significant contribution of transport and industrial emissions to ecological footprint further warrants sector-specific resource-efficiency and decarbonization strategies. These should encompass cleaner transport systems, improved energy performance of industrial processes, technological upgrading, and incentives for less energy- and carbon-intensive production. Rather than pursuing efficiency as an isolated technical objective, policy should target reductions in the ecological intensity of economic activity.

Finally, the sustainability of energy transition depends on institutional coherence. Renewable-energy, environmental, land-use, industrial, and rural-development policies should be coordinated through integrated planning frameworks, with local communities incorporated into project appraisal, implementation, and benefit-sharing arrangements. Such institutional alignment can reduce policy fragmentation and improve the fit between energy investments, ecological constraints, and local livelihood systems. Collectively, these measures would position energy transition not merely as an expansion of energy supply, but as a coordinated restructuring of Mozambique's energy–production–environment nexus.

5.2 Limitations and future studies

Despite its contributions, this study has several limitations. First, the analysis relies on annual time series data from 1985 to 2015, which may not fully capture recent developments in Mozambique's energy sector, including the expansion of natural gas projects and renewable energy investments. Second, the use of aggregate national-level indicators may obscure sector-specific and regional variations in environmental pressure. Third, the ARDL framework assumes linear relationships and may not adequately capture potential nonlinearities or asymmetric effects in the energy-environment nexus.

Future studies could extend this study by incorporating more recent data and applying advanced econometric techniques that account for nonlinear and asymmetric relationships. Sector-specific analyses, particularly in transport, agriculture, and energy production would provide deeper insights into the sources of ecological pressure. Additionally, integrating institutional, governance, and policy variables could improve understanding of how regulatory frameworks shape environmental outcomes. Expanding the analysis to a comparative or regional level across Sub-Saharan Africa may also help identify broader patterns and context-specific differences in energy transition pathways.

Author Contributions

Lukwago Moses Mwesige and John Atsu Agbolosoo were responsible for investigation, conceptualization, methodology, formal analysis, and drafting the original manuscript. Helder Zavale provided supervision and reviewing. Basil Mugonola contributed by reviewing, supervision, editing, and review. Collins Yeboah Asiedu contributed by reviewing and editing the manuscript. All authors gave their approval for the final version of the manuscript.

Data availability statement

“Data shared with manuscript or Supplementary Information:

The author confirms that all data generated or analyzed during this study are included in this published article”

Ethics statement

Not applicable

Conflict of interest statement

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