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# Assessment of the role of renewable energy consumption and trade policy on environmental degradation using innovation accounting: Evidence from the US

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A B S T R A C T

Renewable energy technologies are promising, yet, very little is known about its role as a limiting factor in fossil fuel-attributable environmental degradation — especially in high-income countries. This study investigated the dynamic effect of renewable energy consumption, economic growth, biocapacity and trade policy on environmental degradation in the United States from 1985Q1 to 2014Q4. To achieve this objective, the study applied an autoregressive distributed lag (ARDL) model to obtain the long-run and short-run dynamic coefficients. Toda-Yamamoto causality test was used to examine the direction of causality while Cholesky decomposition test was for innovative accounting to validate the estimated models. The empirical results divulged that a decline in environmental degradation can be attributed to an increase in renewable energy consumption through its negative effects on ecological footprint. Economic growth and biocapacity were found to exert upward pressure on ecological footprint; however, trade policy exerts downward pressure on ecological footprint. A two-sided causal relationship was established between economic growth and ecological footprint as well as economic growth and biocapacity. In contrast, a one-way causality was confirmed running from trade policy to renewable energy consumption and from renewable energy consumption to biocapacity. The innovative accounting revealed that 14.79% and 8.41% of renewable energy consumption and trade policy caused 0.60% and 9.88% deterioration in the environment. Hence, country-specific energy policies that increase the share of renewable energy in the energy portfolio are recommended.



## 1. Introduction

In the last decades, environmentalists and environmental stakeholders are increasingly overwhelmed with the impact of environmental degradation and ecological distortions of the globe's geographical space. The continued and somewhat unwanted climatic experiences, in most cases, resulting in environmental disasters are the common indications that suggest these drastic 'revolutions' in the earth's climatic systems. With the increasing human activities, which include direct and indirect activities on the atmospheric strata and the biosphere, humans' sustainability has increasingly been endangered [1–3,5,6]. For several decades, the impact of human engagements on the environment has consistently been measured by the environmental response to economic growth, population dynamics, energy usage, and several other notable factors [7–9,11,13]. Such environmental impact has consistently been accounted for by emissions from carbon dioxide ($CO_2$). Specifically, the emissions from $CO_2$ is largely believed to constitute about 76% and 94% of the total United States (US)' anthropogenic greenhouse gas (GHG) and the anthropogenic $CO_2$ emissions [14].

In recent times, following the ecological accounting vis-a-vis the ecological footprint that was put forward by Wackernagel and Rees [15]; environmental wellbeing and distortions have been examined by using the ecological footprint. This is because the ecological footprint measures the capacity of the earth resources that is available for use or already been expanded by human engagements [16]. On one hand, the Global Footprint Network (GFN) presents biocapacity as the earth surface's capacity to produce the human

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basic ecological needs or resources from the fishing grounds, cropland, grazing land, built-up land, and forest area excluding carbon emissions' absorption from land surface. In response, the perpetual demand on the ecological products (assets) is increasingly depleted especially in the developed countries, accounting for the low or ecological deficit in these countries. This ecological deficit (when the population's demand on nature is more than the productive capacity of nature) posits a severe environmental quality and its sustainability.

The US is currently known to be ecologically deficit [16], even though the ecosystem is expected to naturally regenerate and adjust itself to environmental-related changes. However, the ecological accounting for the US suggests otherwise and hence triggers serious environmental sustainability concern. In the previous studies, especially for the US, economic expansion, vast energy consumption especially non-renewable fuels energy consumption, and population growth are among the factors adjudged to be responsible for environmental pollution [17–19]. More so, the recent trade policy of the current US government has created more debate on the country's economic and environmental sustainability. With the changes in the US′ trade protocol like the North American Free Trade Agreement (NAFTA) and the introduction of trade embargoes on trade partners, the dynamics of environmental quality would be affected. For instance, in limiting its trade activities with China, it suggests that more of the previously imported goods would be produced domestically, thus increasing economic activities and hence pollution. In addition to the dynamics of the country's trade policy, the surge in the consumption of renewable energy in the US (18% of power mix) is another factor that continues to compound the demand on its ecological footprint. Significantly, these factors are connected with the degradation of the country's biocapacity. Given the above motivation, this study investigates the dynamic impact of renewable energy consumption, economic growth, biocapacity and trade policy on the ecological footprint in the US. In conducting this investigation, a quarterly dataset from 1985Q1 to 2014Q4 is employed, thus presenting diverse novelty to extant literature.

Following the study of Wackernagel and Rees [15] on the necessity of reducing the human impact of the environment, the use of ecological footprint for sustainability assessment is topical to the environmentalist. Previous studies have thus far used ecological footprint as a proxy for environmental quality. In a recent study that investigated the role of economic growth on environmental degradation in newly industrialized countries, Destek and Sarkodie [21] used ecological footprint in lieu of the conventional $CO_2$ as a proxy for environmental quality to evaluate the environmental Kuznets curve (EKC) hypothesis. Although other factors like the energy consumption, financial development were incorporated along with the Gross Domestic Product (GDP), the study found an inverted U-shaped relationship between GDP and ecological footprint in the selected eleven newly developed countries. Hence, affirming the validity of the EKC hypothesis. Similarly, Al-Mulali et al. [23], utilized the ecological footprint in place of environmental degradation to investigate the EKC hypothesis for 93 countries. In this case, the validity of the EKC was found to increase with the GDP growth, thus indicating low and lower-middle-income countries at severe risk of environmental deterioration. The implication suggested that low-income countries are not likely equipped with technologies that improve energy efficiency, energy-saving and renewable energy, thus, experiencing slower economic growth (lower GDP growth). While the nexus of the ecological footprint and sustainability in the tourism industry was investigated in Seychelles [24], a similar study was conducted for 144 countries by Ozturk et al. [25]. The results found a negative connection between ecological footprint and the GDP growth from tourism, energy consumption, openness to trade and urbanization. The EKC hypothesis was reaffirmed in upper-middle- and high-income countries. Baabou et al. [26] found food consumption, transportation and consumption of manufactured goods as the drivers of EKC hypothesis in 19 Coastal Mediterranean Cities (CMC). The study noted empirically that the differences in the ecological footprint of the 19 cities are associated with socioeconomic factors that include the disposable income, infrastructure, and cultural habits [26].

More so, identifying the importance of sustainable development of the regional ecology and economic system of China, Yue [28] utilized the spatial analysis to examine the supply and demand of biocapacity across the country's North-western region. The study revealed the following impacts of spatial heterogeneity on the biocapacity supply of the Northwestern region. First, it affirmed a decline in the biocapacity supply from the eastern region to the middle, and then arise from the middle to the west is however observed. Second, ecological deficits in the provincial and county levels are observed to be larger notwithstanding small regional ecological deficit resulting from the gap between the biocapacity demand and supply in the region. Third, it suggested that biocapacity supply is also determined by population density and the intensity of human exploitations. Additionally, Liu et al. [29], and Kissinger and Rees [30] revealed the nexus of ecological capacity and different human activities in China and the US respectively. While Liu et al. [29] hinted on the imbalance of the demand-supply ecological carrying capacity across China, the impact of the US's imports of renewable resources on the ecosystem area was examined [30].

This paper contributes to the literature by assessing the role of renewable energy consumption and trade policy on ecological footprint — a measure of environmental degradation in the US. Even though renewable energy technologies are promising in the US, little is known about its role as a limiting factor in fossil fuel-attributable environmental degradation — amidst the recent trade policy dynamics. Therefore, it is important to understand the pivotal role of renewable energy consumption and trade policy on environmental degradation. The findings of this paper will reveal which among the combinations of the variable of renewable energy consumption, economic growth, biocapacity, and trade policy exert upward or downward pressure on environmental degradation in the US. By making use of the flexible ARDL estimation procedure and Toda and Yamamoto [31] causality test, the assumption that all the variables must be integrated of the same order is relaxed while the overall results are validated by the innovation accounting tests. Furthermore, to circumvent the nonstandard distributions in the cointegration test, the Kripfganz and Scheneider [32] critical values and approximate p-values are applied to check the robustness of the bound testing cointegration test.

The remainder of the study is as follows: *Section* 2 covers the material and empirical methodologies; the empirical findings are reported in *Section* 3; *Section* 4 presents a discussion of the results while *Section* 5 provides the concluding remarks and policy implications of this study.

## 2. Materials and data

### 2.1. Data

We use quarterly data from 1985Q1 to 2014Q4 to investigate the dynamic effects of renewable energy and trade policy on the US environmental quality measured by the ecological footprint.[1] To

[1] The size distortions of unit roots and cointegration tests are resolved by using quarter frequency data. In other words, quarter frequency data increases the number of observations thereby ensuring robustness of the results.

achieve this objective, our dataset consist of the variables such as renewable energy, trade policy, gross domestic product (GDP) per capita in constant 2010 USD, ecological footprint per capita, and biocapacity (gha/person). Environmental degradation is proxied by ecological footprint (gha/person) while biocapacity is a proxy for environmental sustainability. Renewable energy is the share of renewables in the total primary energy supply (in billion kilowatt-hours). GDP is a proxy for economic growth while trade policy is an index of regulations and agreements that control imports and exports from and/or to foreign countries. Specifically, trade policy variable explored in this study is a proxy for uncertainty in the US trade policy as also used by Alola [5]. With the aim of stabilizing the variance and ensure clearer economic interpretations in terms of elasticities, we take the natural logarithms of all the variables.

### 2.2. Model estimations and procedures

In this study, we aim at investigating the effects of renewable energy and trade policy on environmental quality and environmental sustainability. Therefore, incorporating the control variable, which includes economic growth, we specify the equations as follows:

$$\ln\mathrm{HFP}_t = \Omega_0 + \wp_1 \ln\mathrm{RE} + \wp_2 \ln\mathrm{GDP} + \wp_3 \ln\mathrm{BIOCAP} + \wp_4 \ln\mathrm{TP} + \varepsilon_t \tag{1}$$

where $\Omega_0$ is the constant and $\varepsilon_t$ is the independently and identically distributed stochastic term. lnHFP is the log of ecological footprint, lnRE is the log of renewable energy consumption, lnTP is the log of trade policy measure, lnGDP is the log of the economic growth (*GDP* per capita) and lnBIOCAP is the log of biocapacity. Equation (1) is concerned with measuring the effects of the fundamental variables on environmental degradation. To this extent, we applied the Autoregressive Distributed Lag (ARDL) model proposed by Pesaran et al., [33]. The transformation of equation (1) based on the unrestricted error correction model (UECM) is stated as follows:

$$\begin{aligned}\Delta \ln\mathrm{HFT}_t &= \Omega_0 + \phi_i \ln\mathrm{HFP}_{t-1} + \wp_1 \ln\mathrm{RE}_{t-1} + \wp_2 \ln\mathrm{GDP}_{t-1} + \wp_3 \ln\mathrm{BIOCAP}_{t-1} + \wp_4 \ln\mathrm{TP}_{t-1}\\ &+ \sum_{i=1}^{p^i} \beta_i \Delta \ln\mathrm{HFP}_{t-i} + \sum_{i=0}^{q^1} \theta_{1,i} \Delta \ln\mathrm{RE}_{t-i} + \sum_{i=0}^{q^2} \theta_{2,i} \Delta \ln\mathrm{GDP}_{t-i} + \sum_{i=0}^{q3} \theta_{3,i} \Delta \ln\mathrm{BIOCAP}_{t-i}\\ &+ \sum_{i=0}^{q^4} \theta_{4,i} \Delta \ln\mathrm{TP}_{t-i} + \varepsilon_t\end{aligned} \tag{2}$$

where *ln* is the natural logarithm for all the variables captured in the model, Δ is the first-difference operator defined as $\Delta x_t = x_t - x_{t-1}$. The first part of equation (2) is aptly used to obtain the long-run coefficients of the HFP equation given as $\phi_i$, $\wp_1$, $\wp_2, \wp_3$, and $\wp_4$ while the second part is used to obtain the short-run coefficients given as $\beta_i, \theta_{1,i}$, $\theta_{2,i}$, $\theta_{3,i}$ and $\theta_{4,i}$.

It could be noted that the ecological footprints, a measure of environmental degradation may not change to the path of long-run equilibrium if there is a shock to any of the independent variables. The speed at which ecological footprints adjusts from short-run to long-run equilibrium level is captured by the estimated error correction model (ECM) equation as follows:

$$\begin{aligned}\Delta \ln\mathrm{HFP}_t &= \alpha_0 + \sum_{i=1}^{p^i} \beta_i \Delta \ln\mathrm{HFP}_{t-1} + \sum_{i=0}^{q^1} \theta_{1,i} \Delta \ln\mathrm{RE}_{t-i}\\ &+ \sum_{i=0}^{q^2} \theta_{2,i} \Delta \ln\mathrm{GDP}_{t-i} + \sum_{i=0}^{q^3} \theta_{3,i} \Delta \ln\mathrm{BIOCAP}_{t-i}\\ &+ \sum_{i=0}^{q^4} \theta_{4,i} \Delta \ln\mathrm{TP}_{t-i} + \lambda ect_{t-1} + \varepsilon_t\end{aligned} \tag{3}$$

where all the variables are the same as defined in equation (2), $ect_{t-1}$ is the lag of the residuals. Using the methodology of ARDL bounds testing, we can estimate our models whether the variables are I(0), I(1) or integrated fractionally. In addition, this estimator performs better compared to other estimators in a small sample size. Therefore, we carry out a cointegration test using Pesaran et al. [33] approach to bounds testing as well as the critical values of Kripfganz and Schneider [32]; which are perhaps approximate p-values test results. The null hypothesis of no level relationship expressed as: $\beta_i = \wp_1 = \wp_2 = \wp_3 = \wp_4 = 0$ against the alternative hypothesis of level relationship expressed as: $\beta_1 \neq \wp_1 \neq \wp_2 \neq \wp_3 \neq \wp_4 = 0$. Before estimation of the model, we test the stationarity properties of the series through the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). The null hypothesis for these tests states that $H_0 : \phi = 0$, tested against the alternative of $H_0 : \phi < 0$.

### 2.3. Causality test

For the understanding of the causal interaction between variables, which is essential for crafting energy and environmental policies for sustainable development, we, therefore, applied Toda-Yamamoto conditional Granger causality test. This test aptly examines the direction of causality of between variables using a VAR($p$) model with a modified Wald test statistic. The test has several advantages over the Pairwise Granger causality approach, which assumes that all the variables are indeed stationary at I(0). Should in case the variables are stationary at I(0) and I(1), Toda-Yamamoto can be conveniently applied and produce robust results. According to Toda and Yamamoto [31]; this test is implemented on the framework of the Vector Autoregressive Distributed Lag model as specified below:

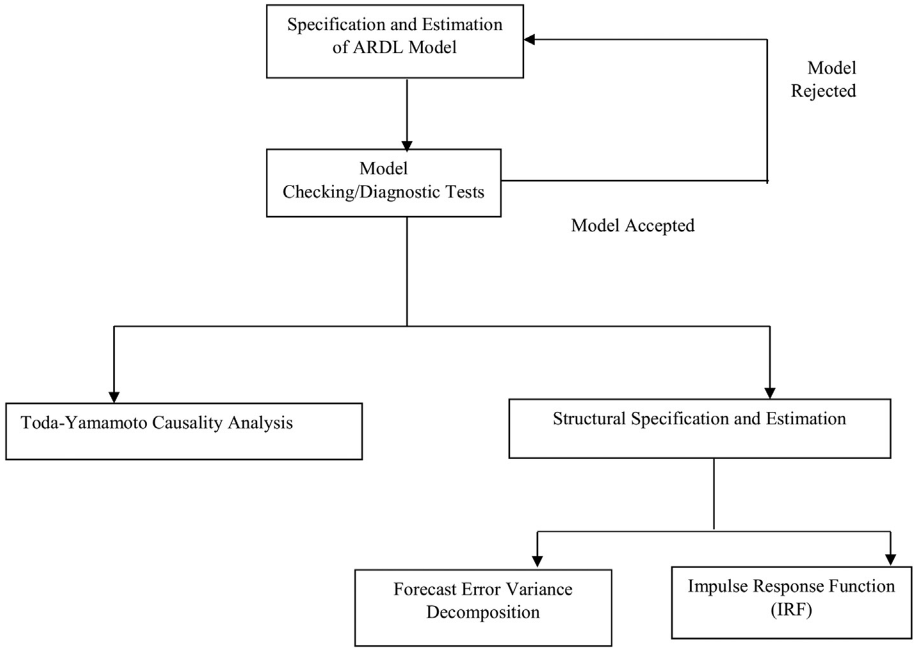


**Fig. 1.** Flow chart of the model.

$$\begin{bmatrix} \ln HFP_t \\ \ln RE_t \\ \ln GDP_t \\ \ln BIOCAP_t \\ \ln TP_t \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \\ \rho \\ \delta \\ \phi \end{bmatrix} + \sum_{i-1}^{p} \begin{bmatrix} \lambda_{11i}\lambda_{12i}\lambda_{13i}\lambda_{14i}\lambda_{15i} \\ \lambda_{21i}\lambda_{22i}\lambda_{23i}\lambda_{24i}\lambda_{25i} \\ \lambda_{31i}\lambda_{32i}\lambda_{33i}\lambda_{34i}\lambda_{35i} \\ \lambda_{41i}\lambda_{42i}\lambda_{43i}\lambda_{44i}\lambda_{45i} \\ \lambda_{51i}\lambda_{52i}\lambda_{53i}\lambda_{54i}\lambda_{55i} \end{bmatrix} \times \begin{bmatrix} \ln HFP_{t-i} \\ \ln RE_{t-i} \\ \ln GDP_{t-i} \\ \ln BIOCAP_{t-i} \\ \ln TP_{t-i} \end{bmatrix} + \sum_{j=p+1}^{d_{\max}} \begin{bmatrix} \lambda_{11j}\lambda_{12j}\lambda_{13j}\lambda_{14j}\lambda_{15j} \\ \lambda_{21j}\lambda_{22j}\lambda_{23j}\lambda_{24j}\lambda_{25j} \\ \lambda_{31j}\lambda_{32j}\lambda_{33j}\lambda_{34j}\lambda_{35j} \\ \lambda_{41j}\lambda_{42j}\lambda_{43j}\lambda_{44j}\lambda_{45j} \\ \lambda_{51j}\lambda_{52j}\lambda_{53j}\lambda_{54j}\lambda_{55j} \end{bmatrix} \times \begin{bmatrix} \ln HFP_{t-j} \\ \ln RE_{t-j} \\ \ln GDP_{t-j} \\ \ln BIOCAP_{t-j} \\ \ln TP_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \tag{4}$$

where $p$ is the VAR order with $d$ extra lags ($d_{max}$). The asymptotic $\chi^2$ distribution of the Wald statistic is estimated with a $VAR\,(p + d_{\max})$, where $d_{\max}$ denotes the maximum order of integration in the VAR system. The null hypothesis for the test $H_0 : \lambda_{15i} \neq 0 \forall_i$ which implies for example that Granger causality runs from $TP_t$ to $HFP_t$.

Fig. 1 depicts the flow chart of the ARDL model employed. This flow chart was adopted and modified from Lutkepohl [34]. It begins with specifying and estimating the model and then check its adequacy. If the model is not adequate and stable, the process is repeated until we find a more suitable model. In addition, causality analysis and structural analysis, which comprises of impulse response and forecast error variance decomposition are performed.

**Table 2**
Pairwise correlations.

| Variable | LNHFT | LNRE | LNGDP | LNBIOCAP | LNTP |
|---|---|---|---|---|---|
| LNHFP | 1.000000<br>– | | | | |
| LNRE | −0.888832<br>(-21.070) | 1.000000<br>– | | | |
| LNGDP | −0.567155<br>(-7.4803) | 0.635684<br>(8.9453) | 1.000000<br>– | | |
| LNBIOCAP | 0.547055<br>(7.0981) | −0.611425<br>(-8.3935) | −0.897010<br>(-22.045) | 1.000000<br>– | |
| LNTP | −0.603883<br>(-8.2299) | 0.628068<br>(8.7676) | 0.581310<br>(7.7606) | −0.606881<br>(-8.2945) | 1.000000<br>– |

Notes: The values in the parenthesis are the t-statistic.

## 3. Empirical results

### 3.1. Descriptive statistics and pair-wise correction

Table 1 discloses the summary of the variables, their

**Table 1**
Summary of descriptive statistics.

| Variable | Notation | Source | Number of Obs. | Mean | Min | Max | Std. Dev. |
|---|---|---|---|---|---|---|---|
| Ecological Footprint (gha/person) | LNHFP | Global Ecological Footprint (2018) | 120 | 2.26 | 2.105 | 2.348 | 0.069 |
| Renewable Energy Consumption | LNRE | OECD Database (2018) | 120 | 11.59 | 11.38 | 11.92 | 0.127 |
| Biocapacity (gha/person) | LNBIOCAP | Global Ecological Footprint (2018) | 120 | 1.354 | 1.247 | 1.513 | 0.062 |
| GDP per capita (constant 2010 US$) | LNGDP | World Development Indicator (2018) | 120 | 9.151 | 9.783 | 8.352 | 0.424 |
| Trade Policy Index | LNTP | Economic Policy Uncertainty (EPU) Database (2018) | 120 | 4.754 | 3.228 | 6.998 | 0.725 |

Notes: The Ecological footprint, Renewable energy consumption, GDP, and Biocapacity were converted from annual to quarter frequency through the method of quadratic interpolation using the E-Views Software.
Source: Authors' computation

measurements, and sources as well as the statistical characteristics. The results show that the highest mean score of variables is own by renewable energy consumption with about 11.59 while biocapacity has the lowest. The results further display that all the variables tend to be less volatile with trade policy exhibiting the most volatile variable. Furthermore, Table 2 discloses the results of the pair-wise correlations. We find a negative correlation between ecological footprint and fundamental variables such as consumption of renewable energy, GDP, and trade policy while a positive correlation between ecological footprint and biocapacity. We equally find a positive correlation between consumption of renewable energy and GDP as well as renewable energy consumption and trade policy. The correlation between GDP and biocapacity is negative while GDP and trade policy is positive. Finally, the correlation between biocapacity and trade policy is negative. The correlations between the variables are all statistically significant at 1% significance level.

### 3.2. Time-series plots of variables used

The time plots of the log of ecological footprints, renewable energy consumption, economic growth measured by GDP, biocapacity, and trade policy are presented in Fig. 2. Based on this figure, we find that there is no clear-cut evidence of a trend in ecological footprint before 2005 and in renewable energy before 2000. In the case of GDP, it trends upward over the period with no evidence of structural breaks while biocapacity trends downward with evidence of fluctuations. The variable of trade policy exhibits a high level of fluctuations with no clear-cut evidence of a trend. We also observe that the variables are all characterized by fluctuations except in the case of GDP. The fluctuations observed are more conspicuous in the trade policy variable. This result, therefore, supports the results of the descriptive statistics of the variables revealed in Table 1.

### 3.3. Results of unit root tests

Prior to the model estimation, the study tested for the stationarity properties of the series, used as a benchmark to select the appropriate estimation method. The results from the ADF test by Dickey and Fuller (1979) and the PP test by Phillips and Perron (1988) (See Table 3), indicate that ecological footprint, renewable energy consumption, and GDP are integrated of order one, I(1) while trade policy and biocapacity which are I(0) process. This means that the integrating properties of the variables are mixed order process.

### 3.4. Results of cointegration tests

Having established the integrating properties of the series, the next stage was to establish a cointegration relationship between the investigated variables. The test was performed using the ARDL bounds testing framework. We considered the ARDL bounds testing approach to cointegration as the most appropriate method due to the mixed order of integration revealed by the unit root tests See Ref. [33]. The bounds test cointegration applied in this study was based on the unrestricted constant and no Trend. The maximum lag order was 2 and the optimal lag order was selected by the Akaike Information Criterion (AIC). The results as displayed in Table 4 show that the null hypothesis of no long-run relationship based on F-statistic and t-statistic is rejected at the significance test of 1%. In other words, a well-established long-run relationship among the variables has been observed. Furthermore, for the purpose of robustness, we applied the Pesaran et al. [33] bounds testing cointegration using Kripfganz and Scheneider [32] critical values and approximate p-values. The results as shown in Table 5 indicate that the null hypothesis of no cointegration is, however, rejected based on the significance of probability values at the lower bound and upper bound. Hence, we proceed to estimate our models specified in Equations (2) and (3).

### 3.5. Results of ARDL for long-run coefficients

Table 6 shows the estimates of the long-run and short-run environmental degradation functions. According to the long-run results, a 1% increase in renewable energy consumption and trade policy causes ecological footprint to decline by 0.35% and 0.05%, while a 1% increase in GDP and biocapacity increases ecological footprint by 0.13% and 0.64%. Similarly, in the short run, the coefficient of the renewable energy consumption is negatively related to ecological footprints but there is no evidence of statistical significance. However, a 1% increase in GDP, biocapacity and trade policy increases ecological footprint by 0.55%, 0.51% and 0.004% respectively. More so, the coefficient of the error correction term is ~ -0.12, which is negatively significant at 1% level. This suggests that ecological footprint converges to the long-run equilibrium level by about 12% speed of adjustment in every quarter via the changes in renewable energy consumption, GDP, biocapacity and trade policy.

To check the residual and stability diagnostics of the model, the serial correlation, heteroscedasticity, functional misspecification, and normal distribution tests were applied to the residuals of the estimated models. The results of these tests reveal no evidence of serial correction and heteroscedasticity. While the functional form of the model is correctly identified and specified but no evidence is found to support residual normal distribution. The stability of the model was checked using the cumulative sum (CUSUM) and CUSUM squared tests. The results obviously indicate the stability of the model at a 5% significance level.

### 3.6. Results of causality test

Table 7 presents the results of the Toda-Yamamoto causality test. The results show a two-sided causal relationship between GDP and ecological footprints as well as GDP and biocapacity. The results further show a one-way causal relationship running from trade policy to ecological footprint and from trade policy to renewable energy consumption. In addition, renewable energy consumption Granger-cause biocapacity while there is no evidence that any of the variables captured Granger-cause trade policy. These results are supported by Apergis and Payne [35,36]; Chang et al. [35,36]; Lin and Moubarak [35,36]; Al-Mulali et al. [35,36]; Kahia et al. [35,36]; Ben Jebli and Ben Youssef [35,36]; Destek and Sarkodie [35,36]. Furthermore, the causal relationship running from GDP to ecological footprints supports the hypothesis of growth-led pollutant emissions established in the existing literature See Refs. [6,8,37–39].

### 3.7. Results of innovative accounting tests

In furtherance to the ARDL bounds testing technique and Toda-Yamamoto causality test, we used an innovative accounting test to investigate the dynamic contribution of each variable to ecological footprint. The tests are a combination of the error forecast variance decomposition and impulse response functions. Table 8 reveals the analysis of the error forecast variance decomposition using 10 periods ahead of the sample period. Based on the results, the error forecast variance decomposition of the ecological footprint (environmental degradation) attributed to its innovative shock is the largest contributor with a rate of 65.10%. This is followed by the contribution of biocapacity with about 10.40% while trade policy and economic growth contribute about 9.60% and 8.70% to the ecological footprint in the US. Renewable energy consumption is the lowest contributor to shocks in ecological footprint, at a rate of 6.30%.

Our results further show that the contribution of renewable energy to its own shocks s as high as 81.09%, followed by 16.85% shock in ecological footprint, 0.60%, 1.00% and 0.46% contribution of GDP, biocapacity and trade policy to the error forecast of renewable energy consumption. The results depict further that the contribution of GDP to its own shocks s 61.86%, which s distantly followed by biocapacity (14.79%), ecological footprints (13.23%), trade policy (8.41%) and renewable energy consumption (1.71%). In the case of biocapacity, the results show the ecological footprint as its main contributor. Ecological footprint contributes about 49.50% to the error forecast decomposition of biocapacity. This is followed by its own shocks with ~43.48% and GDP with ~5.68%. The contributions of renewable energy consumption and trade policy are just 0.92% and 0.41% respectively. The error forecast variance decomposition of trade policy due to its innovative shocks is ~84.10%, followed by ecological footprint with ~9.88%, and biocapacity with ~2.92%, while renewable energy and GDP contribute 1.62% and 1.48% to trade policy.

The major findings observed following these results suggest that the variables in the model estimation are bi-directionally related. More so, an increase in renewable energy consumption improve economic growth and slow the deterioration of environmental quality while an increase in trade policy improve growth and facilitate the deterioration of environmental quality. As shown in Table 8, a 14.79% increase in renewable energy consumption corresponds to ~0.60% rise in environmental degradation while 8.41% increase in trade policy leads to ~9.88% increase in environmental deterioration. These results corroborate our earlier results of the estimated model — which reveal the importance of renewable energy consumption in the pursuit of economic development based on its role in low environmental pollution levels compared to fossil energy sources.

The second part of the innovative accounting approach presents the impulse response analysis. As depicted in Fig. 3, the response of ecological footprint to a shock in renewable energy consumption, biocapacity and trade policy are all negative. Renewable energy consumption is statistically significant while the significance of trade policy begins from the fifth horizon. Similarly, for biocapacity, statistical significance is only found between the fifth and seventh horizons. Regarding the response of renewable energy to external shocks, we find interesting results. For example, the response of renewable energy consumption to own shock is positive and statistically significant. Renewable energy consumption first responds positively and insignificantly to the shocks in GDP and trade policy. However, for GDP, the response turns negative after the seventh horizon. In the case of trade policy, the response becomes unnoticeable and consequently crosses to the negative region after the seventh horizon. The response of renewable energy consumption to trade policy is initially negative up to the fifth horizon and turns positive afterwards even though the response is insignificant. The empirical results further demonstrate that the response of GDP to a shock in ecological footprint and renewable energy consumption is positive. This response is significant up to the seventh horizon in the case of a shock in ecological footprint while insignificant in the case of renewable energy consumption. The response of GDP to own shocks is positive and statistically significant while the response of GDP to biocapacity and trade policy is negative and

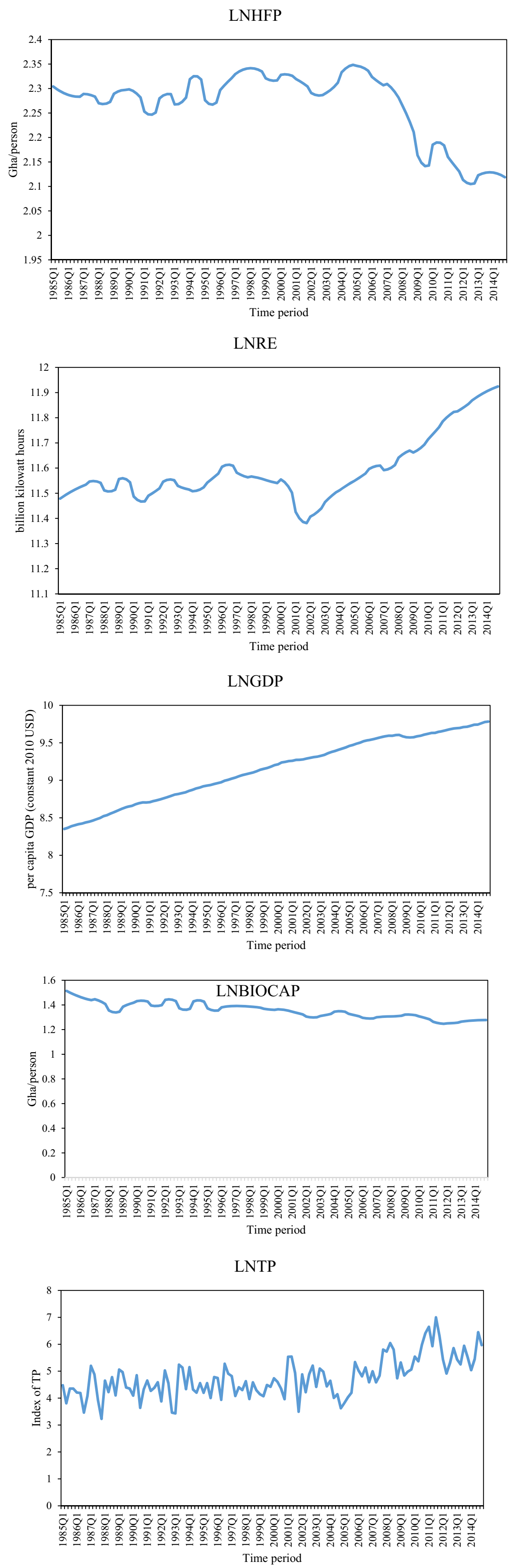


**Fig. 2.** Time plots of the log of ecological footprints, renewable energy consumption, GDP, biocapacity and trade policy.

**Table 3**
ADF and PP unit root tests.

| Variables | Augmented Dickey-Fuller Test | | Phillips-Perron Test | |
|---|---|---|---|---|
| | Intercept | Intercept & Trend | Intercept | Intercept & Trend |
| | −0.4245 (0.9000) | −1.1732 (0.9105) | −0.4366 (0.8981) | −1.2376 (0.8976) |
| | 0.3129 (0.9780) | −0.9387 (0.9471) | 0.7065 (0.9919) | −0.4340 (0.9852) |
| | 0.0276 (0.9584) | −4.5653*** (0.0019) | −2.3101 (0.1705) | −3.2833* (0.0741) |
| | −1.9796 (0.2955) | −1.1034 (0.9235) | −2.8608* (0.0531) | −0.9142 (0.9502) |
| | −3.7620*** (0.0043) | −7.2961*** (0.0000) | −5.3807*** (0.0000) | −7.4707*** (0.0000) |
| | −5.9321*** (0.0000) | −5.4234*** (0.0000) | −5.6213*** (0.0000) | −5.7974*** (0.0000) |
| | −4.7811*** (0.0024) | −4.2989*** (0.0082) | −5.5071*** (0.0000) | −5.4802*** (0.0000) |
| | −3.6550*** (0.0061) | −3.6337** (0.0315) | −8.1195*** (0.0000) | −8.2302*** (0.0000) |
| | −4.2831*** (0.0008) | −7.1338*** (0.0000) | −6.8502*** (0.0000) | −7.4139*** (0.0000) |
| | −11.7785*** (0.0001) | −11.7383*** (0.0004) | −33.1562*** (0.0000) | −33.8863*** (0.0000) |

Notes: ***, ** and * denote significance level at 1%, 5%, 10% levels.

**Table 4**
Bounds testing cointegration analysis.

| Model | Statistic | K |
|---|---|---|
| $\ln HFP = f(\ln RE, \ln GDP, \ln BIOCAP, \ln TP)$ | F-Stat: 6.8486*** t-Stat: −5.4039*** | 4 |
| Critical Value Bound Tests | Lower I(0) | Upper I(1) |
| F-Statistic at 1% | 3.74 | 5.06 |
| t-Statistic at 1% | −2.548 | −3.644 |

Notes: *** implies that the null hypothesis of no cointegration is rejected at 1% level of significance and the critical value is determined where $k = 4$ independent variables with unrestricted intercept and no trend. The maximum lag order is 2 and the optimal lag order is selected by the Akaike Information Criterion (AIC).

**Table 5**
Bounds testing cointegration using Kripfganz and Scheneider [32]] critical values and approximate p-values.

| K = 4 | 10% | | 5% | | 1% | | P-value | |
|---|---|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| F-crit. | 2.458 | 3.601 | 2.904 | 4.147 | 3.889 | 5.327 | 0.000 | 0.001 |
| t-crit. | −2.530 | −3.614 | −2.844 | −3.964 | −3.457 | −4.631 | 0.000 | 0.001 |
| F-cal. | 6.752*** | | | | | | | |
| t-cal. | −5.367*** | | | | | | | |

Notes: F-crit. and t-crit. represent the critical values for F-statistic and t-statistic while F-cal. and t-call represent the values of F-calculated and t-calculated. The maximum lag order is 2 and the optimal lag order is selected by the Akaike Information Criterion (AIC).

statistically significant for biocapacity but in the case of trade policy, the response turns statistically significant only after the fourth horizon.

Our empirical results further divulge that the response of biocapacity to a shock in ecological footprint is positive and statistically significant up to the fifth horizon and gradually declines until it stabilizes in the eighth horizon. For renewable energy, the response to its internal shocks is positive and insignificant. This gradually falls to its steady-state after the fourth horizon. The result of the response of GDP to biocapacity is negative and statistically significant up to the ninth horizon, after which it becomes neutral. The response of biocapacity to own shock is positive and significant up to the fifth horizon. This perhaps declines gradually and turns negative in the ninth horizon. Finally, the response biocapacity to a shock in trade policy is positive and insignificant. This dampens gradually to its steady-state after the ninth horizon. Similarly, the response of trade policy to a shock in ecological footprint is negative and insignificant. The positive effect of renewable energy consumption is statistically insignificant and obscures in the first three horizons. The response of trade to a shock in GDP is negative and moves to its equilibrium after the second horizon. The results show that trade policy positively responds to a shock in biocapacity. This becomes negative after the second horizon and gradually moves toward a steady state after the sixth horizon, while the response of trade policy to own shocks is positive and gradually declines until it becomes neutral after the third horizon.

## 4. Discussion

The negative relationship between renewable energy consumption and ecological footprint, in the long run, indicates a decline in environmental degradation through the negative effect of renewable energy consumption on ecological footprint. In other words, the results of this study suggest that the incorporation of renewable energy technologies in the US' energy mix improves environmental quality. The results of the short-run indicate a statistically insignificant negative coefficient. The reason was traceable to the combustible renewables and waste in the renewable energy consumption data explored; though this variable was adjudged to emit less pollution compared to fossil fuel energy consumption. Therefore, our finding supports the recent environmental policy thrust of countries across the world as fine-tuned by the Kyoto Protocol arrangements and the Intergovernmental Panel on Climate Change (IPCC) [47]. This finding is also supported by Apergis and Payne [35,36]; Shahbaz et al. [35,36]; Ben Jebli and Ben Youssef (2016). On the contrary, our findings contradict Apergis et al. [35,36]; Ben Jebli et al. [35,36] Ben Jebli and Ben Youssef [35,36] who argued that even though renewables considered contain combustible renewables and waste, which have a low level of pollution, it has a positive relationship with environmental degradation.

The result of the positive linkage between GDP and ecological footprint indicates that GDP is a major source of environmental degradation in the US. This can be attributed to the intensive use of fossil fuel energy sources required by the firms for the production process. As economic development increases, economic activities in the area of transportation, agriculture and other activities that emit greenhouse gases (GHGs) exert more pressure on the components of ecological footprint such as fishing grounds, cropland, grazing land, built-up land, forest area, and the absorption of carbon emissions from land surface. This subsequently leads to environmental damage [19,23,37–44].

The adverse effect of trade policy on ecological footprint, in the long run, suggests that as trade policy in the US encourages trade with other countries, the pressure on biocapacity and ecological footprint reduces. The cost required to produce goods and services in countries with most trading partners such as, inter alia, China,

**Table 6**
Long-run and short-run ARDL coefficients.

| Dependent variable = LNHFP<br>ARDL (2, 2, 2, 2, 2) Regression | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Standard Error | T-statistic | P-value |
| $\ln RE_t$ | −0.3509*** | 0.0669 | −5.35 | 0.000 |
| $\ln GDP_t$ | 0.1317*** | 0.0328 | 4.01 | 0.000 |
| $\ln BIOCAP_t$ | 0.6364*** | 0.2352 | 2.71 | 0.008 |
| $\ln TP_t$ | −0.0482*** | 0.0167 | −2.89 | 0.005 |
| Constant | 0.5207*** | 0.1557 | 3.34 | 0.001 |
| $\Delta \ln RE_t$ | −0.0102 | 0.5073 | −0.20 | 0.841 |
| $\Delta \ln GDP_{t-1}$ | 0.5475*** | 0.1236 | 4.43 | 0.000 |
| $\Delta \ln BIOCAP_t$ | 0.5139*** | 0.0495 | 10.37 | 0.000 |
| $\Delta \ln TP_t$ | 0.0038*** | 0.0016 | 2.45 | 0.016 |
| $ect_{t-1}$ | −0.1159*** | 0.0216 | −5.37 | 0.000 |
| Diagnostic Test | | Statistic | | P-value |
| $\chi^2 ARCH$ | | [1]: 0.7547 | | 0.3868 |
| $\chi^2 SERIAL$ | | [1]: 1.3475 | | 0.2484 |
| $\chi^2 RESET$ | | [1]: 0.6815 | | 0.4110 |
| $\chi^2 NORMAL$ | | 589.3070 | | 0.0000 |
| $R-$ squared | | 0.7326 | | |
| $Adj.R-$ squared | | 0.6963 | | |
| Root MSE | | 0.0065 | | |

Notes: ***, ** and * denote rejection of the null hypothesis at 1%, 5% and 10% level of significance. The maximum lag order is 2 and the optimal lag order is selected by the Akaike Information Criterion (AIC). $\chi^2_{SERIAL}$, $\chi^2_{ARCH}$, $\chi^2_{RESET}$ and $\chi^2_{NORMAL}$ denote are tests for serial-correlation, heteroscedasticity, functional as well as normality test. [ ] represents the optimal lag selection for diagnostic tests; case 3: Unrestricted Constant and No Trend is used.

Canada, Mexico, Japan, Brazil, the United Kingdom (UK), and the European Union (EU-28) is lower compared to the US. The long-term implication of this result is the improvement of environmental quality through the negative effect of trade policy on ecological footprint. Therefore, our finding on the short-run positive relationship between trade policy and ecological footprint could be attributed to the present efforts of the US government to reprioritize the country's trade policy in such that the long-standing trade deficit, particularly in goods, is reverted. Interestingly, the official report from the United State Bureau of Economic Analysis and Census Bureau [45] shows a positive dimension of the government's trade policy perspective. For instance, the trade deficit trajectory of the US reportedly declined by $2.6 billion (from $55.0 billion to $52.5 billion) in September 2019 [45]. However, the drive for a more favourable balance of trade by the United State has not been, without other salient concerns, such as in the agricultural and energy sectors. For instance, the disagreement on domestic content requirements and subsidies between India and the United States as well the trade in agricultural commodity between China and the United States are largely associated with the renewable energy development in these countries [46,50]. The positive relationship between biocapacity and environmental degradation suggests the need for the US to improve on the share of renewables from the clean sources in their energy mix as emphasized by the Intergovernmental Panel on Climate Change (IPCC) and other international treaties on the environment and climate change.

## 5. Conclusions

The adverse effect of environmental degradation resulting from human activities has received much global attention within the last decade. This results from the changes in the natural levels and the distribution of chemical elements as well as their compounds posing as a threat to humanity and its natural ecosystem. In the US, the government has pursued various environmental and energy policies such as renewable energy consumption to lessen the dependence on fossil fuel energy sources, underpinning the high levels of environmental pollution which is detrimental to human health. Here, we investigated the overarching impact of renewable energy consumption, economic growth, biocapacity and trade policy on the ecological footprint in the US.

The results showed that ecological footprint converges to the long-run equilibrium level with the adjustment speed of 12% quarterly. Renewable energy consumption and trade policy were found to decline ecological footprint, hence, increasing environmental quality contrary to GDP and biocapacity. Evidence of a

**Table 7**
Toda-Yomamoto causality test for environmental degradation.

| Dependent Variable | $\ln HFP_t$ | $\ln RE_t$ | $\ln GDP_t$ | $\ln BIOCAP_t$ | $\ln TP_t$ | Overall $\chi^2$-stat (prb.) |
|---|---|---|---|---|---|---|
| $\ln HFP_t$ | – | 4.8627 (0.6767) | 12.5180* (0.0848) | 6.6459 (0.4666) | 13.5288* (0.0602) | 39.1847* (0.0780) |
| $\ln RE_t$ | 4.3847 (0.7346) | – | 9.6029 (0.2122) | 10.2794 (0.1733) | 16.1386** (0.0239) | 54.0467*** (0.0022) |
| $\ln GDP_t$ | 21.3219*** (0.0033) | 7.2203 (0.4063) | – | 13.4634* (0.0616) | 7.7057 (0.3593) | 41.4992** (0.0483) |
| $\ln BIOCAP_t$ | 3.7009 (0.8135) | 12.558* (0.0836) | 14.4243** (0.0441) | – | 2.7183 (0.9098) | 36.0371 (0.1417) |
| $\ln TP_t$ | 3.4420 (0.8413) | 3.4422 (0.8413) | 8.8377 (0.2645) | 7.71307 (0.3586) | – | 46.9183*** (0.0140) |

Notes: ***, ** and * denote rejection of the null hypothesis at 1%, 5% and 10% level of significance. The maximum lag order is 2 and the optimal lag order is selected by the Akaike Information Criterion (AIC).

**Table 8**
Innovation accounting approach.

| Variance Decomposition of LNHFP: | | | | | | |
|---|---|---|---|---|---|---|
| Period | S.E. | LNHFP | LNRE | LNGDP | LNBIOCAP | LNTP |
| 1 | 0.009796 | 100.0000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 2 | 0.016893 | 97.95296 | 0.046272 | 1.692339 | 0.111747 | 0.196678 |
| 3 | 0.022700 | 94.02464 | 0.211570 | 3.392090 | 0.913724 | 1.457975 |
| 4 | 0.027403 | 88.74846 | 0.547173 | 4.900442 | 2.480738 | 3.323188 |
| 5 | 0.031255 | 83.18550 | 1.082313 | 6.161902 | 4.449336 | 5.120944 |
| 6 | 0.034471 | 78.03041 | 1.819478 | 7.150976 | 6.392767 | 6.606365 |
| 7 | 0.037198 | 73.63164 | 2.739255 | 7.861624 | 8.018014 | 7.749467 |
| 8 | 0.039535 | 70.07540 | 3.810252 | 8.317766 | 9.209122 | 8.587459 |
| 9 | 0.041557 | 67.28708 | 4.995957 | 8.563321 | 9.982108 | 9.171531 |
| 10 | 0.043326 | 65.12271 | 6.258070 | 8.648738 | 10.41857 | 9.551917 |
| Variance Decomposition of LNRE: | | | | | | |
| Period | S.E. | LNHFP | LNRE | LNGDP | LNBIOCAP | LNTP |
| 1 | 0.012037 | 0.000000 | 99.68959 | 0.310408 | 0.000000 | 0.000000 |
| 2 | 0.021659 | 0.219946 | 99.24795 | 0.127491 | 0.001157 | 0.403460 |
| 3 | 0.029774 | 0.476426 | 98.61033 | 0.621906 | 0.039815 | 0.251524 |
| 4 | 0.036472 | 0.593657 | 97.30525 | 1.841026 | 0.085723 | 0.174341 |
| 5 | 0.042001 | 0.584893 | 95.44018 | 3.735793 | 0.089960 | 0.149171 |
| 6 | 0.046625 | 0.509030 | 93.15334 | 6.140268 | 0.073050 | 0.124313 |
| 7 | 0.050596 | 0.432271 | 90.51198 | 8.839608 | 0.105154 | 0.110982 |
| 8 | 0.054124 | 0.408058 | 87.56464 | 11.62589 | 0.256246 | 0.145173 |
| 9 | 0.057369 | 0.465008 | 84.38689 | 14.33058 | 0.559837 | 0.257683 |
| 10 | 0.060435 | 0.604734 | 81.09218 | 16.83896 | 1.003697 | 0.460433 |
| Variance Decomposition of LNGDP: | | | | | | |
| Period | S.E. | LNHFP | LNRE | LNGDP | LNBIOCAP | LNTP |
| 1 | 0.005188 | 5.631263 | 0.000000 | 94.24394 | 0.124793 | 0.000000 |
| 2 | 0.008285 | 13.75165 | 1.292345 | 84.37146 | 0.565872 | 0.018668 |
| 3 | 0.011520 | 16.46393 | 3.909010 | 77.79547 | 0.975746 | 0.855846 |
| 4 | 0.014756 | 16.72182 | 6.801406 | 72.80514 | 1.301494 | 2.370134 |
| 5 | 0.017913 | 16.06493 | 9.330895 | 69.19627 | 1.526246 | 3.881653 |
| 6 | 0.020916 | 15.23546 | 11.30444 | 66.61433 | 1.663569 | 5.182198 |
| 7 | 0.023718 | 14.50182 | 12.73749 | 64.76917 | 1.733831 | 6.257679 |
| 8 | 0.026298 | 13.93228 | 13.72443 | 63.45297 | 1.756122 | 7.134196 |
| 9 | 0.028650 | 13.51883 | 14.37479 | 62.51853 | 1.745724 | 7.842123 |
| 10 | 0.030786 | 13.23010 | 14.78641 | 61.85999 | 1.714147 | 8.409347 |
| Variance Decomposition of LNBIOCAP: | | | | | | |
| Period | S.E. | LNHFP | LNRE | LNGDP | LNBIOCAP | LNTP |
| 1 | 0.012183 | 53.47959 | 1.256648 | 0.916672 | 44.34709 | 0.000000 |
| 2 | 0.019867 | 52.68523 | 1.129229 | 2.490321 | 43.69480 | 0.000418 |
| 3 | 0.024365 | 51.57713 | 1.029717 | 3.623474 | 43.74944 | 0.020241 |
| 4 | 0.026519 | 50.64769 | 0.960791 | 4.505179 | 43.78859 | 0.097744 |
| 5 | 0.027335 | 50.05624 | 0.922409 | 5.111701 | 43.69704 | 0.212615 |
| 6 | 0.027563 | 49.77014 | 0.907756 | 5.459795 | 43.54602 | 0.316293 |
| 7 | 0.027608 | 49.65841 | 0.906430 | 5.618301 | 43.43809 | 0.378772 |
| 8 | 0.027624 | 49.60328 | 0.910333 | 5.672564 | 43.41120 | 0.402618 |
| 9 | 0.027642 | 49.55287 | 0.915895 | 5.685097 | 43.43966 | 0.406477 |
| 10 | 0.027659 | 49.50356 | 0.922604 | 5.687217 | 43.48066 | 0.405967 |
| Variance Decomposition of LNTP: | | | | | | |
| Period | S.E. | LNHFP | LNRE | LNGDP | LNBIOCAP | LNTP |
| 1 | 0.519783 | 0.720530 | 0.006664 | 1.367049 | 1.934229 | 95.97153 |
| 2 | 0.540562 | 2.474262 | 0.006250 | 1.503411 | 1.790483 | 94.22559 |
| 3 | 0.547921 | 4.471150 | 0.032302 | 1.516549 | 2.237004 | 91.74300 |
| 4 | 0.555048 | 6.327406 | 0.126109 | 1.503986 | 2.639078 | 89.40342 |
| 5 | 0.560232 | 7.678328 | 0.293407 | 1.486802 | 2.779966 | 87.76150 |
| 6 | 0.563711 | 8.539228 | 0.518310 | 1.469952 | 2.775423 | 86.69709 |
| 7 | 0.566259 | 9.069671 | 0.779782 | 1.457817 | 2.752595 | 85.94013 |
| 8 | 0.568473 | 9.414272 | 1.058431 | 1.455415 | 2.771070 | 85.30081 |
| 9 | 0.570634 | 9.666840 | 1.340335 | 1.463786 | 2.834720 | 84.69432 |
| 10 | 0.572817 | 9.881538 | 1.617903 | 1.479877 | 2.922844 | 84.09784 |

Cholesky Ordering: LNHFP LNRE LNGDP LNBIOCAP LNTP.

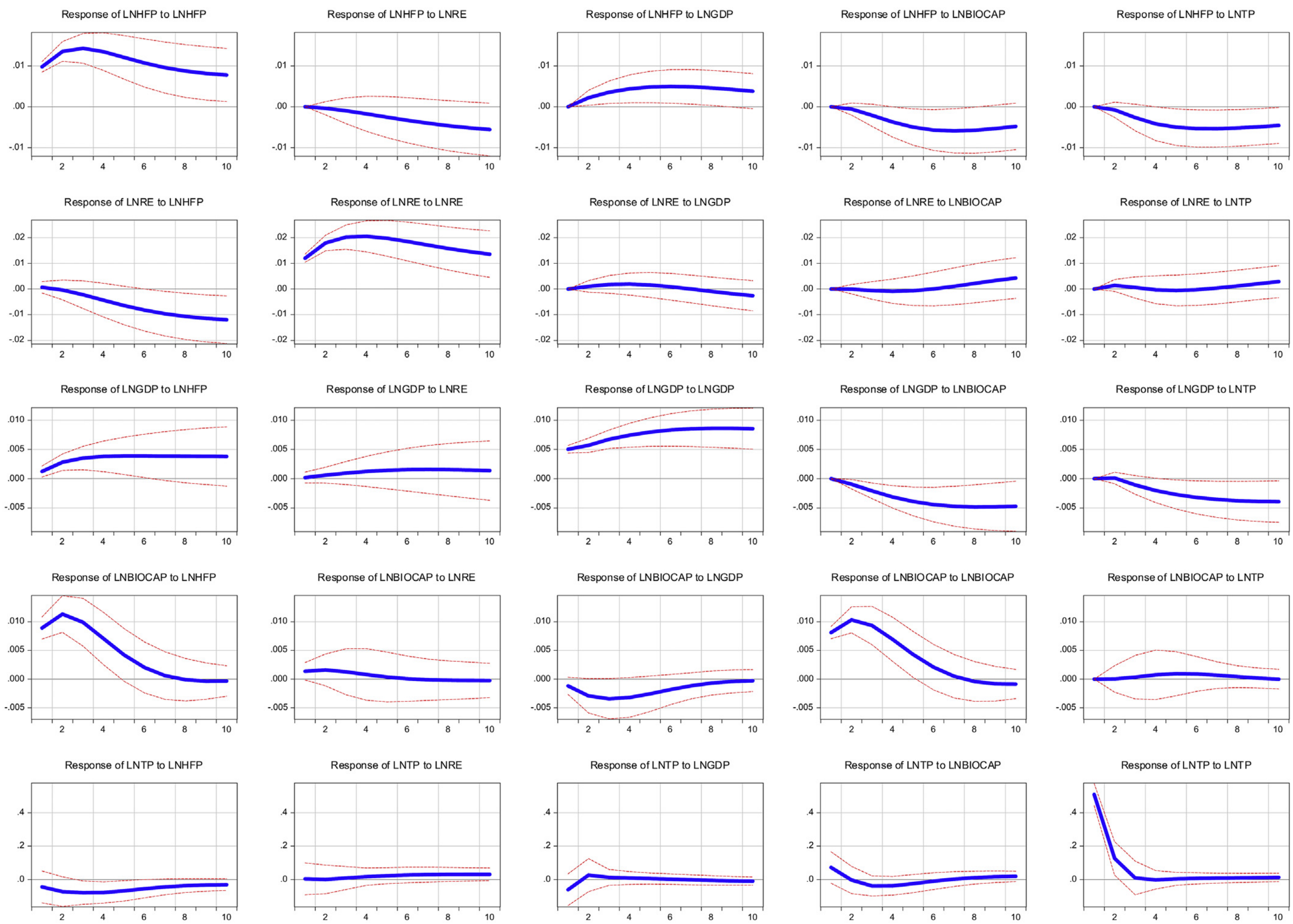


**Fig. 3.** Impulse response function (IRF).

feedback causal effect between GDP and ecological footprints, as well as, GDP and biocapacity was validated. The variance decomposition analysis showed that apart from the effect of own shocks, the shocks to biocapacity had the highest effect on ecological footprint, followed by trade policy, GDP and renewable energy consumption. However, in terms of driving economic growth with less environmental pollution, renewable energy consumption played a dominant role. The impulse response function showed that the response of ecological footprint to a shock in renewable energy consumption, biocapacity and trade policy was negative while the response of ecological footprint to a shock in GDP was found positive. The policy implications of the findings include:

- A decarbonized economy and clean and modern energy mix are essential to reduce environmental degradation and improve environmental quality. Interestingly, this environmental policy pursuit has been central to the goal of energy efficiency, energy security and environmental sustainability in the US.
- Energy policies should encourage investments, research and development in renewables like solar power, hydropower, wind, and wave, biofuels, biomass etc. These are critical to achieving a sustainable and clean environment.
- In addition, stringent environmental policies and regulations such as polluter-pays, carbon taxes, emission credits, and among others, are essential to curtailing the rising levels of anthropogenic GHG emissions.
- Trade policy could be used as an instrument to improve environmental quality in the long-run even though in the short-run, it deteriorates the environment.

## Contribution

O.U was in charge of conceptualization, data curation, analysis and writing; A.A.A played a role in data interpretation and writing; and S.A.S contributed to writing, review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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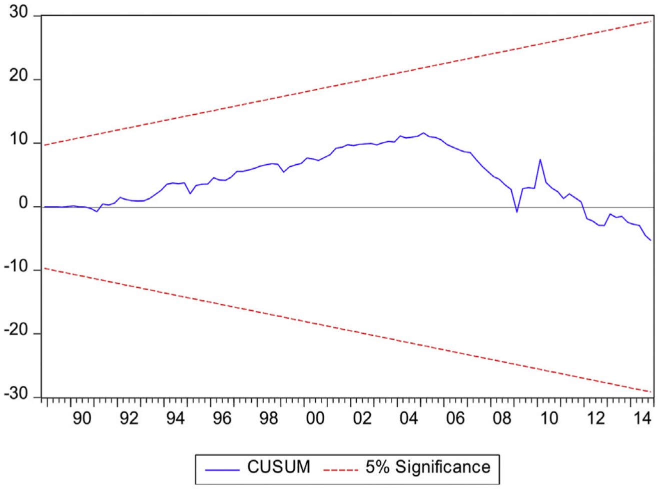
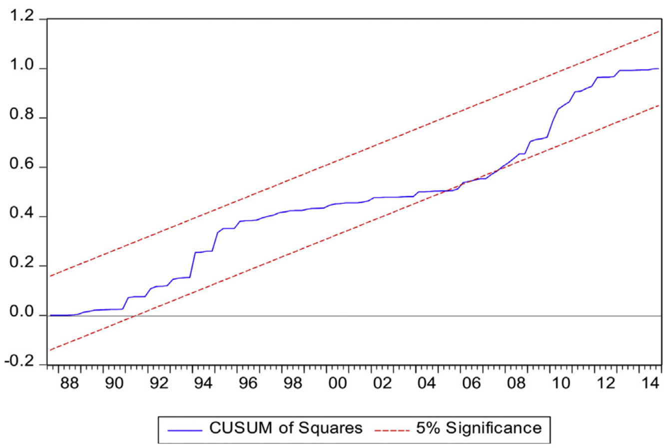
## Appendix A. Stability test showing CUSUM and CUSUM of squares

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