The effect of the population's age distribution on the ecological footprint in Sri Lanka

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Abstract

This study investigates the effect of population age distribution on Sri Lanka's ecological footprint (EF) from 1980 to 2022, integrating demographic variables into the Environmental Kuznets Curve (EKC) framework. Using the Autoregressive Distributed Lag (ARDL) bounds testing approach, the analysis reveals a U-shaped relationship between GDP and EF, contradicting the traditional inverted U-curve hypothesis. The working-age population (15–64 years) exerts the most significant long-term pressure on the EF, with an impact five times greater than that of the young population (0–14 years). In contrast, the elderly population (65+ years) shows a negligible negative association. Short-run dynamics highlight rapid equilibrium restoration (error correction term = -3.33), with lagged GDP terms exacerbating EF and GDP^2 terms mitigating it. The findings underscore the environmental cost of economic productivity driven by the working-age cohort and suggest that Sri Lanka's current development trajectory risks accelerating ecological degradation. Policy recommendations include green employment initiatives, sustainable urban planning, and carbon taxation to align economic growth with sustainability. This study contributes to developing-country literature by demonstrating the applicability of demographic-EKC frameworks and advocating for age-sensitive environmental policies.

Keywords: *Ecological footprint, Population age distribution, Environmental Kuznets Curve, ARDL bounds test*

1. Introduction

The interaction between demographic transitions and environmental sustainability has emerged as a pivotal area of study in recent decades, particularly in the context of ageing global populations and rising economic activities. A key indicator used to evaluate the environmental impact of human actions is the ecological footprint (EF), which measures the extent of pressure exerted on ecosystems due to human consumption and activities (Global Footprint Network, 2025). Sri Lanka, a developing country undergoing significant demographic shifts, offers a compelling example to explore the relationship between age distribution and ecological footprint. This research investigates how the age composition of the population, categorized into young dependents (ages 0–14), the working-age group (ages 15–64), and elderly dependents (ages 65 and above), affects the ecological footprint in Sri Lanka. Additionally, the study incorporates the influence of economic growth, as reflected by gross domestic product (GDP), to provide a more comprehensive understanding of the dynamics at play.

Background and Context

Sri Lanka has experienced profound demographic and economic changes over the past few decades, reshaping the nation's societal and environmental landscape. A notable shift in the population's age structure has occurred, driven by declining fertility rates and increasing life expectancy. This demographic transition has resulted in a growing proportion of older adults within the population (World Development Indicators, 2025). Simultaneously, the nation's economic growth has accelerated, accompanied by heightened resource consumption and escalating environmental degradation, sparking concerns over achieving sustainable development goals. The ecological footprint, which quantifies the biologically productive land and water area required to sustain human consumption and absorb waste, is a critical measure of environmental strain (Wackernagel & Rees, 1996). Analyzing how demographic factors, particularly shifts in age distribution, influence the EF is crucial for crafting policies that balance environmental conservation with economic advancement.

The Environmental Kuznets Curve (EKC) hypothesis provides a framework to study the interplay between economic growth and environmental degradation, suggesting an inverted U-shaped relationship where environmental damage initially rises with economic expansion but eventually declines as economies mature (Grossman & Krueger, 1995). However, the influence of demographic variables, especially age distribution, on this relationship remains insufficiently examined. Research indicates that different age groups exhibit distinct consumption behaviors and environmental impacts (Cole & Neumayer, 2004; Liddle, 2014). For example, the working-age population, being more economically active, tends to drive higher resource consumption and waste production. In contrast, older populations generally demonstrate lower consumption levels, potentially exerting a less significant environmental impact. Understanding these dynamics is essential for developing targeted strategies that address environmental challenges while supporting sustainable economic growth.

Research Problem and Objectives

Despite the extensive body of literature examining the Environmental Kuznets Curve (EKC) and the impact of demographic factors, there remains a noticeable gap in research specifically addressing Sri Lanka. Most existing studies have predominantly focused on developed countries or regions with distinct demographic and economic characteristics, such as those analyzed by Alam et al. (2012) and Shahbaz et al. (2016). This lack of country-specific research highlights the importance of conducting an analysis tailored to Sri Lanka's unique socioeconomic and demographic dynamics. To bridge this gap, the present study explores the following research questions.

How does the population's age distribution (young, working-age, and old dependents) influence the ecological footprint in Sri Lanka?

What is the relationship between economic growth (GDP) and ecological footprint in Sri Lanka, and does it align with the EKC hypothesis?

Are there short-term and long-term dynamics between these variables, and what are their policy implications?

The primary objective of this study is to empirically analyze the impact of age distribution on Sri Lanka's ecological footprint, using time-series data from 1980 to 2022. By employing the Autoregressive Distributed Lag (ARDL) bounds testing approach, the study captures long-run and short-run relationships among the variables, ensuring robust and reliable results.

Significance of the Study

This research significantly contributes to the existing body of literature in several distinct ways. Firstly, it offers valuable empirical evidence on the influence of age distribution on environmental degradation, addressing a critical yet underexplored area, particularly within the context of developing countries. By shedding light on this relationship, the study fills an important gap in understanding how demographic factors shape environmental outcomes. Secondly, it enhances the Environmental Kuznets Curve (EKC) framework by integrating demographic variables, providing a more comprehensive and nuanced perspective on the dynamic relationship between economic growth and environmental sustainability. This integration allows a deeper exploration of how population characteristics interact with economic development to impact environmental conditions. Lastly, the findings hold practical relevance for policymakers, particularly in Sri Lanka and other similar economies. The research underscores the importance of formulating age-sensitive environmental policies. For instance, if the analysis reveals that the working-age population significantly contributes to an increase in the ecological footprint, targeted interventions such as promoting sustainable consumption patterns and advancing green technologies among this demographic group could be prioritized to mitigate environmental harm effectively.

Methodology Overview

The study utilizes time-series data from 1980 to 2022, sourced from the Global Footprint Network (2025) and the World Development Indicators (2025). The key variables include per capita ecological footprint (EF), per capita GDP, the square of GDP (to test the EKC hypothesis), and the ratios of young, working-age, and old populations. The ARDL bounds testing approach is employed to examine cointegration and dynamic relationships, as it accommodates variables with different orders of integration (Pesaran et al., 2001). Additionally, diagnostic tests, stability tests, and Granger causality analysis are conducted to ensure the robustness of the results.

Structure of the Study

The remainder of the manuscript is organized: Section 2 reviews the relevant literature on ecological footprints, demographic changes, and the EKC hypothesis. Section 3 details the data and methodology, including the ARDL framework. Section 4 presents the empirical results and discussion, covering descriptive statistics, unit root tests, cointegration analysis, and causality tests. Section 5 concludes with policy recommendations and directions for future research.

2. Review of Literature

The relationship between demographic dynamics and environmental sustainability has garnered significant scholarly attention in recent decades, particularly as global populations age and economic activities intensify. This section synthesizes existing literature on three interconnected themes: (1) the ecological footprint as a measure of environmental impact, (2) demographic factors, particularly age distribution, and their environmental implications, and (3) the Environmental Kuznets Curve (EKC) hypothesis and its integration with demographic variables. The review concludes by identifying gaps in the literature, particularly in the context of developing nations like Sri Lanka, and establishes the rationale for the current study.

Ecological Footprint: Conceptual Foundations and Empirical Applications

The ecological footprint (EF), introduced by Wackernagel and Rees (1996), quantifies the biologically productive land and water area required to sustain human consumption and absorb waste. It is a comprehensive metric for assessing humanity's demand on ecosystems, offering a tangible measure of environmental pressure (Global Footprint Network, 2025). Over time, the EF framework has been applied globally to evaluate the sustainability of resource use, with studies highlighting disparities between developed and developing nations (Borucke et al., 2013; Lin et al., 2018). For instance, developed countries often exhibit larger per capita footprints due to higher consumption levels, whereas developing nations face challenges balancing economic growth with ecological preservation (Galli et al., 2014).

Recent research has expanded the EF framework to incorporate socioeconomic and demographic variables. For example, Caviglia-Harris et al. (2009) linked urbanization and income inequality to EF trends in Brazil. Charfeddine and Mrabet (2017) explored the role of energy consumption and trade openness in MENA countries. These studies underscore the multidimensional drivers of environmental degradation, emphasizing the need for context-specific analyses.

Demographic Factors and Environmental Impact

Demographic changes, including population growth, urbanization, and age structure shifts, are critical determinants of environmental outcomes. The role of population size in driving resource depletion has been widely debated since Ehrlich and Holdren's (1971) IPAT (Impact = Population × Affluence × Technology) model. However, contemporary research emphasizes the nuanced effects of age distribution, particularly the proportions of young, working-age, and elderly populations (Cole & Neumayer, 2004; Liddle, 2014).

Age Distribution and Consumption Patterns

The working-age population (ages 15–64) is often associated with heightened environmental pressure due to greater economic activity, energy consumption, and resource utilization. Liddle (2014) found that a 1% increase in the working-age share elevated CO_2 emissions by 0.6% in OECD countries, attributing this to higher production and consumption levels. Similarly, O'Neill et al. (2012) demonstrated that aging populations in developed nations could reduce emissions over time, as older individuals typically consume less energy-intensive goods.

Conversely, young populations (ages 0–14) may exert indirect environmental impacts through household consumption. For instance, Jiang and Hardee (2011) noted that larger youth cohorts in developing countries drive demand for education, healthcare, and housing, indirectly increasing resource use. However, the environmental effects of elderly populations (65+) remain contested. While some studies suggest reduced consumption patterns among the elderly (Zagheni, 2011), others highlight increased healthcare-related energy use (Meneses & Palacio, 2020).

Regional and Contextual Variations

The environmental implications of age distribution vary across regions. In sub-Saharan

Africa, rapid population growth and a high youth dependency ratio have exacerbated deforestation and soil degradation (Bilsborrow & DeLargy, 1991). In contrast, aging societies in Europe and Japan have seen slower growth in energy demand but face challenges in sustaining pension systems, which may indirectly influence environmental policies (Dalton et al., 2008). Few studies have examined these dynamics in South Asia, particularly in Sri Lanka, where demographic transitions and economic development intersect uniquely.

The Environmental Kuznets Curve (EKC) Hypothesis

The Environmental Kuznets Curve (EKC) hypothesis, introduced by Grossman and Krueger (1995), suggests an inverted U-shaped relationship between economic growth and environmental degradation. During the initial stages of industrialization and urbanization, pollution levels rise; however, technological progress and policy measures reduce environmental harm beyond a certain income threshold. Empirical studies testing the EKC have produced mixed results, varying by environmental indicators and regional contexts (Stern, 2004). In Sri Lanka, the observed U-shaped EKC deviates from the traditional inverted U-curve, which predicts that environmental degradation declines as economies mature. This deviation in developing nations like Sri Lanka may be attributed to structural economic transitions and delayed adoption of green technologies. During the early industrialization phase (1980s–2000s), Sri Lanka's ecological footprint (EF) declined due to agricultural modernization and light manufacturing. However, post-2010 economic growth, driven by resource-intensive sectors such as construction and tourism, reversed this trend, increasing environmental strain (Al-Mulali et al., 2015). Similar trends are evident across South Asian economies, where rapid urbanization and reliance on fossil fuels undermine early environmental improvements (Sarkodie & Strezov, 2019; Ecological Indicators). Furthermore, weak regulatory frameworks and inadequate investments in renewable energy exacerbate this U-shaped trajectory (Usman et al., 2023).

Integrating Demographic Variables into the EKC Framework

Recent studies have expanded the EKC model to include demographic variables. For example, Shahbaz et al. (2016) incorporated urbanization and population density into an EKC analysis for Malaysia, finding that urban sprawl exacerbated CO_2 emissions. Similarly, Alam et al. (2016) demonstrated that population growth skewed the EKC relationship in Brazil and Indonesia, delaying the transition to sustainable development.

However, the integration of age distribution into EKC models remains limited. Notable exceptions include Liddle and Lung (2010), who found that aging populations in 17 OECD countries reduced energy-related emissions, supporting the EKC hypothesis. Conversely, Buzkurt and Akan (2014) reported a U-shaped relationship between GDP and EF in Turkey, with a rising working-age population amplifying environmental pressure. These conflicting findings highlight the need for further research, particularly in developing economies with ongoing demographic and economic transitions.

Gaps in the Literature and Rationale for the Study

Despite the growing academic interest in the relationship between demographic changes and environmental outcomes, several critical gaps remain unaddressed:

Focus on Developing Countries: A significant proportion of existing studies predominantly focus on developed nations or regions such as the OECD and MENA, often sidelining the unique contexts of South Asian countries (Farhani & Rejeb, 2012). Sri Lanka, in particular, represents an underexplored case, characterized by its distinctive demographic transition marked by declining fertility rates and increasing life expectancy. This unique demographic shift warrants closer examination to better understand its implications for environmental sustainability.

Role of Age Distribution Dynamics: While considerable attention has been given to population size and urbanization in environmental studies, the influence of age-specific cohorts, such as the young, working-age population, and the elderly, on environmental factors like the ecological footprint (EF) remains insufficiently studied. This gap is especially pronounced in time-series analyses, where the interplay between age distribution and environmental outcomes has been largely overlooked.

Methodological Constraints: Many existing studies rely heavily on cross-sectional data or traditional cointegration techniques, often inadequate for capturing both short-term and long-term dynamics, particularly in studies with small sample sizes (Pesaran et al., 2001). These methodological limitations hinder a comprehensive understanding of the nuanced relationships between demographic variables and environmental outcomes.

This study addresses these research gaps by investigating the relationship between Sri Lanka's age distribution and ecological footprint from 1980 to 2022, employing the Autoregressive Distributed Lag (ARDL) bounds testing approach. By incorporating demographic variables into the Environmental Kuznets Curve (EKC) framework, this research offers fresh insights into how age-specific consumption and production patterns influence environmental outcomes in a developing economy, contributing to the existing body of knowledge.

The literature underscores the complex interplay between demographic changes, economic growth, and environmental sustainability. While the EKC hypothesis offers a foundational framework, its integration with age distribution variables remains nascent, particularly in developing nations. Sri Lanka's demographic and economic trajectory provides a compelling context to explore these dynamics, offering policy-relevant insights for sustainable development. The subsequent sections build on this foundation, employing advanced econometric techniques to unravel the temporal and causal relationships underpinning Sri Lanka's ecological footprint.

3. Materials and Methods

Variables and data

The EKC approach is utilized to comprehensively understand both long-term and short-term dynamics, as well as the causal relationships between ecological footprint, gross domestic product, and the age distribution of the population in Sri Lanka. This approach uses three key variables to represent the age distribution percentages of young dependents, the working-age population, and old dependents in Sri Lanka as indicator variables.

This study uses the per capita ecological footprint as the dependent variable. Per capita gross domestic product, square of gross domestic product, young population (Age 0 -14) ratio, working-age population ratio (Age 15 – 64), and old population (Age 65+) are explanatory variables.

Table 1- Data (Main Variables) to be Considered for the Study and Data Sources

Label	Variable	Definition	Unit	Source
EF	Ecological Footprint (per capita)	Metrics of human demand on ecosystems	global hectares per person	Global Footprint Network (2025)
GDP	Gross Domestic Product (per capita)	Gross domestic product divided by midyear population	Constant 2017 US$	World Development Indicators (2023)
YP	Young population	Population ages 0-14 (% of total population)	%	World Development Indicators (2023)
WAP	Working age population	Population ages 15-64 (% of total population)	%	World Development Indicators (2023)
OP	Old population	Population ages 65 and above (% of total population)	%	World Development Indicators (2023)

Source: *Created by the author*

The study used the time series data of Sri Lanka from 1980 to 2022. The data sources with codes of variables are presented in Table 1. Keeping the view with the prime objective of the study, the functional form of the model is as follows:

Per capita ecological footprint = f (Per capita gross domestic product, Square of the per capita gross domestic product, young population (Age 0 -14) ratio, Working-age population ratio (Age 15 – 64), and old population (Age 65+) ratio).

The variables are transformed to natural log, and the econometric form of the above model is as follows (Eq. (1)):

$$LnEF_i = \beta_0 + \beta_1\, LnGDPi + \beta_2\, LnGDPi^2 + \beta_3\, Ln\,YPi + \beta_4\, LnWAPi + \beta_5\, LnOPi + \varepsilon_i \quad \text{Eq(1)}$$

where all the variables are the same as described above, β_(0) is the intercept, and β1-β5 are the coefficients of explanatory variables, and ε_i is the error term.

Unit root testing

In the ARDL (Auto Regressive Distributed Lag) approach of cointegration, unit root pre-testing is not essential because it can test for the presence of cointegration between a set of variables of order I(0) or I(1) or a mixture of both. However, the ARDL Bounds Testing methodology of Pesaran and Shin (1999) and Pesaran et al. (2001) requires that no variable should be integrated of order 2 or I(2), as such data will invalidate the methodology. It is therefore justified to test the stationarity of each variable before proceeding to the next level of analysis and inference.

Cointegration testing using the ARDL bounds testing approach

The ARDL Bounds Testing technique will examine the potential presence of cointegration among the variables under analysis, determining whether they share a long-run equilibrium relationship while capturing both long-run and short-run dynamics. This method was chosen over traditional cointegration techniques (e.g., Engle-Granger) due to its flexibility in handling variables with mixed integration orders (I(0) and I(1)) and its robustness in small-sample scenarios (Pesaran et al., 2001). Such features are particularly crucial in demographic-environmental research, where data granularity is often constrained (Usman et al., 2023). For example, Liddle and Lung (2010) applied the ARDL framework to disentangle the effects of age structure on emissions in OECD countries, effectively mitigating biases from non-stationary data. The method's capacity to simultaneously estimate short- and long-run dynamics makes it especially relevant to Sri Lanka's evolving economic and demographic context.

The ARDL approach offers several advantages over traditional cointegration methods: (i) it is highly adaptable, enabling the analysis of variables integrated at I(0), I(1), or a combination of both; (ii) its single-equation setup simplifies implementation and interpretation; (iii) it allows for the use of different lag lengths for different variables within the model; (iv) it is well-suited for small sample sizes; (v) it provides unbiased estimates of long-run relationships and parameters; and (vi) it effectively addresses issues of autocorrelation and endogeneity (Harris & Sollis, 2005; Jalil & Ma, 2008).

Following Rahman (2017) and Shahbaz et al. (2013), for bounds testing of cointegration, the ARDL model used in this study is:

$$\begin{aligned}\Delta LnEF = \propto &+ \sum_{i=1}^{P} \beta_i \, \Delta LnEF_{t-i} + \sum_{i=1}^{q} \gamma_i \, \Delta LnGDP_{t-i} + \sum_{i=1}^{R} \delta_i \, \Delta LnGDP^2{}_{t-i} \\ &+ \sum_{i=1}^{S} \theta_i \, \Delta LnYP_{t-i} + \sum_{i=1}^{T} \sigma_i \, \Delta LnWAP_{t-i} + \sum_{i=1}^{U} \phi_i \, \Delta LnOP_{t-i} + \emptyset_0 LnEF_{t-i} \\ &+ \emptyset_1 LnGDP_{t-i} + \emptyset_2 LnGDP^2{}_{t-i} + \emptyset_3 LnYP_{t-i} + \emptyset_4 LnWAP_{t-i} + \emptyset_5 LnOP_{t-i} + \varepsilon_i\end{aligned}$$

Eq. (2)

where LnEF, LnGDP, LnGDP2, Ln YD, Ln WA and Ln OD are variables of the study, and ε_i is a "well-behaved" random disturbance term, ε_i is serially independent, homoscedastic and normally distributed.

The model in Eq. (2) is a particular type of Error Correction Model (ECM), where the coefficients are not restricted. Pesaran et al. (2001) term it as a "conditional ECM". In Eq. (2), the three terms with summation signs represent the error correction dynamics and the second part (terms with Ø_s) correspond to the long-run relationship (Shahbaz, Shrestha and Chowdhury et al., 2013, 2005).

The appropriate values for the maximum lags, p, q, R, s, T,and u will be determined using one or more of the "information criteria" – AIC, SC (BIC), HQ, etc.

Under the above equation, the null and alternative hypotheses are as follows:

H_0. No cointegration exists.

H_1. Cointegration exists.

The null hypothesis is tested by conducting an F-test for the joint significance of the coefficients of the lagged levels of the variables. Thus

H_0: $\emptyset_0 = \emptyset_1 = \emptyset_2 = \emptyset_3 = \emptyset_4 = \emptyset_5 = 0$
H_1: at least one $\emptyset_i \neq 0$, where *i = 0,1,2,3,4,5*

The distribution of the test statistics is purely non-standard and exact critical values for the F-test are not available for an arbitrary mix of I(0) and I(1) variables. However, Pesaran et al. (2001) developed bounds on the critical values for the asymptotic distribution of the F-statistic. For various situations (e.g., different numbers of variables, (k + 1)), they supply lower and upper bounds on the critical values. However, since the study is based on a relatively smaller sample size, we shall also compare the computed F-test value with the bounds critical value tables provided by Narayan (2005) as these are more suitable for small samples.

In each case, the lower bound assumes that all variables are I(0), and the upper bound assumes that all variables are I (1). If the computed F-statistic falls below the lower bound, the variables are I (0), so no cointegration is possible. If the F-statistic exceeds the upper bound, we conclude that we have cointegration. Finally, if the F-statistic falls between the bounds, the test is inconclusive, and we will have to resort to other cointegration techniques.

Following Giles (2013), it is also necessary to conduct, as a cross-check, a "Bounds t-test" as stated below:

H_0: $\emptyset_0$, against H_1: $\emptyset_0 < 0$.

The decision rule for this test is as follows:

If the t-statistic for 〖LnEF〗_(t-i) in Eq. (1) is greater than the "I (1) bound" tabulated by Pesaran et al. (2001; pp.303–304), which would support the conclusion that there is a long-run relationship between the variables. If the t-statistic is less than the "I (0) bound", we would conclude that the data are all stationary. Short-run parameters are estimated using the regular error correction mechanism (ECM) as depicted in Eq. (3) below:

$$\Delta Ln\text{EF} = \propto + \sum_{i=1}^{P} \beta_i \, \Delta LnEF_{t-i} + \sum_{i=1}^{q} \gamma_i \, \Delta LnGDP_{t-i} + \sum_{i=1}^{R} \delta_i \, \Delta LnGDP^2{}_{t-i} + \sum_{i=1}^{S} \theta_i \, \Delta LnYP_{t-i} + \sum_{i=1}^{T} \sigma_i \, \Delta LnWAP_{t-i} + \sum_{i=1}^{U} \phi_i \, \Delta LnOP_{t-i} + \; + \tau ECT_{t-1} + \varepsilon_t \quad \text{Eq. (3)}$$

The error correction model results indicate the speed of adjustment back to the long run equilibrium after a short run shock. ECM integrates the short-run and long-run coefficients without losing long-run information. Under the ECM technique, the long-run causality is depicted by the negative and significant value of the error correction term (ECT) coefficient τ, and the short-run causality is shown by the significant value of the coefficients of other explanatory variables (Rahman & Mamun, 2016; Shahbaz et al., 2013).

Diagnostic tests of the model

One of the most crucial assumptions in the ARDL Bounds Testing methodology is that Eq. (2) errors must be serially independent and normally distributed. Therefore, both 'Q-Statistics' and 'Breusch-Godfrey Serial Correlation LM test' will be used for testing Serial Independence and 'Jarque-Bera' test for testing Normality of the model errors. The heteroscedasticity will also be checked using the 'Breusch-Pagan-Godfrey' test.

$$Y_t = g_0 + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + b_1 X_{t-1} + \cdots + b_p X_{t-p} + u_t \quad \text{Eq. (4)}$$

$$X_t = h_0 + c_1 X_{t-1} + \cdots + c_p X_{t-p} + d_1 Y_{t-1} + \cdots + d_p Y_{t-p} + \tau_t \quad \text{Eq. (5)}$$

Then, testing H0: b1 = b2= ... = bp = 0, against H1: X Granger causes Y. Similarly, testing H0: d1 = d2= ... = dp = 0, against H1: Y Granger causes X. In each case, a rejection of the null hypothesis implies there is Granger causality. Note that X and Y series are in 'level' form, which means that the data is not in 'difference' form, where ut and τ_t are white noise error terms. In the long-run equilibrium, these errors should be zero. In these two equations, the Yt and Xt are co-integrated when at least one of the coefficients bi or di is statistically different from zero. If bi ≠ 0 and di = 0, Xt will lead Yt in the long run. The opposite will occur if di ≠ 0 and bi = 0. If both bi ‡ 0 and di ‡ 0, a feedback relationship exists between Yt and Xt. However, if both bi = 0 and di= 0, then no cointegration exists between Yt and Xt such conflicting results (with prior result of ARDL) can come out if the sample size is too small to satisfy the asymptotic that the cointegration and causality tests rely on (Giles, 2011). The coefficients ai's and ci's represent the short-run dynamics between Yt and Xt. If ai's are not all zero, movements in the Xt will lead to Yt in the short run, and conversely, if ci's are not all zero, movements in the Yt will lead to Xt in the short run.

Following Toda-Yamamoto (1995) procedure, the Granger Causality among the variables under an augmented Vector Autoregression (VAR) framework will be estimated. We will determine the appropriate maximum lag length for the variables in the VAR using the usual methods. Specifically, the basis of the choice of lag length is on the standard information criteria, such as AIC. We will also ensure that VAR is well specified; that is, VAR does not contain serial correlation in the residuals.

Stability test of the model

Ensuring the 'dynamic stability' of any model with an autoregressive structure is obligatory. The model's stability will be checked using the Recursive CUSUM and CUSUM of squares (Brown et al., 1975) tests. These tests are also suggested by Pesaran and Pesaran (1997) for measuring the parameter stability.

Granger causality test

If two or more time series are cointegrated, Granger causality between them must be either one-way or in both directions. However, the converse is not true (Giles, 2011). Again, according to Granger (1969), measuring the correlation between variables is insufficient to construct a complete understanding of the relationship between two or more time series. This is because some correlations may be spurious and useless, as there might be a hint of a third variable that cannot be accounted for. Further, only correlation does not confirm causation between (/among) variables. That is, if we get our series to be cointegrated, then we must cross-check causality results. It can test for the absence of Granger causality by estimating the following VAR model:

4. Results and Discussion

Table 2 presents the descriptive statistics of the study variables. The mean values of variables vary widely, from 0.009 for LnEF to 11.12 for LnGDP2, reflecting significant differences. Median values are generally close to the means, indicating moderate symmetry, though LnEF's lower mean suggests slight left-skewness. LnGDP2 shows the highest variability (SD = 1.40), while LnWAP has the least (SD = 0.02), indicating differing data spreads. LnEF spans -0.123 to 0.099, while LnOP ranges from 0.646 to 1.056, highlighting dispersion differences. LnEF and LnWAP exhibit moderate negative skewness (-0.64, -0.81), while other variables show mild positive skewness. All kurtosis values are below 3, indicating platykurtic distributions. The Jarque-Bera test suggests normality for most variables (p > 0.05), except LnWAP (p = 0.045), which may require further review.

Table 2 – Descriptive Statistics of the Study Variables

	LnEF	LnGDP	LnGDP2	LnYP	LnWAP	LnOP
Mean	0.009026	3.328810	11.12358	1.449660	1.809918	0.825189
Median	0.033428	3.290566	10.82782	1.425305	1.819347	0.797191
Maximum	0.099033	3.652798	13.34294	1.561566	1.829569	1.056235
Minimum	-0.123286	3.006478	9.038909	1.355840	1.771808	0.646502
Std. Dev.	0.070014	0.208860	1.399850	0.064074	0.020046	0.111010
Skewness	-0.639091	0.206222	0.267799	0.461322	-0.807897	0.501030
Kurtosis	1.910668	1.714416	1.722372	1.825109	2.075810	2.385530
Jarque-Bera	5.053203	3.265915	3.438564	3.998360	6.207975	2.475544
Probability	0.079930	0.195351	0.179195	0.135446	0.044870	0.290030
Sum	0.388129	143.1388	478.3141	62.33536	77.82648	35.48312
Sum Sq. Dev.	0.205883	1.832152	82.30236	0.172431	0.016877	0.517574
Observations	43	43	43	43	43	43

Source: Author's calculations

Unit root testing

The Levin, Lin & Chu, Im, Pesaran and Shin, ADF – Fisher, and Phillips Peron - Fisher unit root testing results are displayed in the following table (Table 3):

Table 3 – Results of Unit Root Tests.

Test	Level		1st Deference		Integration
	Intercept	Intercept and Trend	Intercept	Intercept and Trend	
Levin, Lin & Chu	-0.72363	-5.74761*	-2.25882**	-3.50357*	*I (1)*

Im, Pesaran and Shin W-stat	-0.50709	-3.10527*	-1.88342**	-3.61613*	*I (1)*
ADF - Fisher Chi-square	20.5586***	46.0230*	20.8676**	45.1584*	*I (1)*
PP - Fisher Chi-square	5.61993	1.37403	40.7041*	31.6233*	*I (1)*

Source: Author's calculation

The analysis of the above estimates indicates that all variables in the model become stationary after taking their first difference at a 1% significance level, classifying them as being of order I(1). However, except for the Phillips-Perron Fisher test, all variables in the model are stationary at their levels at a 1% significance level. This implies that the model exhibits stationarity at the level itself. Consequently, the variables could belong to the I(0) or I(1) category. This mixed and somewhat ambiguous order of integration among the variables provides a strong rationale for employing the ARDL (Autoregressive Distributed Lag) approach to cointegration analysis. Furthermore, as mandated by the ARDL bounds testing methodology introduced by Pesaran and Shin (1999) and further elaborated by Pesaran et al. (2001), the results of the unit root tests confirm that none of the variables are integrated of order I(2).

ARDL model estimation

The Akaike Information Criterion (AIC) has been used to determine the optimum lag length of the model. The selected model is ARDL (3, 4, 4, 4, 4, 4). Therefore, the optimum lag lengths of the variables LnEF, LnGDP, LnGDP2, LnYP, LnWAP, and LnOP are: p = 3, q = 4, R = 4, s = 4, T = 4 and u = 4, respectively.

Diagnostic tests of the model

The model demonstrates an excellent fit, successfully passing all diagnostic evaluations. The R-squared value of 0.939596 (Adjusted R-squared: 0.856540) indicates that the model effectively explains approximately 93% of the dependent variable variations. In comparison, the remaining 7% are attributed to the error term. Furthermore, the Durbin-Watson (DW) statistic of 2.1751 confirms the absence of spurious relationships in the model.

As detailed in Table 4, the model satisfies several critical diagnostic tests. It passes the serial correlation tests, including the Q-Statistics and Breusch-Godfrey Serial Correlation LM tests, ensuring no significant autocorrelation in the residuals. The Jarque-Bera test confirms the normality of the residuals, while the Breusch-Pagan-Godfrey test verifies that the model does not suffer from heteroscedasticity. These results collectively affirm the robustness and reliability of the model.

Table 4 -Model diagnostic test results.

Test	Estimate	Probability
Jarque-Bera test	0.317379	0.8533
Breusch-Pagan-Godfrey Heteroskedasticity test	25.08236	0.5698
Breusch-Godfrey Serial Correlation LM test	2.8069	0.2457

Source: Author's calculation

ARDL bounds test

The model successfully passed all diagnostic evaluations, confirming its robustness and reliability, thereby enabling progression to the subsequent analysis phase: conducting the bounds test for cointegration. Utilizing the ARDL Bounds Testing approach, the analysis yielded an F-test statistic of 7.398421. This value strongly signifies the presence of a long-term equilibrium relationship among the variables under consideration. For detailed reference, Table 5 presents the comprehensive results, including the critical values associated with the bounds test.

Table 4 - F-Bounds Test Estimate and Critical Values

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.398421	10%	1.81	2.93
k	5	5%	2.14	3.34
		2.5%	2.44	3.71
		1%	2.82	4.21

Source: Author's calculation

Significantly, the computed F-statistic exceeds the upper bound critical value (I(1)) at the stringent 1% significance level. This finding provides robust evidence supporting the existence of cointegration within the model. Consequently, we deduce that the model is well-suited for reliable long-run estimation purposes. Furthermore, the F-statistic surpasses the upper-bound critical values outlined in the Pesaran and Narayan tables, even at the 1% significance threshold. This reinforces the conclusion that there is substantial evidence of a long-run relationship among the time-series variables incorporated in the model.

Long-run and short-run relationships

The long-run equilibrium relationship among the variables estimated using the ARDL (3, 4, 4,4,4,4) approach is given in the table below:

Table 6 - Estimated long-run coefficients using the ARDL approach.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP	-14.52688*	4.472314	-3.248179	0.0078
LNGDP2	2.227142*	0.681332	3.268807	0.0075
LNYP	2.278627**	0.878383	2.594114	0.0250
LNWAP	11.34916*	3.302849	3.436172	0.0056
LNOP	-0.208843	0.274713	-0.760223	0.4631

**, and ** denote statistical significance at the 1%, and 5% levels respectively*
Source: Author's calculation

The analysis reveals that the coefficients for the variables LNGDP, LNGDP2, LNYP, and LNWAP are statistically significant, underscoring their importance in the model. The Environmental Kuznets Curve (EKC) model illustrates a U-shaped relationship, indicating a dynamic interaction between economic growth and environmental impact. The young population (LNYP) and the working-age population (LNWAP) play a substantial role in increasing the ecological footprint over the long term. Interestingly, the ecological footprint driven by the working-age population is five times larger than that of the young population, highlighting the significant environmental pressures associated with this demographic group. In contrast, the older population exhibits a negative relationship with the ecological footprint, suggesting a mitigating effect; however, this negative influence lacks statistical significance, implying it may not be a reliable factor in the broader context.

Short run dynamics

The following OLS equation is tested for the short-run causality in the ARDL (3, 4, 4,4,4,4) framework:

The results derived from Equation (2) are summarized in Table 7 above. These findings reveal both short-term dynamics and long-term relationships within the model, as demonstrated by the value and sign of the lagged error correction term (ECT), represented by the coefficient α[Coint Eq (−1)]. Consistent with theoretical expectations, the ECT exhibits a negative sign and is statistically significant at the 1% level. This strongly supports a stable long-term relationship between the dependent and explanatory variables. Furthermore, the ECT coefficient, with a value of −3.333015, indicates a robust and swift adjustment toward equilibrium, signifying that deviations from the long-term path are corrected rapidly.

Table 7 - Estimates from the error correction mechanism.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNEF (-1))	1.603724*	0.279371	5.740478	0.0001
D(LNEF (-2))	0.768400*	0.193259	3.976003	0.0022
D(LNGDP)	15.88448*	3.355748	4.733513	0.0006
D(LNGDP(-1))	46.02309*	7.360775	6.252479	0.0001
D(LNGDP(-2))	24.81015*	7.353819	3.373778	0.0062
D(LNGDP(-3))	22.12452*	6.079964	3.638924	0.0039
D(LNGDP2)	-2.156406*	0.484384	-4.451853	0.0010
D(LNGDP2(-1))	-6.854645*	1.098270	-6.241310	0.0001
D(LNGDP2(-2))	-3.709570*	1.093630	-3.391980	0.0060
D(LNGDP2(-3))	-3.369852*	0.911113	-3.698609	0.0035
D(LNYP)	-4.016042	27.05330	-0.148449	0.8847
D(LNYP(-1))	29.78106	58.86305	0.505938	0.6229
D(LNYP(-2))	-125.1209***	59.10203	-2.117033	0.0579
D(LNYP(-3))	136.8135*	30.54661	4.478846	0.0009
D(LNWAP)	11.30544	52.56621	0.215071	0.8336
D(LNWAP(-1))	22.99433	110.9551	0.207240	0.8396
D(LNWAP(-2))	-199.4204***	110.4103	-1.806175	0.0983
D(LNWAP(-3))	212.1743*	55.02324	3.856085	0.0027
D(LNOP)	-26.83168*	6.808688	-3.940800	0.0023
D(LNOP(-1))	8.376796	12.79498	0.654694	0.5261
D(LNOP(-2))	-23.47046***	12.83193	-1.829067	0.0946
D(LNOP(-3))	23.22902*	6.598442	3.520380	0.0048
Coint Eq(-1)	-3.333015*	0.414790	-8.035424	0.0000

, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively*
Source: Author's calculation

The analysis reveals that the first and second lags of ecological footprint (EF) have a significant and positive impact on the current EF in the short term. This suggests that the EF of the present year is heavily influenced by the EF levels of the two preceding years. Furthermore, the first, second, and third lags of the natural logarithm of Gross Domestic Product (LnGDP) significantly increase EF in the short term. In contrast, the first, second, and third lags of the square of the natural logarithm of GDP ($LnGDP^2$) significantly decrease EF in the short term, providing evidence for the existence of the Environmental Kuznets Curve (EKC) effect during this timeframe.

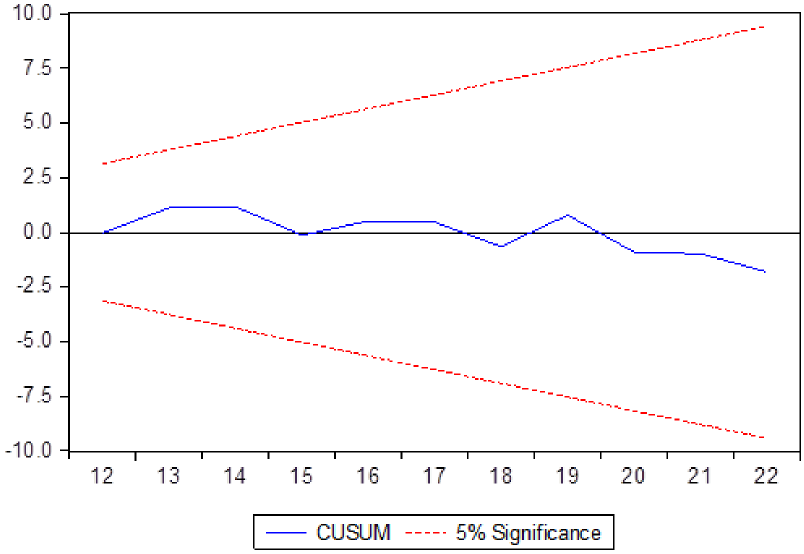
Only its second and third lags are statistically significant for the YP variable. The second lag negatively influences EF, while the third lag contributes positively. Similarly, for the working-age population (WAP), the second and third lags are also significant, with the second lag showing an adverse effect on EF and the third lag demonstrating a positive effect.

n terms of oil prices (OP), the short-run estimates reveal that OP initially causes a significant reduction in EF but leads to an enhancement in EF at the third lag. These results underscore the dynamic and variable impacts of the study variables on EF, highlighting that their effects vary over the short run.

Stability of the model

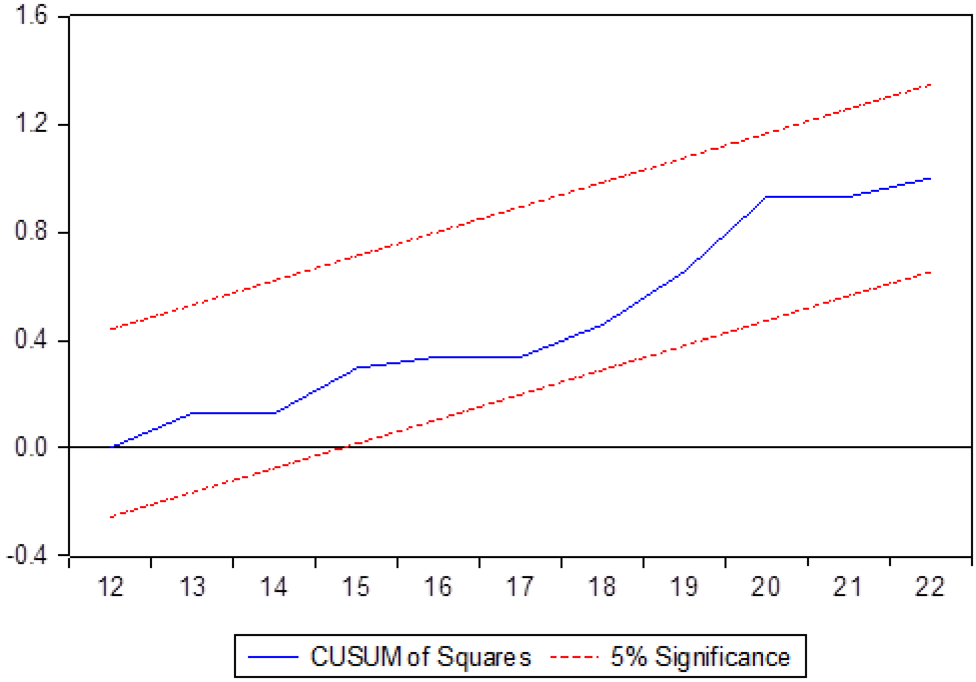
To ensure the reliability and robustness of the study's findings, structural stability tests are applied to the parameters of the long-run results. These tests utilize the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ), as recommended by Pesaran and Pesaran (1997). Figures 1 and 2 illustrate the graphical representations of the CUSUM and CUSUMSQ statistics, respectively.

Fig. 1. Plot of CUSUM tests.



Source: Author's calculation

Fig. 2. Plot of CUSUM of squares tests.



Source: Author's calculation

The stability of the model is determined by examining whether the CUSUM and CUSUMSQ plots remain within the 5% critical bounds. Parameter constancy and model stability are indicated if the plots do not breach these boundaries. Upon evaluation, the CUSUM plot and the CUSUMSQ plot hover consistently around the zero line.

These results confirm that the model exhibits stability over the study period, with no significant systematic changes detected in the coefficients at the 5% significance level. Thus, the applied tests validate the model's structural integrity and the reliability of the long-run results.

Granger causality test

The study analyzes the long-term relationship between the variables and applies the Granger causality test to identify causal links. Given the evidence of cointegration among the variables, uni- or bidirectional causality is anticipated. Table 8 presents the short-run Granger causality results for the variables.

Table 8 - Pairwise Granger Causality Tests

	LNEF	*LNGDP*	*LNGDP2*	*LNYP*	*LNWAP*	*LNOP*
LNEF		2.23501	2.43831	3.85214**	1.04750	5.27093**
LNGDP	0.54341		2.08490	7.96332*	1.49574	9.62972*
LNGDP2	0.61476	2.07114		7.63254*	1.31439	9.91434*
LNYP	0.79484	3.16210**	3.20046**		0.89774	14.6816*
LNWAP	4.80092**	4.50349**	4.49502*	5.76948*		13.6122*
LNOP	0.38437	5.90916*	5.24042**	7.98995*	1.22269	

, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively*
Source: Author's calculation

According to the estimates, only the WAP course is available on EF. However, the EF course applies to both YP and OP. All variables are based on YP and OP. However, none of the variables are associated with WAP.

Dynamic ordinary least squares (DOLS)

The long-run estimates derived from the ARDL estimator are further validated for robustness using an alternative single-equation estimation technique, namely dynamic ordinary least squares (DOLS). A key advantage of the DOLS method is its ability to account for mixed-order integration of variables within a cointegrated framework, if present in the data. The estimation process involves regressing I(1) variables against other I(1) variables, incorporating leads (p) and lags of first differences (-p), as well as variables integrated at order I(0), along with a constant term. One of the primary benefits of DOLS estimation is its effectiveness in addressing two critical issues: potential endogeneity and small-sample bias. Moreover, DOLS estimators yield efficient cointegrating vectors, and the regression results align with ARDL estimates, as they remain significant and maintain consistent variable signs. The results of the DOLS regression are presented in Table 9.

Table 9 – DOLS estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP	-13.91807	3.761594	-3.700047	0.0014
LNGDP2	2.124138	0.562747	3.774590	0.0012
LNYP	1.848962	0.773553	2.390218	0.0268
LNWAP	11.29693	2.783977	4.057838	0.0006

LNOP	-0.476582	0.372746	-1.278568	0.2157

R-squared	0.976686	Mean dependent var	0.013616
Adjusted R-squared	0.954538	S.D. dependent var	0.069602
S.E. of regression	0.014840	Sum squared resid	0.004405
Long-run variance	7.31E-05		

Source: Author's calculation

The results derived from the DOLS estimates strongly correspond with those obtained from the ARDL estimates, providing clear evidence of consistency and reinforcing the reliability and robustness of the study's findings.

5. Conclusions

Summary

This study investigated the impact of population age distribution on Sri Lanka's ecological footprint (EF) from 1980 to 2022, integrating demographic variables into the Environmental Kuznets Curve (EKC) framework. Using the Autoregressive Distributed Lag (ARDL) bounds testing approach, the analysis revealed critical insights into how age-specific cohorts—young dependents (0–14 years), the working-age population (15–64 years), and elderly dependents (65+ years)—interact with economic growth to influence environmental outcomes.

Key findings include:

Economic Growth and EKC Dynamics: A U-shaped relationship between GDP and ecological footprint was identified, contradicting the traditional inverted U-curve hypothesis (Grossman & Krueger, 1995). This suggests that environmental degradation in Sri Lanka initially decreases with economic growth but worsens beyond a certain income threshold, highlighting the need for proactive policy interventions even as the economy matures (Shahbaz et al., 2016).

Demographic Influences:

The working-age population exerted the most substantial pressure on the EF, with its long-run impact five times greater than that of the young population. This aligns with global patterns where economically active demographics drive resource-intensive consumption (Liddle, 2014).

The young population also significantly increased the EF, likely due to indirect household consumption demands (Jiang & Hardee, 2011).

The elderly population showed a statistically insignificant negative relationship with the EF, contrasting with studies emphasizing aging populations' reduced environmental impact in developed nations (Zagheni, 2011).

Short-Term Dynamics: Short-run adjustments revealed rapid convergence to equilibrium (ECT = -3.33), indicating swift corrective mechanisms after economic or demographic shocks. Lagged GDP terms exacerbated EF in the short term, while GDP^2 terms mitigated it, reinforcing the EKC's applicability to transitional phases (Alam et al., 2016).

Conclusions

The study underscores the complex interplay between demographic transitions, economic growth, and environmental sustainability in Sri Lanka. Three major conclusions emerge:

Economic Growth's Dual Role: While GDP growth initially reduces environmental strain through technological advancements or efficiency gains, its long-term trajectory exacerbates ecological degradation. This challenges the conventional EKC hypothesis and implies that Sri Lanka's current development path risks accelerating environmental harm unless structural changes are implemented (Stern, 2004).

Working-Age Population as a Key Driver: The working-age cohort's disproportionate impact on the EF highlights the environmental cost of economic productivity. This demographic's high energy consumption, urbanization trends, and resource-intensive lifestyles mirror findings from OECD countries (Liddle & Lung, 2010). Sri Lanka's ongoing demographic transition—marked by a growing working-age share—could thus intensify ecological pressures unless consumption patterns are redirected toward sustainability.

Limited Role of Aging Populations: The elderly cohort's negligible influence on the EF contrasts with studies from aging societies like Japan or Europe, where older populations reduce emissions (O'Neill et al., 2012). This discrepancy may stem from Sri Lanka's lower elderly consumption levels, limited healthcare infrastructure, or cultural factors favoring multi-generational households that dilute per capita resource use (Meneses & Palacio, 2020).

Methodological Robustness: The ARDL and DOLS models confirmed the reliability of long-run estimates, while stability tests (CUSUM/CUSUMSQ) validated the model's structural integrity. Granger causality tests further emphasized bidirectional relationships between EF and demographic variables, reinforcing the need for holistic policy frameworks.

Recommendations

To harmonize Sri Lanka's economic ambitions with ecological sustainability, the following recommendations are outlined:

Targeted Interventions for the Working-Age Population

Green Employment Initiatives: Strengthen and promote industries such as renewable energy, sustainable agriculture, and eco-tourism, ensuring economic growth aligns with environmental protection goals (Charfeddine & Mrabet, 2017). These initiatives can create job opportunities while reducing ecological footprints.

Sustainable Urban Planning: Prioritize investments in public transportation networks, energy-efficient housing solutions, and advanced waste management systems. These measures aim to mitigate the adverse environmental effects of urban sprawl and enhance the quality of urban living (Shahbaz et al., 2016).

Awareness Campaigns: Develop and implement educational programs on resource conservation, recycling practices, and adopting low-carbon lifestyles. Such campaigns can empower economically active populations to make environmentally responsible choices (Cole & Neumayer, 2004).

Leverage Demographic Dividends

Youth Education: Incorporate sustainability principles into school curricula to nurture environmentally conscious behaviors from an early age. This strategy can instill lifelong values of ecological responsibility (Jiang & Hardee, 2011).

Elderly Inclusion: Foster the involvement of older populations in ecological activities such as community gardening, biodiversity conservation, or preserving traditional ecological knowledge. Their participation can contribute positively to environmental efforts while promoting intergenerational collaboration.

Reinforce the EKC (Environmental Kuznets Curve) Transition

Green Taxation: Introduce carbon taxes or levies targeting industries with high pollution levels. These financial incentives can drive businesses toward cleaner and more sustainable production methods (Buzkurt & Akan, 2014).

Subsidize Renewable Energy: Provide financial support and incentives for renewable energy projects, including solar, wind, and hydroelectric power. Transitioning from fossil fuels to renewable energy sources can significantly reduce carbon emissions (Farhani & Rejeb, 2012).

To mitigate the U-shaped EKC effect, Sri Lanka can adopt policies proven successful in comparable contexts:

Renewable Energy Subsidies: Bangladesh's Solar Home Systems program, which subsidized solar panels for 20 million households, reduced carbon emissions by 4.5 million tons annually (Alam et al., 2021). Sri Lanka could replicate this model to decentralize energy access.

Green Urbanization: Vietnam's Eco-City Initiative integrated green spaces and public transit in Ho Chi Minh City, lowering per capita EF by 12% (World Bank, 2022).

Circular Economy Incentives: Rwanda's ban on single-use plastics (2019) cut plastic waste by 80%, demonstrating the efficacy of strict regulatory measures (UNEP, 2021).

Policy Integration

Demographic-Environmental Nexus: Embed age-specific demographic considerations into national policies, such as Sri Lanka's 2030 Sustainable Development Agenda. This integration ensures that policy frameworks address different age groups' unique needs and contributions.

Data-Driven Monitoring: Establish real-time ecological footprint (EF) tracking systems for demographic changes. These systems will enable adaptive and evidence-based policymaking to respond effectively to evolving challenges (Global Footprint Network, 2025).

Future Research Directions

Regional Comparisons: Conduct comparative studies across South Asian countries to identify common challenges and best practices for addressing demographic and environmental issues (Bilsborrow & Delargy, 1991).

Longitudinal Analyses: Extend research timelines to examine the long-term effects of aging trends on Sri Lanka's environment and economy as the elderly population grows.

Disaggregated Data: Investigate variations within population cohorts, such as differences between urban and rural working-age groups, to develop more targeted and effective interventions (Caviglia-Harris et al., 2009).

Sri Lanka's journey toward sustainable development hinges on harmonizing its demographic evolution with ecological limits. The nation can mitigate ecological degradation by addressing the working-age population's environmental footprint and reorienting economic growth toward green pathways while fostering inclusive prosperity. This study fills a critical gap in developing-country literature and provides a replicable framework for analyzing demographic-environmental linkages in similar contexts.

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