The role of forest and agriculture towards environmental fortification: designing a sustainable policy framework for top forested countries

Abstract

Over geological time, the climate of the planet has continuously shifted, with large variations in global average temperatures which become a global challenge. Therefore, the research analyses the asymmetric relationship for the world's top 22 forested countries between overall energy consumption (EC), agricultural value added (AVA), agricultural land (AL), forest area (FA), and real GDP with CO2 emissions. The study uses over the period from 1980 to 2019. We adopted novel panel nonlinear autoregressive distributed lag (NARDL) model. The novel advantage of panel NARDL is that it is capable of catching positive and negative shock for the independent variable in the long and short term. The empirical analysis indicates that positive and negative EC and AL shocks have a favorable and statistically significant long-term effect on CO2 emissions. Nevertheless, positive shocks in AVA and FA, have a significant negative effect on CO2 emissions, while negative shocks have a significant long-term positive effect on CO2. On the other hand, positive shock in real GDP, is negligible, while negative shock shows adverse and substantial long-term impacts on CO2 emissions. The study suggested that, in order to achieve their energy requirement, these countries should introduce energy saving measures, combating deforestation and destruction of forests helps improve prevention and climate change adaptation.

Keywords: energy consumption; agricultural land; forest area; real GDP; panel NARDL

1. Introduction

Forest agriculture is an intentional, integrated, intensive and interactive agro forest. It is an intentional cultivation of edible, medicinal or decorative specialty crops that are managed for wood and understory crop production. This involves intentional, intensive, integrated and interactive land management system that combines trees with crop or livestock on the same piece of land with the aim of increasing the benefit to the landowner while maintaining forest integrity and environmental health. This may include cultivating non-timber forest products or niche crops such as mushrooms with high market value.

However, in today’s world, farms are recorded to be the second emitter of greenhouse gases after the energy sector and this is because they produce about 13% of the total global emissions. It should be noted that most farm related emissions results from cattle bleaching (CH_4) and the addition of natural and synthetic fertilizers to soils. These emissions may also be as a result of manure management, field burning of crop residues as well as fuel consumption on the farm. According to world resource institute, global emissions from agriculture increased by 8% between 1990 & 2010 and are projected to increase by 15% above this by 2030 where the amount of emissions may increase to 7 billion tonnes per year.

Also, there is a co-integration between carbon emissions, agriculture, real income and energy consumption. Also the EKC hypotheses is valid (Doğan, 2019) this is because in the long run, agriculture activities increase the carbon emissions of countries. The agricultural-induced environmental Kuznets curve is U-shaped, (Doğan, 2019). It is therefore important for government, policy makers and agricultural producers to set and adopt policies which will cover energy intensive economic activities as well as agriculture to provide solutions to environmental issues.

Considering the rapid climate change of the 21st century, the last decade has experienced deforestation and this may be considered as factor responsible for emissions. The carbon mitigation potentials associated with minimizing deforestation, forest management, afforestation and agro-forestry differ by operations of each region, boundaries and time horizons within which any of these policies are made or compared. In the long run there is a two-way causal relationship between emissions and agriculture i.e. agricultural activities affects carbon emissions. However, this effect may be supplemented by adequate afforestation to reduce the adverse effects of emissions, (Mehdi & Slim, 2017). It is worthy of note that increasing the forest area may affect food production through agricultural processes without adequate government policies, this may however be avoided by adopting energy efficient tools for farming so as to reduce emissions from machineries.

Accordingly, forest area which is the percentage of a country's land covered with either natural or planted trees which is at least 5meters and whether or not they are productive, and this excludes trees in agricultural production systems. However, forest areas of countries differ as a result of either the region or relevance placed on afforestation by the government. To a large extent afforestation reduces the risk of global warming due to their ability to absorb carbon emissions. As indicated in World Bank Database (2020), for some countries of the world, the larger the forest area and value-added agriculture, the higher the emissions while the reverse is the case for some other countries. However, countries with largest forest areas like Guinea-Bissau, Seychelles, Gabon, and Finland may have minimum carbon emissions and significant changes may not be experienced in the carbon emissions. According to figure 1, there is only slight increase in the forest areas and emissions from 2006-2016. For instance, in 2006-2016, Austria had its forest area to be about 46.6%. Also, in Guinea Bissau 73% of its land to forest and its forest area in subsequent years until 2016 maintained this range.

Thus, the metric tons of carbon emissions per capita or Benin for 2006 was 0.5 and forest area about 42% and agricultural added value was 26%. As indicated by the data from the world development indicator on carbon emissions, forest area and agricultural and forestry value added, it is quite obvious that there is no obvious variation in the forest percentage of land in most of the countries over the years. In countries like Maldives, Niger, South Africa, Togo, Chad, Iceland have limited forest area below 10% of total land area. It should be noted that these countries agricultural value added is also limited and this implies despite not using its land for afforestation, its agricultural value added still low which implies inadequate land usage.

According to World Bank Database (2020), forest area and emissions data indicates that countries with higher forest areas seem to have lower carbon emissions. For instance, Zambia has its forest area to be 65% of total land and 0.3 tons carbon emissions per capita same with Guinea Bissau. Meanwhile these countries with lower forest areas seem to have higher emissions for instance Iceland has its forest area around 5% of its land mass and have its carbon emissions to be 6%. This simply implies that increased forest area may help in the absorption of carbon dioxide emissions. Importantly, this study seeks to investigate whether or not agricultural exports encourages forestry and agricultural contaminants in most forested countries in the world with evidence from Quantile ARDL. The next section discusses key state of the art discus of forest, agriculture, and emissions, while section three presents variables used, data and model used. Section four discusses the results with vital implications for climate change discourse, while the study concludes in section five with important policy recommendations.

2. Literature Review

Addressing carbon emissions and its effect on environmental degradation a vast majority of papers focus on the effect of energy consumption on carbon emissions, how fossil fuel consumption affects carbon emissions and only a few considered agriculture and forest agricultural impact on carbon emissions or emissions of greenhouse gases generally.

2.1 The forest-agricultural-emissions nexus

Even though it is commonly believed that forests help reduce carbon dioxide from the environment, it may contribute carbon dioxide emissions to the environment by releasing heavy carbon dioxide to the atmosphere. This can be through photosynthesis process in the forest where carbon dioxide is turned to organic compound by releasing carbon dioxide back to the atmosphere. Having known that environmental sustainability has become the focus of many countries of the world and they strive to reduce the emissions of carbon dioxide and other greenhouse gasses which is a major contributor to environmental pressure and degradation. Not only is the adoption of renewable energy important for CO2 emissions reduction, forest impacts carbon emissions negatively thus leading to its reduction while agricultural activities increase carbon emissions. Meanwhile, agricultural sectors are known to consume non-renewable energy such as fossil fuel and diesel for irrigation farming thereby increasing emissions. This effects can however be reduced drastically by encouraging modern agriculture and increasing afforestation, (Waheed et al., 2018). However, the increased deforestation may hinder the contrition of forest agriculture to emissions reduction this is because despite the UN framework convention creating incentives towards reducing deforestation, capital at national and international levels of forest agriculture continue to be a barrier. In an attempt to improve afforestation governments of the country like Pakistan created policies such as the Billion Tree Tsunami which is aimed at growing a billion tees by the end of 2017 so as to increase the forest area and reduce emissions.

Similarly, reducing carbon emissions requires deliberate effort cutting across most of the sectors of economies of the world. This is because the emissions of carbon dioxide, which is as a result of industrial activities, energy consumption, transportation exerts detrimental effect on the environment thereby increasing global warming and environmental degradation. The agricultural sector is one of the major economic activities and responsible for food, fruits, vegetables including forest agriculture. However, the activity involved in the agricultural process involves energy consumption, usage of fossil fuels results to the emissions of carbon dioxide and other greenhouse gases. In the short and long run, a two-way causal relationship exists between agricultural activities and the level of carbon dioxide emissions. This implies that an increase in the agricultural activities affects emissions of greenhouse gases and carbon emissions results from agricultural activities(Mehdi & Slim, 2017). Renewable energy consumption affects the growth of GDP of countries, this may occur in the long run due to its resultant effect on the reduction of environmental degradation, (Mehdi & Slim, 2017).

Importantly, changes to government spending induces forest land clearing for the purpose of agricultural production thereby increasing deforestation induced emissions and the decline in afforestation may be lingering for a while since the expansion of agricultural activities. This implies that increased government spending on agricultural policies and expansion implies forest- agriculture emissions due to more frequent deforestation and forest burning. This effect may be averted by having more spending towards enforcing property rights so as to raise the cost involved in land clearing, (Galinato & Galinato, 2016).

Also, agriculture is found to be the major determinant of carbon dioxide emissions (CO2) in a country like china. Projects such as organic farming through the use of environmentally friendly technologies, minimum use of pesticides as well as reasonable use of chemical fertilizers so as to reduce emissions and reduction in pollution level. There is need to pay considerable attention to using energy savings lightening and irrigation systems in farmlands so as to minimize energy consumption. As a way of ensuring public compliance, it is imperative to create adequate public awareness regarding the risks associated with emissions of greenhouse gases and the need to adjust activities towards minimizing it, (Doğan, 2019). Importantly, the effect of agriculture on carbon emissions may differ in different countries and regions depending in their agricultural policies such as concern for afforestation as a means of minimizing emissions. Similarly, with higher economic growth, livestock and crop and livestock production contributes significantly to increase in CO2 emissions, (Appiah et al., 2018).

However, abatement costs which involves the cost of reducing issues affecting the environment such as pollution. The integration of agriculture into the climate change policy requires going beyond assessments of marginal abatement costs and the need to address issues such as uncertainties affecting emissions and abatement costs as well as the resulting difficulties of monitoring the activities of the agricultural sector. The flexibility in the use of nitrogen and the effect it has on crop yields also contributes immensely in reducing marginal abatement costs also reduction may result to the reduction in the agricultural supply and increasing agricultural prices which may in the long run result to an equilibrium effect on abatement costs, (Vermont & De Cara, 2010). This cost incurred by the government and regulatory agencies towards reducing environmental pollution and degradation is necessary to avoid the adverse effects of global warming on economic activities and the environment. Also, agricultural value added leads to reduction in carbon dioxide emissions (CO2), (Mehdi & Slim, 2017).

The agriculture induced environmental Kuznets curve hypotheses is an indication that environmental degradation tends to rise as agricultural activities increases until a certain level of economic growth then a decline in environmental degradation occurs. Also, the level of income growth to a large extent determines the energy consumption, agriculture and the agriculture-induced environmental Kuznets curve. The agriculture-induced environmental Kuznets curve is valid, and it is evident that there is a two-way causal relationship between GDP, energy use, agriculture and CO2 emissions. this implies that the impact GDP has on carbon emissions, energy use is elastic while the relationship between agricultural value added have inelastic and negative effect on emissions, (Katircioglu et al., 2018).

2.2 Other determinants of Emissions

Carbon emissions results from energy consumption, biomass production, transportation, trade openness, per capita GDP, urbanization and this level of emissions differ. One of the major determinants of carbon dioxide emissions is energy consumption. However, the source of energy consumed to a large extent determines the amount of carbon emitted to the environment and this implies that the consumption of energy from renewable sources is reduces carbon emissions from energy consumption. Therefore, it is important to consider replacement of non-renewable energy consumption with renewable energy. Also, the gross domestic product may also affect the level of carbon emissions. An increase in GDP and REC (including combustible and waste) leads to increase in carbon dioxide emissions. As a matter of urgency, it is imperative to encourage the consumption of renewable energy such as wind or solar as this will help improve agricultural production and help reduce global warming drastically, (Mehdi & Slim, 2017).

On another note, trade liberalization has significant effect on the agricultural greenhouse gases and by 2030 its effect is expected to be moderate. This may be as a result of adoption of mitigation technologies which contributes immensely to emissions reduction. It has become a necessity to address emission leakage in EU countries and beyond by GHG mitigation perspective, trade agreements and being conditional on participating nations and other measures aimed at reducing emissions and global warming, (Himics et al., 2018). Nevertheless, the emissions of carbon dioxide from biomass production is mainly from the use of fossil fuel during the process such as transportation by truck, biomass transportation by tractor etc, (Börjesson, 1996). These plants or animals which serve as materials for energy production and the process involve emission of carbon dioxide into the atmosphere and back into plants. A long run equilibrium relationship exists between biomass production, energy consumption, real income and emissions, (Dogan & Inglesi-Lotz, 2017).

As expected of developing and sometimes developed countries, urbanization which leads to increase in the proportions of people living in towns and cities. People move from rural to urban areas especially in developing countries in search for better standard of living. This usually implies increased energy consumption, transportation which means increased emission of greenhouse gases. The elastic relationship between Urbanization and carbon emissions is positive at early stage and thereby turns negative at a later stage. Also, there is a one way causal relationship between urbanization and carbon emissions in the short run and a bi directional relationship in the long run. This implies that in the short run urbanization leads to increase in carbon dioxide emissions and this is as a result of the urban congestions associated with urbanization including population increase, increased energy consumption and transportation. In the long run, urbanization increases carbon emissions and carbon emissions affect urbanization. Further, there is a two-way causal relationship between energy consumption, domestic investment, GDP, CO2 and same relationship exists between financial development carbon emissions, (Bekhet & Othman, 2017).

Meanwhile, the measure of economic success of countries is the monetary value of all finished goods and services made within a country during a specific period in the form of gross domestic products (GDP). There is a long run relationship between CO2 emissions, real GDP, energy consumption and tourism. While real income and tourism reduces carbon emissions with a one-way causal relationship running from the former to the later and two way relationship exists between CO2 emissions and energy consumption and between real income and CO2 emissions implying that energy consumption contributes immensely to carbon emissions, (Dogan & Aslan, 2017).

Just as important, positing that as income increases environmental pressure, increases until a certain point when it begins to decline. The EKC hypothesis exists and in the short and long run, fossil fuel consumption, GDP, energy consumption and trade openness increases air pollution. Also, mitigating carbon emissions in the short and long run requires renewable energy consumption. However, only in the short run does financial development reduces air pollution, (Ozturk et al., 2016). The agriculture-induced environmental Kuznets curve hypothesis is valid, (Gokmenoglu & Taspinar, 2018). On the contrary economic growth leads to the largest amount of carbon emissions before urbanization and financial development. Contrary to the usual expectations, renewable energy consumption does not lead to the reduction in carbon dioxide emissions, (Pata, 2018).

Considering our review of literature, it is apparent that only few literatures consider the effect of forest-agriculture on carbon dioxide emissions. Although the effect of agriculture on carbon emissions has been examined by previous studies. This study however investigates whether or not Agricultural Exports Motivate Agricultural and Forestry Contaminants in Most Forested Countries in The World with Evidence from Quantile ARDL.

3. Methods and material

3.1. Data and preliminary analysis

The study used yearly panel data of Carbon dioxide emissions (thousands of tonnes), Total energy consumption (QBtu), (EIA, 2019), Agriculture value added (billion USD),(WDI, 2019) Agricultural land (sq. km), Forest area (sq. km), and Agriculture, forestry, and fishing, value added (% of GDP) (Global-economy, 2020). The data is covering the period from 1980 to 2019. The study selected 22 top forested countries in the world such as, Belize, Bhutan, Brazil, Brunei, Congo, Dominica, Gabon, Guyana, Japan, Malaysia, Panama, Peru, Republic of the Congo, Saint Vincent and the Grenadines, Samoa, Seychelles, South Korea, Suriname, Sweden, Zambia, Dominican Republic, and Finland. Suriname has been known as the most forested nation in the world, according to the (CEO-WORLD, 2020) magazine, while Federated States of Micronesia and Gabon ranked second and seventh, respectively. Forests make up a large proportion of the land area of most of the world's top 10 most forested nations, from just 74 percent of Papua New Guinea to more than 98 percent in Suriname in South America. Figure 1 represents the top 10 forested countries and its land in percentage.

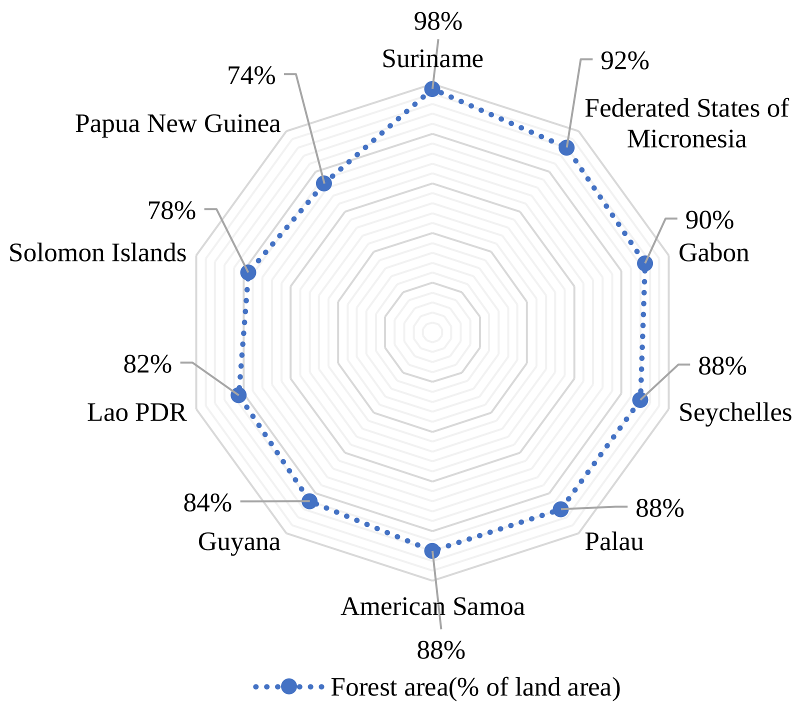

Figure **1**. Top ten forested countries in the world.

3.2. The model Estimation & procedure

As noted earlier, the nonlinear ARDL model of (Shin et al., 2014) is built in panel form, and is also a nonlinear version of the complex heterogeneous panel data model that is ideal for large T panels. For three motives, we are following this strategy. Firstly, it helps one to nonlinearly catch asymmetries. Secondly, it adjusts the implicit influence of variability in the results. Thirdly, it is far more suitable if no more than I(1) is included in the unit root or mixed order of integration. The asymptotic of large N, large T dynamic panels are distinct from the asymptotic of standard large N, small T dynamic panels, as stated by (Blackburne and Frank, 2007). Small T panel estimation typically relies on estimation methods of fixed or random impacts or a mixture of estimators of fixed effects and dynamic panel estimators, such as the generalized technique-of-moments assessment tool of (Bond, 1991). However, one of the main results from the Large N, Large T studies is that the concept of slope parameter homogeneity is sometimes inaccurate (Blackburne and Frank, 2007). For this analysis, the dynamic heterogeneous panel data model is therefore deemed acceptable so we deal mostly with broad T panels such that the (Pesaran, 2007) CD test also demonstrates the existence of heterogeneity. The Pooled Mean Group (PMG) estimator and the Mean Group (MG) estimator are the two popular techniques used throughout the calculation of a complex heterogeneous panel data model. The MG estimator depends on the estimate and average of the coefficients of N time series regressions, while the PMG estimator requires the combination of coefficients pooling and averaging (Salisu and Isah, 2017). The Hausman test, however, is used to test if there is any formal distinction between the two estimators. In order to verify the effectiveness of panel regression, the MG and PMG also obtain results for the single components by design. Therefore, the processing of individual responses to Co2 emission (for both symmetric and asymmetric scenarios) if necessary is less computationally efficient related to time series computing procedures. It is also possible to test both the long-run and short-run responses each variable on CO2 emission.

3.3. The symmetric panel ARDL

We begin our research by assuming that the CO2 emission reacts symmetrically to changes in the EC, AVA, Al, FA and RGDP, then we relax this assumption in order to accommodate positive and negative changes in the EC, AVA, Al, FA and RGDP. The symmetrical version of the ARDL panel is therefore given as:

$$\Delta CO2_{it} = \beta_{0i} + \beta_{1i}CO2_{it} + \beta_{2i}EC_{t-1} + \beta_{3i}AVA_{t-1} + \beta_{4i}AL_{t-1} + \beta_{5i}FA_{t-1} + \beta_{6i}RGDP_{t-1}$$
$$+\sum_{j=1}^{N1}\lambda_{ij}\Delta CO2_{i,t-j} + \sum_{j=0}^{N2}\lambda_{ij}\Delta EC_{t-j} + \sum_{j=0}^{N3}\lambda_{ij}\Delta AVA_{t-j} + \sum_{j=0}^{N4}\lambda_{ij}\Delta AL_{t-j} + \sum_{j=0}^{N5}\lambda_{ij}\Delta FA_{t-j} + \sum_{j=0}^{N6}\lambda_{ij}\Delta RGDP_{t-j}$$
$$+\mu_i + \varepsilon_{it}$$
$$i = 1,2,....,N; t = 1,2,......T. \qquad (1)$$

where $CO2_{it}$ is the carbon dioxide emission for each unit i over a period of time t; EC, AVA, Al, FA and RGDP denotes the energy consumption, agricultural value added, agricultural land, forest area, and real gross domestic product at period t; μ_i is the group-specific effect; i is the sampled units; and t is the number of periods. For each cross-section, the long run slope (elasticity) coefficient is computed as $-\frac{\beta_{5i}}{\beta_{1i}}$ since in the long run, it is assumed that $\Delta CO2_{i,t-j}, = 0$ and $\Delta AVA_{t-j},...1,2.... = 0$ Therefore, the short run estimate for oil price is obtained as λ_{ij} . Eq. (1) can be re-specified to include an error correction term as follows:

$$\Delta CO2_{it} = \delta_i\upsilon_{i,t-1} + \sum_{j=1}^{N1}\lambda_{ij}\Delta CO2_{i,t-j} + \sum_{j=0}^{N2}\lambda_{ij}\Delta EC_{t-j} + \sum_{j=0}^{N3}\lambda_{ij}\Delta AVA_{t-j} +$$
$$\sum_{j=0}^{N4}\lambda_{ij}\Delta AL_{t-j} + \sum_{j=0}^{N5}\lambda_{ij}\Delta FA_{t-j} + \sum_{j=0}^{N6}\lambda_{ij}\Delta RGDP_{t-j} + \mu_i + \varepsilon_{it} \qquad (2)$$

where $\upsilon_{i,t-1} = CO2_{i,t-1} - \phi_{0i} - \phi_{1i}EC_{t-1},,..1,2..$ is the linear error correction term for each unit; the parameter δ_i is the error-correcting speed of adjustment term for each unit which is also equivalent to β_{1i} .The parameters ϕ_{oi} and ϕ_{1i} are computed as $-\frac{\beta_{0i}}{\beta_{1i}}$ and $-\frac{\beta_{2i}}{\beta_{1i}}$ respectively. That's what you can observe in both Eqs. (1) and (2), no decomposition exists. Positive and negative shifts in the EC, AVA, AL, FA and RGDP, hence the presumption. In this case, there is a symmetrical effect on CO2 emissions.

3.4. The asymmetric panel ARDL

This form of the ARDL panel, pointed to as the nonlinear ARDL panel, makes, unlike the symmetrical scenario, an asymmetrical reaction of the EC, AVA, AL, FA and RGDP on the CO2 emission. In other words, positive and negative shocks are not supposed to have similar effects on the CO2 emission in this situation. Consequently, the asymmetric form of Eq. (1) as mentioned below:

$$\Delta CO2_{it} = \beta_{0i} + \beta_{1i} CO2_{i,t-1} + \beta_{2i}^{+} EC_{t-1}^{+} + \beta_{2i}^{-} EC_{t-1}^{-} + \beta_{3i}^{+} AVA_{t-1}^{+} + \beta_{3i}^{-} AVA_{t-1}^{-}$$
$$+ \beta_{4i}^{+} AL_{t-1}^{+} + \beta_{4i}^{-} AL_{t-1}^{-} + \beta_{4i}^{+} FA_{t-1}^{+} + \beta_{4i}^{-} FA_{t-1}^{-} + \beta_{5i}^{+} RGDP_{t-1}^{+} + \beta_{5i}^{-} RGDP_{t-1}^{-} +$$
$$\sum_{j=1}^{N1} \lambda_{ij} \Delta CO2_{i,t-j} + \sum_{j=0}^{N2} (\gamma_{ij}^{+} \Delta EC_{t-j}^{+} + \gamma_{ij}^{-} \Delta EC_{t-j}^{-}) + \sum_{j=0}^{N3} (\gamma_{ij}^{+} \Delta AVA_{t-j}^{+} + \gamma_{ij}^{-} \Delta AVA_{t-j}^{-}) +$$
$$\sum_{j=0}^{N4} (\gamma_{ij}^{+} \Delta AL_{t-j}^{+} + \gamma_{ij}^{-} \Delta AL_{t-j}^{-}) + \sum_{j=0}^{N5} (\gamma_{ij}^{+} \Delta FA_{t-j}^{+} + \gamma_{ij}^{-} \Delta FA_{t-j}^{-}) + \sum_{j=0}^{N6} (\gamma_{ij}^{+} \Delta RGDP_{t-j}^{+} + \gamma_{ij}^{-} \Delta RGDP_{t-j}^{-}) + \mu_t + \varepsilon_{it} \tag{3}$$

where (EC^{+}, EC^{-} AVA^{+}, AVA^{-} AL^{+}, AL^{-}, FA^{+}, FA^{-} and $RGDP^{+}$, $RGDP^{-}$) denote the positive and negative shocks in agricultural value added, agricultural land, forest area, and real gross domestic product, respectively. The long run (elasticity) coefficients for (EC^{+}, EC^{-} , AVA^{+}, AVA^{-} AL^{+}, AL^{-}, FA^{+}, FA^{-} and $RGDP^{+}$, $RGDP^{-}$) are calculated as $-\frac{\beta_{2i}^{+}}{\beta_{1i}}$ and $-\frac{\beta_{2i}^{-}}{\beta_{1i}}$. These shocks are respectively computed as positive and negative partial sum decompositions changes among the variables as defined below:

$$EC_t^{+} = \sum_{k=1}^{t} \Delta EC_{ik}^{+} = \sum_{k=1}^{t} \max(\Delta EC_{ik}, 0) \tag{4}$$

$$EC_t^{-} = \sum_{k=1}^{t} \Delta EC_{ik}^{-} = \sum_{k=1}^{t} \max(\Delta EC_{ik}, 0) \tag{5}$$

$$AVA_t^{+} = \sum_{k=1}^{t} \Delta AVA_{ik}^{+} = \sum_{k=1}^{t} \max(\Delta AVA_{ik}, 0) \tag{6}$$

$$AVA_t^{-} = \sum_{k=1}^{t} \Delta AVA_{ik}^{-} = \sum_{k=1}^{t} \max(\Delta AVA_{ik}, 0) \tag{7}$$

$$AL_t^{+} = \sum_{k=1}^{t} \Delta AL_{ik}^{+} = \sum_{k=1}^{t} \max(\Delta AL_{ik}, 0) \tag{8}$$

$$AL_t^{-} = \sum_{k=1}^{t} \Delta AL_{ik}^{-} = \sum_{k=1}^{t} \max(\Delta AL_{ik}, 0) \tag{9}$$

$$FA_t^{+} = \sum_{k=1}^{t} \Delta FA_{ik}^{+} = \sum_{k=1}^{t} \max(\Delta FA_{ik}, 0) \tag{10}$$

$$FA_t^{-} = \sum_{k=1}^{t} \Delta FA_{ik}^{-} = \sum_{k=1}^{t} \max(\Delta FA_{ik}, 0) \tag{11}$$

$$RGDP_t^{+} = \sum_{k=1}^{t} \Delta RGDP_{ik}^{+} = \sum_{k=1}^{t} \max(\Delta RGDP_{ik}, 0) \tag{12}$$

$$RGDP_t^- = \sum_{k=1}^{t} \Delta RGDP_{ik}^- = \sum_{k=1}^{t} \max(\Delta RGDP_{ik}, 0) \tag{13}$$

The error correction form of Eq. (2) yields the following:

$$\begin{aligned}
&\Delta CO2_{it} = \tau_i \xi_{i,t-1} + \sum_{j=1}^{N1} \lambda_{ij} \Delta CO2_{i,t-j} + \\
&\sum_{j=0}^{N2} (\gamma_{ij}^+ \Delta EC_{t-j}^+ + \gamma_{ij}^- \Delta EC_{t-j}^-) + \\
&\sum_{j=0}^{N3} (\gamma_{ij}^+ \Delta AVA_{t-j}^+ + \gamma_{ij}^- \Delta AVA_{t-j}^-) + \\
&\sum_{j=0}^{N4} (\gamma_{ij}^+ \Delta AL_{t-j}^+ + \gamma_{ij}^- \Delta AL_{t-j}^-) + \\
&\sum_{j=0}^{N5} (\gamma_{ij}^+ \Delta FA_{t-j}^+ + \gamma_{ij}^- \Delta FA_{t-j}^-) + \\
&\sum_{j=0}^{N6} (\gamma_{ij}^+ \Delta RGDP_{t-j}^+ + \gamma_{ij}^- \Delta RGDP_{t-j}^-) + \mu_i + \varepsilon_{it}
\end{aligned} \tag{14}$$

The error-correction term captures the long run equilibrium: In the asymmetric panel ARDL defined in Eq, (12) the error-correction term captures $(\xi_{i,t-1})$ the long-term equilibrium. while its related parameter is the change speed term, which calculates how long it takes for the system to converge in the presence of a shock to its long-term equilibrium.

4. Results and discussions

The individual and group statistical characteristics of the series beginning with the descriptive statistics are considered according to the normal procedures for variables with time series properties (see Table 1 and 2), respectively. For example, the mean stats found that the average CO2 values of Japan, South Korea, Brazil, Malaysia, Finland, and Sweden are significantly higher than other countries producing carbon emission in top forested countries among the world. even though we have suppressed Nigeria with a drastically different figure compared to others (see Table 1). Further energy consumption (EC) revealed mean value Dominican – republic, Japan, and South Korea are the higher energy consumer than other countries. Further, agricultural value added (AVA) shows the higher mean value of Japan, Brazil, South Korea and Malaysia than other countries. The average agricultural land (AL) indicates that Brazil, democratic republic-Congo, Peru, Gabon, Malaysia using maximum land for the agriculture among the top forested countries in the world. Additionally, forest area (FA) of Brazil, Peru, Zambia, Finland, Gabon, Guyana, Japan and Malaysia are maximum than other countries. The real GDP mean values reveals Bhutan, Guyana, Dominican-Republic and Belize are higher than others.

Table **1**. Descriptive Statistics country-wise Analysis

Country	**Stats**	***CO2***	***EC***	***AVA***	***AL***	***FA***	***RGDP***
Belize	mean	385.175	0.007475	0.117	1391.05	14666.79	14.7775
	sd	127.1224	0.003382	0.058974	225.6864	779.5114	3.140512
	min	172	0.003	0.03	960	13612.8	9.6

	max	601	0.013	0.23	1612	16160.3	22.9
Bhutan	mean	458.85	0.027475	0.157	5092.925	26253.61	26.59
	sd	460.3404	0.022618	0.097775	504.7566	884.5796	10.15055
	min	22	0.001	0.06	4130	25067.1	14
	max	1843	0.062	0.41	5930	27946.1	42.9
Brazil	mean	310326.7	0.461425	50.8475	2587178	5179033	6.195
	sd	105124.5	0.134266	29.3081	194346	176411.2	2.155845
	min	166632	0.199	19.98	2242780	4925540	4.1
	max	533530	0.739	113.6	2840830	5467050	10.5
Brunei	mean	5744.275	0.104375	0.07425	120.875	3953	1.0525
	sd	2324.939	0.047411	0.036717	15.64541	119.0518	0.341931
	min	1470	0.05	0.03	100	3800	0.6
	max	9696	0.192	0.15	144	4130	2.2
DR- Congo	mean	2404.125	0.104	4.39525	258636.5	1567663	7.75
	sd	1242.87	0.021069	1.806913	2244.362	26898.33	3.070872
	min	-430	0.072	1.92	255500	1522666	3.4
	max	4672	0.166	9.45	262000	1603630	13.9
Dominica	mean	107.025	0.002	0.04275	208.75	468.625	9.6075
	sd	54.81741	0.00122	0.018115	29.28091	22.70493	4.373486
	min	37	0.001	0.02	170	430.6	5.1
	max	192	0.006	0.09	250	500	19.8
Dominican Republic	mean	16599.47	76.68101	2.18175	24931.75	15225.83	14.3225
	sd	6604.118	18.41474	1.121741	1068.481	3013.111	3.275902
	min	6168	33.9	0.66	23520	11050	10.4
	max	28624	92.03005	4.59	26410	20162	21.5
Finland	mean	53931.6	1.1666	5.056	23200.28	221824	3.8875
	sd	6705.968	0.121246	1.058298	938.8305	1377.739	1.962754
	min	41576	0.911	3.58	21500	218750	2
	max	68672	1.346	7.63	25360	224450	8.6
Gabon	mean	5033.6	0.047225	0.45875	51578.5	217042.1	6.2925
	sd	676.9315	0.012887	0.185171	34.82925	14833.18	1.866491
	min	4023	0.028	0.22	51520	166524	3.3
	max	6634	0.073	0.95	51600	232000	11

Guyana	mean	1656.25	0.021	0.272	17115.25	166024.3	25.8575
	sd	518.8746	0.005923	0.149618	222.2725	476.9219	9.129212
	min	1045	0.009	0.09	16780	164860	12.4
	max	3485	0.032	0.55	17350	166600	43.8
Japan	mean	1116633	19.83495	65.6	51707.5	249274.4	2.1875
	sd	119143.2	2.458298	12.67032	5843.47	286.3578	1.38475
	min	883839	14.923	47.9	44710	248760	1.1
	max	1262394	22.922	95.29	60610	249660	5.5
Malaysia	mean	136921.3	1.90745	14.2885	69257.75	218919.3	12.9225
	sd	81389.55	1.085101	9.027965	9956.721	3907.96	4.922085
	min	27998	0.413	5.46	48861	208900	7.3
	max	288684	3.899	34.13	86270	223760	23
Panama	mean	6139.85	0.2495	0.844	21524.85	48392.22	5.6625
	sd	2948.973	0.092295	0.369086	1177.209	1438.989	1.917355
	min	2523	0.145	0.34	18550	46006	2.1
	max	11635	0.51	1.51	22664	50400	8.5
Peru	mean	32197.5	0.629825	5.81775	220123.8	760102.7	7.605
	sd	13868.4	0.251413	4.432092	19886.28	13110.64	0.640092
	min	407	0.374	0.2	186790	738054	6.6
	max	58067	1.118	15.3	243740	779210	8.5
Congo	mean	1661.8	0.0368	0.3385	105597.8	225305.1	7.75
	sd	884.8081	0.03341	0.18275	363.5331	1289.041	3.070872
	min	407	0.011	0.15	105180	223186	3.4
	max	3282	0.105	0.83	106270	227260	13.9
Saint Vincent	mean	152.45	0.00225	0.03225	109.75	260.15	8.43
	sd	73.61436	0.001104	0.012908	10.97491	6.996519	2.840928
	min	37	0.001	0.01	100	250	5.2
	max	312	0.005	0.06	130	270	14.2
Samoa	mean	151.825	0.002925	0.05475	509.825	1607.5	27.45
	sd	44.62257	0.001269	0.014674	157.4409	134.5477	22.73713
	min	99	0.001	0.04	349	1300	8.7
	max	246	0.006	0.09	784	1710	82.3
Seychelles	mean	375.625	0.01005	0.02075	37.2	406.7	3.765
	sd	210.3819	0.004739	0.008286	14.9258	0	1.662027
	min	84	0.002	0.01	15	406.7	1.9

	max	737	0.017	0.04	60	406.7	7.8
South Korea	mean	396858.8	7.367225	22.12325	19799.5	62797.85	5.53
	sd	162473.4	3.595285	6.495178	1912.8	621.9672	4.05445
	min	134869	1.88	9.33	17008	61764	1.7
	max	620302	12.501	31.38	22470	63700	15
Suriname	mean	1918.3	0.034025	0.184	823.975	153826.4	9.5925
	sd	261.0135	0.006208	0.151112	67.38542	329.0306	2.705587
	min	1375	0.019	0.03	690	153282	4.9
	max	2402	0.047	0.48	890	154300	18.9
Sweden	mean	52468.88	2.214375	7.12	32652.13	281153.8	2.6725
	sd	7378.922	0.112924	1.400602	2056.547	451.0938	1.341638
	Min	38181	1.887	4.71	30315	280630	1.3
	Max	71760	2.412	10.06	37040	282180	5
Zambia	Mean	2919.9	0.1272	0.95575	220819.5	512547.8	13.045
	Sd	974.4317	0.024327	0.621462	14333.28	18905.14	5.209653
	Min	1808	0.096	0.2	198080	484684	2.7
	Max	5142	0.179	2.38	238360	544660	30.5

As standard for large T macro frames, the related variables are subject to the panel unit root test. Currently, where non-stationarity is a problem, the dynamic heterogeneous panel data model (the chosen model in this study) is widely considered. We examine six distinct kinds of unit root tests for panel units at level and first difference. Panel unit root tests with the null hypothesis of unit root with common method are the first form followed by (Hadri, 2000; Harris and Tzavalis, 1999; Im et al., 2003; Jorg Breitung, 2015; Levin et al., 2002) as stated in Table 3. We notice that CO2, EC, AVA, AL, FA and RGDP indices are integrated with order zero I(0) by (Hadri, 2000), while AVA, AL, and RGDP also integrated at level confirmed by (Im et al., 2003; Levin et al., 2002). However, all the variables are integrated with order one I(1) irrespective of the form of test. The overall outcomes are mixed. Therefore, the empirical estimation method in this paper that accounts for the intrinsic variability and non-stationarity in the series of panel data is appropriate for our analysis. In particular, in the perspective of this analysis, the unit root test findings further validate the acceptability of our panel-ARDL model collection as the chosen estimation method.

We first approximate all the coefficients of both the MG and PMG estimators after the unit root test, and then we apply the results of these estimators to the Hausman test. The acceptance of the PMG estimator suggests a non-rejection of the null hypothesis, whereas the rejection reveals the acceptance of the MG estimator. In other words, under the null, the PMG estimator is the effective estimator, and under the alternate hypothesis, the MG estimator is the effective estimator. The findings of our Hausman test significantly help the PMG estimator as the powerful modelling estimator for CO2 emission for the top forested countries in the world. As seen in Table 3 and 4, for all models, the selection of PMG as the effective estimator under the null hypothesis is compatible and it does not seem to matter if the model is linear (symmetric) or nonlinear (asymmetric). To this end, in this study, only the results acquired from the chosen estimator are mentioned and discussed. We will break our findings into four. First of all, the CO2 emission is assessed without asymmetries (see Table 3). Secondly, we check the asymmetric effect of all the variables on CO2 emission, shown in Table 4. Third, we employ wald test to analyze the long-run asymmetric effect shown in Table 5. If asymmetry occurs only in the long run relying on an asymmetry measure, a Panel NARDL can be measured without short run asymmetry (Salisu and Isah, 2017). Fourth, on the basis of the wald test result the study apply Panel NARDL without asymmetry in the short run see Table 6. This addition is inspired by the statistical overview findings provided in Table 1, in which Japan, South Korea, Brazil, Malaysia, Finland and Sweden are deemed, on the basis of average values, to be critical countries in terms of CO2 emissions. The purpose is to decide if these nations have any possible outlier impact on the results of the analytical concept.

Table **2**. Panel unit root test analysis

Unit root test at level	CO2	EC	AVA	AL	FA	RGDP	Diff
Levin-Lin-Chu (t*)	0.991	1.000	0.999	0.000[a]	0.519	0.000[a]	*I*(0)
Hadri LM test (z)	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	*I*(0)
Im-Pesaran-Shin (W-t-bar)	1.000	1.000	0.000[a]	0.722	0.995	0.000[a]	*I*(0)
Harris-Tzavalis (ρ)	0.993	1.000	0.064	0.999	0.999	0.458	*I*(0)
Breitung (λ)	1.000	1.000	1.000	1.000	1.000	1.000	*I*(0)
Fisher-type Chi-square	0.857	1.000	0.963	0.737	0.999	0.000	*I*(0)
First difference							
Levin-Lin-Chu (t*)	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	*I*(1)
Hadri LM test (z)	0.000[a]	0.000[a]	0.995	0.000[a]	0.981	0.000[a]	*I*(1)
Im-Pesaran-Shin (W-t-bar)	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	*I*(1)
Harris-Tzavalis (ρ)	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	*I*(1)
Breitung (λ)	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	*I*(1)
Fisher-type Chi-square	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	*I*(1)

Note: [a, b, c] denotes 1%,5% and 10% significant level.

The long-term and short-term effects of CO2 due to changes in EC, AVA, AL, FA and RGDP are then calculated as a result of the mixed order of integration demonstrated by the series under concern. Beginning with the regression results of the symmetric model (see Table 3), the approximate coefficients indicate that CO2 emission is likely to effect equally to change in EC, AVA, AL and RGDP in the long-term while EC and AVA are also significant effect on CO2 emission in the short-term at 1% and 5% level. In particular, we see a strong positive association between CO2 emissions and energy use that is compatible with some of the literature 's leading research, such as (Sasana and Putri, 2018) and (Kashif Abbasi et al., 2020). Such results tend to confirm the outcome stated by (Khan et al., 2020) based on the projected findings, it is proposed that policymakers should promote and encourage sustainable energy sources that, by replacing old conventional energy sources such as coal , gas and oil, will help meet the growing demand for energy. Renewable energy sources, which are reusable can minimize CO2 emissions as well as promote balanced economic growth. However, the agricultural value added (AVA) is negative and significant effect on CO2 emission in the short and long-term. The results in line with (Deboe, 2020) imply that AVA can have major environmental consequences. Although adverse consequences are significant and can include food, water and air contamination and depletion, agriculture may also have a beneficial impact on the atmosphere by trapping greenhouse gases within crops and soils, for example, or reducing flood risks by the implementation of such agricultural practices. Additionally, change in forest area (FA) and RGDP also effecting CO2 emission in the long-term. The empirical finding suggesting that forests allow the environment to stable. Ecosystems are managed, biodiversity is preserved, they play an important role in the carbon cycle, livelihoods are assisted and can help promote sustainable development. We need to keep more woodland landscapes intact, maintain them more sustainably, and preserve more of the habitats we have destroyed to streamline the climatic benefits of forests as proposed by (IUCN, 2017).

Table **3**. Panel regression of CO2 (Symmetric)

Variables	EC	AVA	AL	FA	RGDP
CO_2	404.7	-7.49	0.24	-0.01	1.29
	(0.00) [a]	(0.02) [b]	(0.00) [a]	(0.55)	(0.00) [a]
ΔCO_2	280.95	10.26	-1.68	-0.88	-23.07
	(0.03) [b]	(0.08) [c]	(0.43)	(0.48)	(0.38)
Constant	-	56.28	-	71.88	59.7
		(0.02) [b]		(0.00) [a]	(0.02) [b]
υ_{i-t}	-0.29	-0.23	-0.29	-0.26	-0.28
	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]
Hausman test	0.59	2.17	2.28	0.65	0.05
$-\chi_k^2$	(0.44)	(0.14)	(0.13)	(0.42)	(0.82)
log likelihood	-6525.97	6586.95	-6622.91	6640.29	-6628.95
No. of groups	22	22	22	22	22
Number of obs.	858	858	858	858	858

Note: ([a, b, c]) denotes 1%, 5%, and 10% significant level the values in bracket () shows p-value.

For the asymmetrical case, let us now turn to the regression results (see Table 4). In the long term, the positive and negative changes in EC, AVA, Al, FA and RGDP appear to have a large and positive effect on CO2 emissions in the top forested countries, while the positive / negative magnitude is higher. Like the symmetrical scenario, in the long run, the EC, AVA, Al, FA of the top forested countries demonstrate major effects on CO2 emissions irrespective of whether the CO2 emission shock is positive or negative. While the short-term impact on CO2 emissions was noticed by RGDP.

Table **4**. Panel regression of CO2 (Asymmetric)

Variables	Pooled Mean group regression (Asymmetric)				
	EC	AVA	AL	FA	RGDP
Co_2^+	477.05	-15.72	0.27	0.63	28.31
	(0.00) [a]	(0.65)	(0.00) [a]	(0.00) [a]	(0.30)
ΔCo_2^-	175.45	-21.41	-3.63	-3.68	-12.44
	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]

Constant	123.97	53.67	59.3	55.01	72.55
	(0.06) [c]	(0.07) [c]	(0.04) [b]	(0.08) [c]	(0.03) [b]
υ_{i-t}	-0.26	-0.21	-0.21	-0.23	-0.15
	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]
Hausman test	4.74	3.69	2.51	0.88	0.71
$-\chi_k^2$	(0.09)	(0.16)	(0.28)	(0.64)	(0.7)
log likelihood	-6514.69	-6566.72	-6620.64	-6628.89	-6639.71
No. of groups	22	22	22	22	22
Number of obs.	858	858	858	858	858

Note: ([a, b, c]) denotes 1%, 5%, and 10% significant level the values in bracket () shows p-value.

For the final decision of estimate the Full Panel NARDL model the study employ short and long run asymmetry test followed by (Salisu and Isah, 2017). There are separate judgement parameters depending on the asymmetry test. As in the first case: asymmetry exists both in the long and short term, the judgement calculates the Maximum Panel NARDL. Second, asymmetry exists only in the long run. The choice will predict a Panel NARDL without short run, asymmetry. In the third scenario, asymmetry occurs only in the short term; a Panel NARDL without asymmetry will be calculated in the long run by the decision. In case four, the decision will be to approximate the Panel Linear ARDL if asymmetry does not occur in both the long and short term. The study employed second case as the only long run asymmetry exist among the variables as shown in Table 5. Hence, we can proceed towards Panel NARDL without short run asymmetry as suggested by (Salisu and Isah, 2017).

Table **5**. Long run and short run asymmetry using Wald test

Variables	Long run asymmetry				
	EC	AVA	AL	FA	RGDP
$-\chi_k^2$	25.65	13.16	27.80	34.29	7.81
P-value	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.03) [b]
	Short run asymmetry				
$-\chi_k^2$	0.10	1.21	0.02	1.79	1.12
P-value	(0.75)	(0.27)	(0.90)	(0.18)	(0.29)

Note: ([a, b, c]) denotes 1%, 5%, and 10% significant level the values in bracket () shows p-value.

Table 6. reveals the full Panel NARDL result based on the asymmetry test. Particularly, 1% positive change in energy consumption (EC) coefficient shows 336% positive and significant impact on CO2 emission while the 1% negative shock on EC also increasing by 454% which is higher than positive shock in EC. The rise in energy usage, which has compounded carbon dioxide emissions, has become a global problem in the last decade, particularly in developing countries. The Study findings showed that increased use of non-renewable or fossil fuels would increase emissions of carbon dioxide, while consumption of renewable energy could minimize emissions of carbon dioxide. Therefore, it is very meaningful for the forested countries and developing world, where wood still using for major source of fire that is the main cause of carbon dioxide emission, also reduce the use of fossil fuels and transition to sustainable energies. This

finding was close to that of (Bulut, 2017), who claimed that, non-renewable energies or fossils had a beneficial impact on the emissions of carbon dioxide in Turkey. In the meantime, (Shafiei and Salim, 2014) have reported that increased use of non-renewable or fossil fuels has contributed to an increase in CO2 emissions in OECD countries. For four global regions such as, Europe and North Asia, Latin America and Caribbean, and Sub-Saharan, North African and Middle Eastern, (Saidi and Hammami, 2015) stated a major positive effect of CO2 pollution on energy usage. Likewise, (Dogan and Seker, 2016), who conducted a study in European countries, suggested that non-renewable energy use would raise CO2 emissions and that there was an indirect causal correlation between CO2 emissions and the use of non-renewable energy. Also, (Wang and Ye, 2017) shown that reliance on fossil oil induces a rise in emissions of carbon dioxide. Contrary, by findings (Magazzino, 2016) that showed energy is neutral for development and substantially refuted. Also, (Danish et al., 2017) have revealed that consumption of fossil oil has a positive impact on emissions of carbon dioxide in Pakistan. The major trigger of carbon dioxide pollution has been fossil energy use, and the burning of fossil fuels is carbon dioxide gas that may affect the climate and the health of humans.

Further, Positive shock in agricultural value added (AVA) has a negative and significant effect on CO2 emission while, negative shock in AVA shows a positive increase in CO2 emission. The results of this study similar with (Alam, 2018) that showed the agriculture value added has a substantial negative effect on CO2 emissions. Likewise, (Mulatu et al., 2016) analysis findings show that agricultural production are adversely impacted by CO2 emissions. The findings also show that the proper application of the Climate Resilient Green Economy (CRGE) strategy will substantially mitigate the negative impact on agricultural output of CO2 emissions.

The productivity of the global agriculture system has more than doubled since the start of the Green Revolution, enhancing food stability for an expanding population and satisfying the dietary demands of an increasingly wealthy nation. Environmental costs have also been enforced on this impressive productivity. Although global agriculture faces a variety of challenges, the effect of agriculture on our environment may be the most unexpected threat to food security (Tubiello et al., 2015). However, positive shock in agricultural land (AL) increases CO2 emission significantly while negative shock in AL reflects positive and significant effect on carbon emission. Two big global environmental questions are climate change and AL use reform. It is alleged that climate change has created new problems for global land use, although the conversion of land use is hardly seen as a significant cause of climate change. The results endorsed by (Azadi et al., 2020) their findings shows that there is a positive relationship across the globe between CO2 emissions and AL. It can be noted that where agricultural fields are decreasing, CO2 emissions are rising. In the other side, where agricultural fields are growing, CO2 emissions are decreasing. Our findings are in this sense in accordance with the results of other scholars such as (Tasser et al., 2017) whose focus has been on the presence of a negative association between CO2 emissions and AL. (Parajuli et al., 2019) also confirmed that, the agricultural field, however, is considered to be a genuine emitter of CO2. The results imply that, land destruction applies to the deterioration of the condition of the environment and the depletion of potential and profitable ability for agricultural resources, which may contribute to the extension of agriculture into new regions.

Forests are essential reservoirs of carbon that, owing to both natural causes and human activity, constantly share CO2 with the environment. Knowledge the participation of trees in the greenhouse effect argues for a deeper understanding of the forest-level global climate (Fao, 2016). Additionally, 1% positive shock in forest area (FA) increases CO2 emission by 42%, while 1% negative shock in FA decreases CO2 by 2.80%. The results are in line with the recent study conducted by (Parajuli et al., 2019) revealed that forests are a key factor, diminishing CO2 emissions at global level, however the results differ by country. In other words, the increase in forestation is significantly reduces carbon emission while deforestation increases CO2 emission. Our empirical finding is very useful for the policy makers.

Finally, 1% positive shock in the real GDP increases CO2 emission by 3.01% which is insignificant whereas, 1% negative shock in RGDP substantially decreases CO2 emission by 13%. However, rising RGDP, would lead to a rise in CO2 emissions at high, likely due to the growing involvement of the agriculture, forestry, and fishing, value added industry. In other words, CO2 emissions will decrease during the initial stage of development but rise after GDP reaches the threshold limit. Because being in the upper regime means high economic growth, there would be more profits for individuals as well as businesses and this will lead to higher energy consumption from electrical products, transport, appliances, and others that contribute to high emissions. The absolute scale of the coefficient of economic growth indicates that when economic growth is higher, the association between economic growth and CO2 is greater. Our findings in line with (Aye and Edoja, 2017) that provided evidence of strong causal links between CO2 pollution and economic development. The results demonstrate the need to transform low carbon technology aimed at lowering pollution and promoting sustainable economic development. This may entail energy conservation and transitioning to renewable energy from non-renewable resources. The error correction coefficient shows inversely significant in all cases.

Table **6**. Panel NARDL without Asymmetry in the short run

Variables	Pooled Mean group regression (Asymmetric)				
	EC	AVA	AL	FA	RGDP
Co_2^+	335.95	-7.14	0.26	-0.42	3.01
	(0.00) [a]	(0.03) [b]	(0.00) [a]	(0.00) [a]	(0.25)
ΔCo_2^-	454.10	10.71	0.22	2.80	-12.54
	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.01) [b]
Constant	127.19	52.71	64.48	73.83	62.87
	(0.11)	(0.01) [b]	(0.01) [b]	(0.00) [a]	(0.02) [b]
υ_{i-t}	-0.30	-0.23	-0.29	-0.23	-0.16
	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]	(0.00) [a]
Obs. per group (min)	39	39	39	39	39
Obs. per group (max)	39	39	39	39	39
log likelihood	-6521.62	-6585.42	-6622.81	-6640.59	-6654.09
No. of groups	22	22	22	22	22
Number of obs.	858	858	858	858	858

Note: ([a, b, c]) denotes 1%, 5%, and 10% significant level the values in bracket () shows p-value.

5. Conclusion and policy recommendations

The study examined the asymmetric relationship between total energy consumption (EC), agriculture value added (AVA), agriculture land (AL), forest area (FA), real GDP with CO2 emission for the top 22 forested countries in the world declared by (CEO-WORLD, 2020). As noted previously, a variety of articles have highlighted the need to perform separate analyses for these variables. To achieve this goal, the study uses data over the period from 1980 to 2019 by employ panel nonlinear autoregressive distributed lag (NARDL) model. The novel advantage of panel NARDL is that it has capability to capture positive and negative shock in the long and short run for the explanatory variables. This approach is similar to the heterogeneous, non-stationary panel data model, except that asymmetries are not accounted for. Therefore, we also account for variability as well as non-stationarity, in addition to modelling nonlinearities in the nexus, which are the popular statistical characteristics underlying large *T* complex panels. We are also calculating the symmetric variation of the Panel ARDL model for accurate comparative analyses. We note a substantial positive EC effect on CO2 in the long and short term, considering the symmetric edition, whereas AVA demonstrates negative and significant long-term effects on CO2 and positive short-term effects on CO2, respectively. However, in the long term, AL and RGDP have revealed beneficial and substantial effects on CO2 emissions. Our analyses also indicate that asymmetrically effect on CO2 changes in explanatory variables. In the latter group, though, the reaction tends to be greater than the previous. The empirical evidence shows that positive and negative shocks in EC and AL has a positive and statistically significant effect on CO2 emission in the long run. However, positive shock in AVA and FA has a negatively substantial effect on CO2 emission while negative shocks has a positively significant impact on CO2 in the long run. Conversely, positive shock in real GDP shows insignificant whereas negative shock reveals negative and significant effect on CO2 emission in the long run.

In the light of empirical evidence, the study recommendations are as follows: all these countries should also invest in clean energy (green energy resources: solar and wind) and implement energy saving initiatives in order to achieve sustainable economic development. In order to reduce CO2 emissions, as global warming is getting more serious, investments in green energies and more effective use of resources are required. Agriculture and forestry are seen as main elements of global climate policies. In order to minimize pollution levels from the agriculture land use planning and a concerted strategy between government entities and the private sector within a state could play a key role. Restoring forest landscapes helps improve prevention and adaptation to climate change.

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Appendix

A.1 Schematic Review of key findings in recent literature

S/N	Author	Year	Period	Country	Focus of Research	Variables	Methodology	Finindings
1	Waheed, R Chang D, et.al	2018	1990-2014	Pakistan	Investigating energy consumption, agriculture production and orest on CO2 emissions	REC, AGRI, FOREST	ARDL	AGRI → CO2, FOREST → CO2, AGRI PROD → FOREST
2	Gorus M, Aslan m	2019	1980-2013	MENA	Impacts of economic indicators on environmental degradation		Panel cointegration tests	Energy use → FDI
3	Borjesson P	1996			Emissions of CO2 from Biomass production and transportation	NG, Coal, Electricity, CO2 emissions		NR
5	Mehdi B, Slim B	2017	1980-2011	North African countries	The role of renewable energy and agriculture in reducing CO2 emissions	AVA, CO2 GDP	Granger Causality tests	CO2 emissions ↔ Agriculture, Agriculture → GDP, GDP → RE, REC → Agri
6	Dogan N	2019	1971-2010	China	Assessing the impact of agriculture on CO2 missions	Real income, EC, Agri and CO2 emissions	FMOLS, DOLS, ARDL	EKC hypotheses valid
7	Gokmenoglu K, Taspinar N	2018	1971-2014	Pakistan	Testing the agriculture-induced EKC hypothesis	CO2, GDP	FMOLS	
8	Mihaly, H. et.al	2018		Germany	Trade liberalization and emission in agriculture		FMOLS	NR
9	Appiah K, Du J, Poku J	2018	1971-2013	Emerging economies	Causal relationship between agricultural production and CO2 emissions	Agri, CO2 emissions	FMOLS, DOLS, ARDL	NR
10	Gregmar I.G, Suette P.G	2016			Examining the effect of changes in govt spending level and composition on deforestation		OLS, FE, RE, GMM	NR
11	Bekhet H, Othman N	2017	1971-2015	Malaysia	Impact of urbanization growth on carbon emissions	CO2, GDP, EC, UG, domestic investment and	VECM and F-bounds test	Urb → CO2, CO2 Urb

S/N	Author	Year	Period	Country	Focus of Research	Variables	Methodology	Finindings
						financial development		
12	Dogn E, Aslan A	2017	1995-2011	EU	Exporing the relationship between CO_2 emissions, GDP, EC and tourism	CO_2 emissions, GDP, Ecand tourism	OLS, FMOLS	Tourism → CO_2 emissions, CO_2 ↔ EC, Real Income ↔CO_2
13	Al-Mulali U, Solarin S, et.al	2016	1980-2012	Kenya	Investigating the presence of the EKC	Fossil fuel EC, GDP, Urb and trade openess	ARDL	NR
14	Pata U	2018	1974-2014	Turkey	Investigating the dynamic relationship between EC, Urb, financial development, income and CO_2 emissions	REC, Urb, Financial Dvlpt, income and CO_2 emission	FMOLS, CCR	NR