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Agriculture For Sustainable Development: Empirical Evidence on Carbon Footprint in Agriculture Production, Expansion, And Trade

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ABSTRACT

The international food production is reason of almost one-third of the total humans caused Greenhouse Gas (GHG) emissions. The Sustainable Development Goals (SDGs) include agriculture sector growth and management of climate change. Carbon footprint is an indicator of GHG intensity, created from different economic actions. It represents more than fifty percent of the total ecological footprint and used as managing tool for estimating environmental pollution. The current study investigates the relationship between agriculture sector specific indicators and carbon footprint in fifty-six countries by using panel econometrics. The outcomes of the study provide strong evidence on the presence of Environmental Kuznets Curve (EKC). The analysis also shows that there exists negative association between carbon footprint and agricultural development. However agriculture sector expansion by employing environment friendly methods and technologies decreases carbon footprint in selected countries. Furthermore, the relationship between carbon footprint and agricultural exports is found positive. It implies that agricultural exports encourage the carbon footprint growth by stimulating the production and transport of agricultural commodities. Finally, there is positive relationship between carbon footprint and high scale of agricultural production, which supports the concept of production-based emission. These findings emphasizes that too much use of fertilizers in agriculture sector fosters the carbon footprint growth and damages natural environment of countries.

Keywords

Carbon footprint, Agriculture, Determinants, Agricultural development, Agricultural production, Agricultural exports

JEL Classification

Q00, Q01, Q17

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1. Introduction

Serious efforts are required in current decade to achieve SDGs, as deadline is approaching in year 2030. Sustainable development relies on the three domains: social, economic, and environment, which perform the important part in decision making for the policymakers (Dernbach and Mintz, 2011). Sustainable development through environmental sustainability requires that use of resources must be less than refill rate, even though population is raising carbon emissions, but overall level should remain low (Khan, 1995). Green growth, environmentally sustainable economic growth is considered a main tool to accomplish sustainable development. Economic growth with help of ecological and environmental sustainability is regarded as key goal of development policies across world. To attain green growth, control of CO_2 emissions is necessary, which is only possible with innovations in methods of supply and use of green technologies to help cleaner production (Wiebe and Yamano, 2016).

The second and thirteenth SDGs state that the world needs urgent work on climate change and agriculture sector growth. Improvements and rearrangements are required in food production, distribution, and consumption to achieve sustainable economic growth. Current picture of world climate advocates that zero net GHG emissions are required to prevent the world from being adversely affect by climate change in future. International climate policy formulated in the twenty-first Congress of the Parties (COP21) of the UNFCCC in Paris aims to control the rise in the worldwide temperature to sufficiently below two degrees Celsius above preindustrial levels and taking efforts to limit the temperature increase to one and half degree Celsius above preindustrial levels (UNFCCC, 2015). Policy emphasis the part of different sectors in climate change mitigation, particularly focusing on agriculture sector.

Agriculture has been always main part of debate on carbon emission, its sources and effects, and carbon sink. In the past, agriculture production was household-based with short distance transportation, little energy consumption and little use of fuel (Amate and De Molina, 2013). According to Krey et al. (2012) agriculture consumes less electricity and heat, transportation, and industry. Currently, agriculture sector is a major contributor of climate change as it produces a large quantity of GHG emissions. Almost one-third of the total GHG emissions originates from the agriculture sector (Gilbert, 2012). In last decade, GHG emissions has increased due to large scale production in agriculture (Calvin et al., 2016). Mbow et al., 2021 report that the global food system produces twenty-one percent to thirty-seven percent annual GHG emissions. According to International Atomic Energy Agency (IAEA) agricultural activities generates almost thirty percent of total GHG emissions, which are reason of climate change and global warming.

The food system is main reason of CO_2 emissions due to change in land-use, which is result of clearing land for pastures and crop production. Fourteen percent of annual human caused CO_2 emissions are due to change in net land-use (Le Quéré et al., 2018) and ten percent of these are from agriculture (Mbow et al., 2021). Application of urea and lime in agriculture also originate CO_2 emissions. High demand of food by world population, the greater demand for meat and dairy products, and the intensification of agricultural methods has increased rate of GHG emissions. The international food system including fertilizer production, storage of food and its packing is reason for thirty-three percent of total human caused GHG emissions (Gilbert, 2012). These emissions comprise of three gases i.e., N_2O, CH_4, and CO_2.

CO_2 emissions in agriculture sector has increased due to more use of energy in the sector. These include emissions from either tractor and other machines fuel or from fertilizers manufacturing and their transportation (Vermeulen et al., 2012). These emissions are measured as transport and energy emissions in the accounting framework of Intergovernmental Panel on Climate Change (IPCC). These emissions can be reduced by decarbonization of energy generation sources. Agriculture sector consumes around eleven percent of the total land of earth for yield production and employs seventy percent of the entire water surface (FAO, 2003; FAO, 2011). Current scenario of global warming and climate changes has a great impact on the sustainability of agricultural systems. Therefore, Springmann et al. (2018) describe the need to reduce agricultural emissions to maintain world environment. Poore and Nemecek (2018) investigate efforts on reducing environmental effects of food through consumers and producers.

Use of carbon footprint and its estimations in literature has been increased in last decade. The carbon footprint determines the carbon amount being produced by economic activity. The carbon footprint is a demand for biologically productive space, and it is major component of the ecological footprint (GFN, 2018). It is used as managing tool for evaluating the environmental impact of different nations and main indicator of pollution in the environmental economics, as it is significant factor to improve the understanding of environmental degradation. Ecological footprint estimates a nation's usage of grazing land, cropland, forests, and fishing grounds to supply resources and to absorb CO_2 from the burning of fossil fuels (GFN, 2018). Notably, the carbon footprint describes greater than fifty percent of all ecological footprint in several countries. Moreover, the carbon footprint is generally accepted indicator of GHG concentration, resulting from different economic actions. Scientists and policymakers treat it as a control indicator due to its increasing importance.

The paper examines the agriculture specific determinants of carbon footprint, specifically aiming on the economic growth and development, agricultural development, agricultural trade (in terms of agricultural exports) and agricultural production. Next section of paper provides a systematic review of past literature on carbon footprint especially with respect to agriculture and Agri-related subsectors. Third section is development of a conceptual framework to examine agriculture-specific determinants of carbon footprint. Fourth section describes estimation technique including a detailed account of indicators and methodological framework. Fifth section provides estimates of econometric models. It comprises of discussions on findings and determinants of carbon footprint. Last section concludes analysis of the current study.

2. Literature Review

Current literature on agriculture sector emissions focuses on estimations or measurement of emissions (Castesana et al., 2018; Rehman et al., 2019). Different works exist on the macro level estimation methods of GHG emissions. There are two methods to estimate GHG emissions: the production-based and consumption-based approach (Mózner, 2013). The consumption-based method declares emissions are emitted-emissions, which occur during the supply-chain of commodities utilized within a country, regardless of their production tertiary. Therefore, countries are liable for emissions caused somewhere else due to its consumption, while the production-based method is based on domestic emission due to inventories (Peters and Hertwich, 2008; Mózner, 2013).

The association between consumption-based emissions and GDP is higher than the GDP's association with territorial emissions (IPCC, 2014). So, carbon footprint and consumption expenditure strongly correlate. The IPCC (2014) identifies various income and non-income features as main cause of carbon emissions in the recent years, like consumption expenditures, production methods, transport infrastructure, waste management, energy systems, population growth and trends in demographic structure (urbanization). Per capita emission of carbon footprint also depends on some other non-income factors like geography, diet, and lifestyle (GAIA, 2012; Corsten et al., 2013).

Empirical investigations to assess agriculture related determinants of carbon footprint at the nations level are rare in the past works, particularly from global point of view. Only a few studies explore the factors of agriculture sector emissions. Kastratović (2019) examines the consequences of foreign direct investment on agricultural emissions. He only considers CO_2 emissions but does not estimate long run and short run links. Due to globalization, foreign direct investment (FDI) inflows and trade openness has increased. These are also major reasons of gas emissions for the host nations (Pao and Tsai, 2011; Naranpanawa, 2011; Ren et al., 2014; Le et al., 2016). International trade is also a reason of the difference in carbon emissions (Peters and Hertwich, 2008; Bows and Barrett, 2010).

Agriculture is a main cause of nitrogen dioxide emissions to the environment (Audet et al., 2017). Fertilizer and cattle are the key determinants of CO_2 emissions in agriculture sector (Luo et al., 2017). Mineral fertilizers, agriculture waste burning, and manure management are the main causes of ammonia for Argentina. Different studies report their findings related to growth of population in poor and rich countries, which causes to increase GHG emissions. According to Jorgenson and Clark (2010) population elasticity of GHG emissions for developed countries is 1.65 percent and for developing countries it is 1.27 percent. Poumanyvong and Kaneko (2010) estimate the value of population elasticities of GHG emissions as 1.75 for low-income, 1.23 for middle-income, and 1.12 for high-income nations. Furthermore, increase in labor productivity decreases intensity of gas emissions.

Most of past studies only measures gas emissions or don't provide theoretical background for the empirical examination. Robaina-Alves and Moutinho (2014), Luo et al. (2017) and Castesana et al. (2018) analyze the determinants of CO_2 emissions from agriculture sector. Robaina-Alves and Moutinho (2014) decompose agriculture sector emissions into factors like economic growth, human capital accumulation, energy structure, energy intensity, emissions components, and labor productivity. They find that nitrogen use per cultivated area is main determinant of gas emissions. Ben Jebli and Ben Youssef (2019) find that agriculture sector value addition, and per capita increase in renewable combustible material and consumption of waste decrease CO_2 emissions in the long run. They provide long run and short run factors of agricultural emissions at world level instead of individual country.

Studies on carbon footprint also report product-level data and certain geographical area. According to Muthu (2014) among three major Chinese crops rice is producing highest percentage of carbon footprint, wheat is second in the list and maize is third. Fodders of agricultural farms produce more than two-third of the carbon footprint. The work of Jacobsen et al. (2014) on livestock shows that one kg of pig's meat produces carbon footprint equivalent to almost 5.7 kg CO_2. According to Verge et al. (2008) and Desjardins et al. (2014) beef produces largest amount of carbon footprint among meat production of different animals. Among the dairy products, milk powders generate highest carbon footprint in dairy production, butter is second and cheese is third in the list.

Past literature also provides cross-country differences in carbon footprint. In addition to this, within a country agriculture seems to produce varied amount of carbon footprint. Carbon footprint of countries depends on country size, role of agriculture in country, agricultural production, population, and use of technology (Balogh, 2019). China is main producers of the worldwide carbon footprint and contributor of climate change. Carbon footprint of China's crop output are more than eight percent of the country's overall emissions and sixty-six percent of the carbon footprint are of the agrochemical origin. Energy consumption and irrigation produces twenty-two percent on average, while machinery management and plastic film contributes below ten percent of the overall carbon footprint in country's crop output (Muthu, 2014).

Agriculture sector performs an important part in the economy by providing food and nutrition, alongside further environmental, social, and economic effects (Li et al., 2016), but this area of economy is also a major cause of CO_2 emissions causing climate change and global warming (Oenema et al., 2001; Tubiello et al., 2013; Calvin et al., 2016; Agovino et al., 2019). Technological advancement can reduce CO_2, ammonium cation and nitrogen dioxide emissions from the agriculture sector (Cole et al., 1997). Strategies to lessen the gas emissions from agriculture sector can be formed by focusing on demand side factors (Franks and Hadingham, 2012) rather than supply side factors like land use, crop production decisions, soil fertility and forests (De Pinto et al., 2016). Sebri and Abid (2012), Chen et al. (2017), Waheed et al. (2018) and Paul et al. (2018) work on the demand side economic factors of agriculture sector GHG emissions.

Ben Jebli and Ben Youssef (2017) find bidirectional causality between CO_2 emissions and agriculture sector in the long run and short run. GHG emissions from agricultural output per unit have been decreased globally (Bennetzen et al., 2016). The fast growth in technology and economic integration in last decade produced high emissions from agriculture sector (WRI, 2015). Agriculture sector emissions varies country to country (Dace and Blumberga, 2016). Li et al. (2016) work on the importance of long run and short run factors of agriculture sector gas emissions.

Giannadaki et al. (2018) find that agriculture sector ammonia gas emissions increase particulate matter air pollution, have significant harmful effects on human being health and increases rate of mortality. Fifty percent decrease in agriculture sector emissions can save more than two hundred thousand lives per year in the selected fifty-nine countries and can provide economic benefits of billions of US dollars. The mortality rate can be decreased eighteen percent with an annual economic benefit of billions of US dollars. Decrease in agriculture sector emissions creates social and financial benefits. Hence, an analysis of the agriculture-specific determinants of emissions across different income level nations is useful. The topic of the current study is so crucial that it must be focused because reduction in agriculture sector emissions gives significant social and economic benefits. Identification of agriculture-specific factors of gas emissions is important for policy making in this area.

3. Theoretical framework

Consumption side analysis reveals that high income, developed and populated countries consumes processed food products, more meat and demand great amount of food products that cause greater carbon footprint. There exists a positive association between CO_2 emissions per person and GDP per person (Ang, 2007). The EKC hypothesis has been proposed by Grossman and Krueger (1995) for examining the relationship between ecological pollution and economic growth like Kuznets (1955)[1] inverted U-hypothesis for income inequality and economic development. Grossman and Krueger (1995) state that pollution increases and environmental quality decreases at early stage of economic growth, but after achieving certain level of per capita income, environment quality improves with economic growth. Therefore, per capita pollution emissions are the inverted U-shaped function of income per person (Stern, 2004; Ozturk and Acaravci, 2010; Al-Mulali, Saboori, and Ozturk, 2015; Hussain and Dey, 2021). Economic development and industrial growth increase the use of natural resources, which damages environment, but after development environmental quality increases due to usage of cleaner technologies in the post-industrial stage (Munasinghe, 1999). The present study examines EKC hypothesis on carbon footprint. Presence of inverted U-shaped long run link between countries' carbon footprint and economic growth (GDP per capita) suggests:

$$\text{Carbon footptint} = \text{f}(\text{GDP per capita}, \text{GDP per capita}^2) \quad (1)$$

Balogh and Jambor (2017) finds that agricultural development by engaging environment friendly technologies reduces agricultural CO_2. The relationship between carbon footprint and agricultural development implies:

$$\text{Carbon footptint} = \text{f}(\text{Agricultural value added}) \quad (2)$$

[1] Kuznets (1955) suggests that inequality increases in the country at the early stage of income growth, but it moves back towards greater equality as economic growth endures.

Trade of processed meat products and animal feed has increased due to globalization (Kearney, 2010). It has reduced burden on environment (Balogh and Jambor, 2017) and decreased carbon footprint of countries through technological improvements. Agriculture sector trade effects carbon footprints by increasing food production and transport use. So, the relationship between carbon footprint and agricultural exports declares:

$$\text{Carbon footptint} = f(\text{Agricultural exports}) \quad (3)$$

Environmental degradation increases with higher scale of agricultural production (Foley et al., 2011; Baccini et al., 2012; Grace et al., 2014; Henders et al., 2015). So, carbon footprint rises with increase in agricultural production, which depends on agricultural machinery and use of fertilizers. Effect of tractors and fertilizers use on carbon footprint propose:

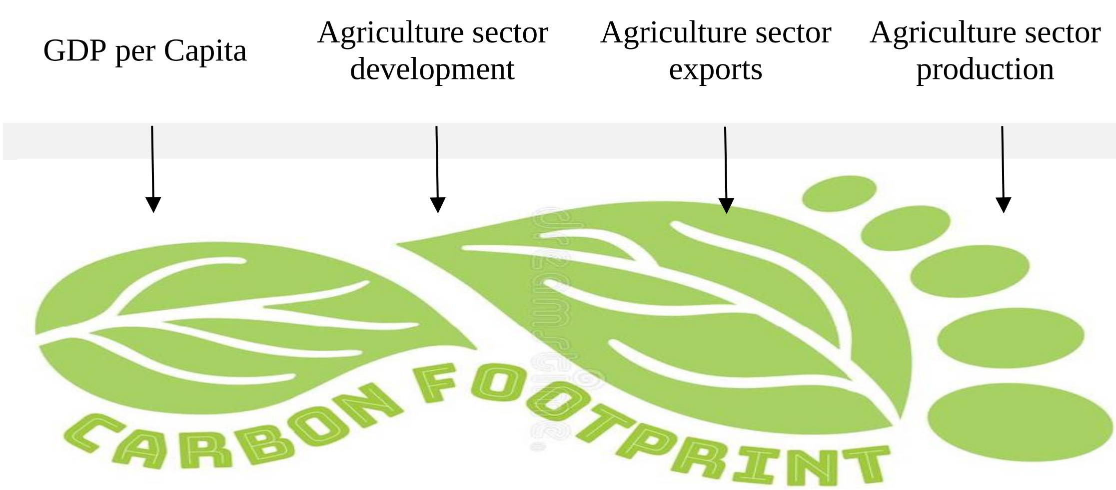
$$\text{Carbon footptint} = f(\text{Fertilizers}, \text{Tractors}) \quad (4)$$

Consumption habits of urban and rural populations have varied effect on the natural resources use. More urbanization in the countries also effect carbon emissions and spatial development of cities cause global warming through GHG emissions (Sethi, 2017). So, countries with greater percentage of rural population have less carbon footprint as compared to a country that has more urban population. Therefore, carbon footprint also depends on percentage of rural population in the country.

$$\text{Carbon footptint} = f(\text{Rural population}) \quad (5)$$

Figure 1 provides framework to find agriculture-specific determinants of carbon footprint.

Figure 1: Carbon Footprint, GDP per capita and Agriculture Sector



Source: Authors' developed theoretical framework based on literature review.

4. Data and Methods

This section describes the path of empirical estimation of discussed phenomena. It includes details of data and methods employed in the analysis.

4.1. Data and variable selection

Data consists of seven indicators for fifty-six countries selected from Barilla Center for food and nutrition list for reference years 1980 to 2017. The list of sample countries with their respective sustainable agriculture index is provided in Table A (appendix). Food and Agriculture Organization (FAO) of the United Nations, World Development Indicators (WDI) of World Bank, and Global Footprint Network (GFN) are the sources of data. Selection of indicators is based on framework developed in last section. Detail description of the selected variables is mentioned in Table B (appendix).

4.2 Econometric specifications

This study employed panel data models in examining the association between the carbon footprint and its determinants. Panel data provides more observations with the help of pooling time series information across cross-sections and permits for informative data, high efficiency, high variability, more degrees of freedom and lesser collinearity among indicators (Gujarati, 2004). These advantages are possible if and only if individual heterogeneity does not exist in the data (Baltagi, 2008). This empirical study is conducted by using the following econometric techniques (also mentioned in Table 1).

Table 1: Methodological framework to study the relationship between the carbon footprint and its determinants

Step	Inquiry	Test/ Method	Objective
1	Cross-sectional Dependence (CD)	CD test by Pesaran (2015)	To unveil cross-country dependence between indicators.
2	Slope homogeneity	Slope homogeneity test by Pesaran and Yamagata (2008)	To reveal the heterogeneity between the cross-sections.
3	Unit root problem	CADF and CIPS tests by Pesaran (2007)	To verify order of integration of variables.
4	Long run cointegration	Westerlund (2007) cointegration tests	To confirm presence of cointegration between variables.
5	Estimation of long run relationship	DCCE MG by Chudik and Pesaran (2015)	To decide long run link between the variables.
6	Granger causality	Dumitrescu and Hurlin (2012) causality test	To study the direction of relationship and causal links between the variables.

Source: Authors' developed framework.

4.2.1 CD test

Firstly, CD test is required to examine cross-country dependence as CD analysis is the basic step in the study of panel data. Cross-correlation between error terms of econometric model and existence of non-zero error covariance between them indicates CD. Presence of CD is crucial problem in panel unit root and cointegration tests. These tests are irrelevant if CD assumption does not hold due to correlations among individual cross-sections (Chang, 2002). Second-generation tests like Cross-sectionally Augmented Im, Pesaran, Shin (CIPS) and tests of Westerlund cointegration assume heterogeneity and dependence among cross-sections. Different factors such as common shocks or model misspecification may cause CD dependence (Cerrato, 2002). If CD exists among units but not considered, results can be significantly biased (Breusch and Pagan, 1980; Pesaran, 2004).

CD is defined as error term of panel individuals is related in the econometric model. Shock of economy effects individuals and influence other units in the panel. This has been described in following equation:

$$y_{(i,t)} = \alpha_{(i)} + \beta_{(i)} x_{(i,t)} + u_{(i,t)} \tag{6}$$

$$\text{where } \operatorname{cov}(u_{(i,t)}, u_{(j,t)}) \neq 0 \tag{7}$$

In all equations of paper, the subscripts ‘i’ and ‘j’ show the cross-sections i.e., i = 1, 2, …, N and j = 1, 2, …, N and the subscript ‘t’ shows the time i.e., t = 1, 2, …, T.

The Lagrange multiplier CD_{LM} test by Pesaran (2015) is applied to exam CD. This CD_{LM} test is effective when N is greater than T. Null hypothesis of CD_{LM} test considers weak CD across countries against the alternative hypothesis in which the strong CD is present. Statistics of CD test is:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{(i,j)} \qquad \sim N(0,1) i, j \tag{8}$$

Here $\hat{\rho}_{(i,j)}$ is the sample approximation of the pairwise correlation of errors.

$$\hat{\rho}_{(i,j)} = \frac{\sum_{t=1}^{T} \hat{u}_{(i,t)} \hat{u}_{(j,t)}}{\sqrt{(\sum_{t=1}^{T} \hat{u}_{(i,t)}^2)} \sqrt{(\sum_{t=1}^{T} \hat{u}_{(j,t)}^2)}} \tag{9}$$

Here $\hat{u}_{(i,t)}^2$ is estimate of $u_{(i,t)}$ in equation 6.

4.2.2 Slope homogeneity test

The second step is application of slope homogeneity test (Pesaran and Yamagata, 2008) to reveal the existence of slope homogeneity among units. This test does not allow CD (Atasoy, 2017). Tests statistics can be expressed as:

$$\tilde{\Delta}_{SH} = \sqrt{N}^{-2}\sqrt[2]{2k}\left(\frac{1}{N}\tilde{S} - k\right) \tag{10}$$

$$\tilde{\Delta}_{ASH} = \sqrt{N}^{-2}\sqrt{\frac{2K(T-k-1)}{T+1}}\left(\frac{1}{N}\tilde{S} - k\right) \tag{11}$$

Here $\tilde{\Delta}_{SH}$ is delta tilde and $\tilde{\Delta}_{ASH}$ is the adjusted delta tilde.

4.2.3 Unit root tests

The third step employs panel unit root tests to confirm integration order of variables. Literature reports two kinds of panel unit root tests. The first type is described as first-generation unit root tests; this type does not allow for CD and may offer deceptive results (Dogan and Seker, 2016). The second type is termed as second-generation unit root tests; which considers CD (e.g., Phillips and Sul 2003; Bai and Ng 2004; Smith et al. 2004; Moon and Perron 2004; Pesaran, 2007). Khan et al. (2020) recommend use of second generation non-parametric and parametric tests to avoid from being wrong.

The current study employed Cross-sectionally Augmented Dicky-Fuller (CADF) and Cross-sectionally Augmented Im Pesaran Shin (CIPS) tests by Pesaran (2007). CIPS test also encounters CD heterogeneity and provides reliable results. Panel unit root test of Pesaran (2007) permits $\frac{N}{T} \longrightarrow \sigma$ to obtain a positive real value. The equations of CADF test can be written as:

$$\Delta Y_{(i,t)} = \alpha_{(i)} + \beta_{(i)}Y_{(i,t-1)} + \gamma_{(i)}\overline{Y}_{(i,t-1)} + \delta_{(i)}\Delta\overline{Y}_{(i,t-1)} + e_{(i,t)} \tag{12}$$

The t-ratio of OLS estimates $\beta_{(i)}$ in equation 12, defined by $t_{(i)}(N,T)$, referred as a CADF statistics for i, and the average of its t-ratios is

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_{(i)}(N,T) \tag{13}$$

This equation provides the panel unit root test statistic. $CIPS(N,T)$ is a cross-sectionally augmented edition of the test statistic suggested by Im, Pesaran and Shin (2003) and is described as a CIPS statistic.

4.2.4 Westerlund panel cointegration tests

The fourth step entails the analysis of the long run relationship among carbon footprint and its determinants. The panel cointegration tests given by Westerlund's (2007) have been used in the current study. These tests check presence of cointegration by deciding whether the error correction exists for individual panel members and for panel. These tests show high power and improved size accuracy as compared to the methodology developed by Pedroni (2004), which are error-based tests. These tests provide robust and reliable results and managing cross-sectional dependency of the residual terms (Kapetanios et al., 2011).

The panels tests and the group-mean tests use null hypothesis of no cointegration to decide existence of cointegration. Westerlund (2007) suggests four panel cointegration test statistics i.e., G_a, G_t, P_a, and P_t. These are normally distributed and based on Error Correction Mechanism (ECM). The logic here is to check the lack of cointegration by deciding whether error correction occurs for individual panel members and for whole panel. The Westerlund cointegration equations can be written as:

Without intercept:

$$Y_{(i,t)} = \beta_{(i)}\Delta Y_{(i,t-1)} + \gamma_{(i)}\Delta X_{(i,t-1)} + \delta_{(i)}(Y_{(i,t)} - \theta_{(i)}X_{(i,t-1)}) + u_{(i,t)} \quad (14)$$

With intercept:

$$\Delta Y_{(i,t)} = \alpha_{(i)} + \beta_{(i)}\Delta Y_{(i,t-1)} + \gamma_{(i)}\Delta X_{(i,t-1)} + \delta_{(i)}(Y_{(i,t-1)} - \theta_{(i)}X_{(i,t-1)}) + u_{(i,t)} \quad (15)$$

With intercept and trend:

$$\Delta Y_{(i,t)} = \alpha_{(i)} + \beta_{(i)}\Delta Y_{(i,t-1)} + \gamma_{(i)}\Delta X_{(i,t-1)} + \omega_{(i)}t + \delta_{(i)}\left(Y_{(i,t-1)} - \theta_{(i)}X_{(i,t)}\right) + u_{(i,t)} \quad (16)$$

Here δ_i provides an estimation of the error-correction speed toward the long run equilibrium. The two statistics G_t and P_t are calculated with the standard errors of the parameters of error correction, calculated in normal way. The other two tests, G_a and P_a are based on two standard errors developed by Newey and West (1994). These statistics are adjusted standard errors for autocorrelations and heteroskedasticity. The test statistics can be described as:

$$G_t = \frac{1}{N}\sum_{i=1}^{N}\frac{\delta_{(i)}}{S.E(\delta_{(i)})} \quad (17)$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\delta_{(i)}}{\delta_{(i)}(1)} \quad (18$$

$$P_t = \frac{\delta_i}{S.E(\delta_{(i)})} \quad (19)$$

$$P_a = T\delta_{(i)} \quad (20)$$

4.2.5 Long run estimation

Final step is evaluation of long run relationship among carbon footprint and agriculture sector variables, in the presence of cointegration. For this purpose, this study estimates different models with Chudik's and Pesaran's (2015) Dynamic Common-Correlated Effects Mean Group (DCCE MG) method. It is extension of CCE method developed by Pesaran (2006) to heterogeneous panel models along with lagged dependent regressor and/or weakly exogenous regressors. This approach involves two conditions: first, enough lags of cross-section means should be involved in individual equations of the panels; and second, the number of cross-section means should be equal to or greater than the number of unobserved common factors.

DCCE MG estimation method requires sufficiently large time series length of the panel. This method also deals CD and heterogenous slope coefficient. The CD is shaped using cross-sectional means of the dependent variable and regressors to account for the unobserved common factors. Estimations are also robust to structural breaks in DCCE MG method. In this approach, set of unobservable common factor is considered as a common dynamic process, which provides useful interpretations. Different models of carbon footprint need to be assessed to ensure long run relationship between variables. DCCE MG specification for estimated models of carbon footprint are:

$$\mathrm{ln\_CarbonFP}_{(i,t)} = \alpha_{0(i)} + \alpha_{1(i)}\mathrm{ln\_CarbonFP}_{(i,t-1)} + \alpha_{2(i)}\mathrm{ln\_GDPpC}_{(i,t)} + \alpha_{3(i)}\,\mathrm{ln\_GDPpC}^2_{(i,t)} + \alpha_{4(i)}\mathrm{AgriVA}_{(i,t)} + \sum(d_{(i)}z_{(i,s)}) + \varepsilon r_{1(i,t)} \quad (21)$$

$$\mathrm{ln\_CarbonFP}_{(i,t)} = \beta_{0(i)} + \beta_{1(i)}\mathrm{ln\_CarbonFP}_{(i,t-1)} + \beta_{2(i)}\mathrm{ln\_GDPpC}_{(i,t)} + \beta_{3(i)}\,\mathrm{ln\_GDPpC}^2_{(i,t)} + \beta_{4(i)}\mathrm{AgriVA}_{(i,t)} + \beta_{5(i)}\mathrm{ln\_AgriExp}_{(i,t)} + \sum(d_{(i)}z_{(i,s)}) + \varepsilon r_{2(i,t)} \quad (22)$$

$$\mathrm{ln\_CarbonFP}_{(i,t)} = \gamma_{0(i)} + \gamma_{1(i)}\mathrm{ln\_CarbonFP}_{(i,t-1)} + \gamma_{2(i)}\mathrm{ln\_GDPpC}_{(i,t)} + \gamma_{3(i)}\,\mathrm{ln\_GDPpC}^2_{(i,t)} + \gamma_{4(i)}\mathrm{AgriVA}_{(i,t)} + \gamma_{5(i)}\mathrm{ln\_AgriExp}_{(i,t)} + \gamma_{6(i)}\mathrm{ln\_Fer}_{(i,t)} + \gamma_{7(i)}\,\mathrm{ln\_Trac}_{(i,t)} + \sum(d_{(i)}z_{(i,s)}) + \varepsilon r_{3(i,t)} \quad (23)$$

$$\mathrm{ln\_CarbonFP}_{(i,t)} = \delta_{0(i)} + \delta_{1(i)}\mathrm{ln\_CarbonFP}_{(i,t-1)} + \delta_{2(i)}\mathrm{ln\_GDPpC}_{(i,t)} + \delta_{3(i)}\,\mathrm{ln\_GDPpC}^2_{(i,t)} + \delta_{4(i)}\mathrm{AgriVA}_{(i,t)} + \delta_{5(i)}\,\mathrm{ln\_Trac}_{(i,t)} + \delta_{6(i)}\mathrm{RuralPop}_{(i,t)} + \sum(d_{(i)}z_{(i,s)}) + \varepsilon r_{4(i,t)} \quad (24)$$

$$\mathrm{ln\_CarbonFP}_{(i,t)} = \lambda_{0(i)} + \lambda_{1(i)}\mathrm{ln\_CarbonFP}_{(i,t-1)} + \lambda_{2(i)}\mathrm{ln\_GDPpC}_{(i,t)} + \lambda_{3(i)}\,\mathrm{ln\_GDPpC}^2_{(i,t)} + \lambda_{4(i)}\mathrm{AgriVA}_{(i,t)} + \lambda_{5(i)}\mathrm{ln\_AgriExp}_{(i,t)} + \lambda_{6(i)}\mathrm{ln\_Fer}_{(i,t)} + \lambda_{7(i)}\,\mathrm{ln\_Trac}_{(i,t)} + \delta_{8(i)}\mathrm{RuralPop}_{(i,t)} + \sum(d_{(i)}z_{(i,s)}) + \varepsilon r_{5(i,t)} \quad (25)$$

Here, natural log of carbon footprint $\mathrm{ln\_CarbonFP}_{(i,t)}$ is dependent variable, $\mathrm{ln\_CarbonFP}_{(i,t-1)}$ is lag of the dependent, $\mathrm{ln\_GDPpC}_{(i,t)}$ is natural log of GDP per capita, $\mathrm{ln\_GDPpC}^2_{(i,t)}$ is square term of natural log of GDP per capita, $\mathrm{AgriVA}_{(i,t)}$ is agricultural value added, $\mathrm{ln\_AgriExp}_{(i,t)}$ is natural log of agricultural exports, $\mathrm{ln\_Fer}_{(i,t)}$ is natural log of fertilizers quantity used in agriculture, $\mathrm{ln\_Trac}_{(i,t)}$ is natural log of tractors employed in agriculture and $\mathrm{RuralPop}_{(i,t)}$ is rural population percentage in total population. Furthermore $z_{(i,s)}$ is a (1 x k+1) vector including the cross-sectional averages at time 's' and the sum is over s = t, t-1, ..., t-p (p are the lags of the cross-sectional means). While $\varepsilon r_{1(i,t)}$, $\varepsilon r_{2(i,t)}$, $\varepsilon r_{3(i,t)}$, $\varepsilon r_{4(i,t)}$, and $\varepsilon r_{5(i,t)}$ are the error terms in DCCE MG equations.

4.2.6 Dumitrescu-Hurlin (D-H) causality test

Application of Dumitrescu-Hurlin causality test (2012) ensures the direction and causal association between indicators after the estimation of long run relationship. The null hypothesis of the D-H causality says that there is no causal association between indicators against the alternative hypothesis, which reflects that there is causal link between indicators. The model can be written as:

$$Y_{(i,t)} = \beta_i + \sum_{j=1}^{p} \delta^{j}_{(i)} Y_{(i,t-j)} + \sum_{j=1}^{p} \theta^{j}_{i} T_{(i,t-j)} \quad (26)$$

Here, j donates the lag length, while $\delta^{j}_{(j)}$ represents the autoregressive parameters.

5. Results and findings

Analysis begins with averages and standard deviations estimates of indicators (reported in Table 2). Selected countries have on average $1.36e^{+08}$ global hectors carbon footprint, 17353.33 US dollars (constant 2010) GDP per capita, agriculture value added equals to 10.58 percent of GDP, $9.1e^{+12}$ US dollars agricultural exports, 503.13 tractors per hundred square kilometer of (arable) land, 145.43 Kg fertilizers per hectare of arable land, and 39.53 percent rural Population out of total population.

Table 2: Descriptive statistics of indicators

Variable	All countries	
	Mean	**Standard deviation**
Carbon footprint (global hectors)	$1.36e^{+08}$	$3.80e^{+08}$
GDP per capita (constant 2010 US$)	17353.33	19259.24
Agriculture value added (% of GDP)	10.58	12.23
Agricultural exports (1000 US$)	$9.1e^{+09}$	$1.7e^{+10}$
Tractors (per 100^2 km of (arable) land)	503.13	929.70
Fertilizers (kg per hectare of arable land)	145.43	152.46
Rural population (% of total population)	39.53	23.23

Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

Due to globalization and liberalization, world has developed a replica of small town. Actions in one economy impact nearby countries. Hence, it is necessary to address the CD in the analysis of panel data. So, application of Lagrange multiplier test of error CD checks CD in carbon footprint model. CD_{LM} statistics values of the Lagrange multiplier test by Pesaran (2015) displays that there is CD in carbon footprint model. P-values of CD_{LM} test statistics reject the null hypothesis of not any cross-sectional independence at one percent significance level. In other words, there exists dependency across nations. Table 3 displays the results of CD tests.

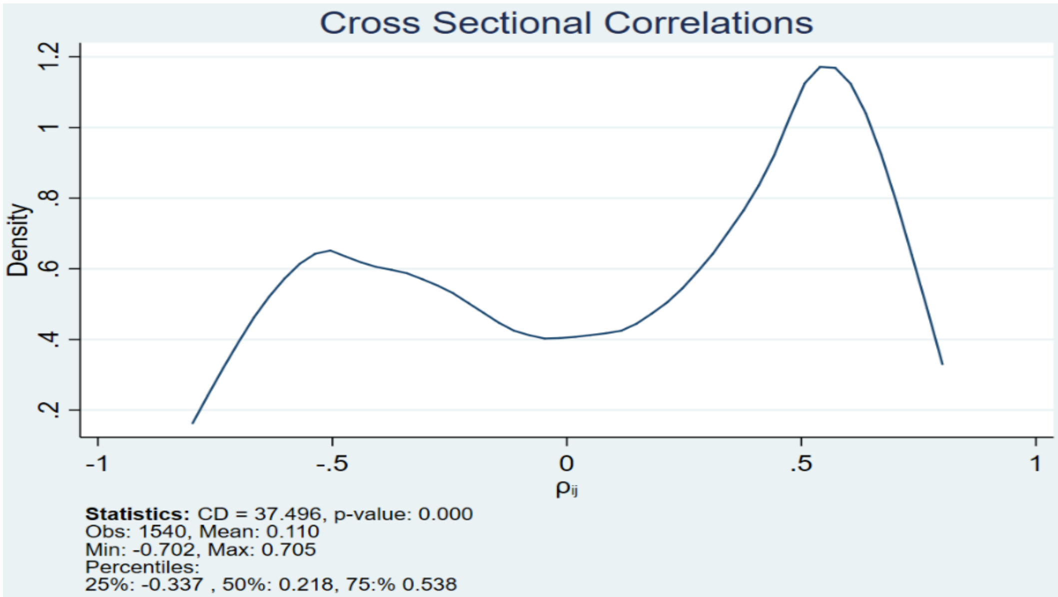
Table 3: Lagrange multiplier tests of error CD

Variables	**CD statistics**	**P-value**
$ln\_CarbonFP_{(i,t)}$	241.811	0.00***
$ln\_GDP_{(i,t)}$	241.747	0.00***
$ln\_GDP^2_{(i,t)}$	241.277	0.00***
$AgriVA_{(i,t)}$	231.824	0.00***
$ln\_AgriExp_{(i,t)}$	241.692	0.00***
$ln\_Fer_{(i,t)}$	218.005	0.00***
$ln\_Trac_{(i,t)}$	194.359	0.00***
$RuralPop_{(i,t)}$	239.339	0.00***
Overall Model	37.496	0.00***

Note: H_0: Errors are weakly cross-sectional dependent.
*** indicates significant at 1% level.
Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

Figure 2 reports Kernel density estimates and graph of residuals of carbon footprint regression model. Density graph confirms that residuals do not follow normal distribution.

Figure 2: Kernel density estimates and graph



Source: Graph is based on authors' estimates of carbon footprint model.

Table 4 reports results of homogeneity Pesaran and Yamagata (2008) test and confirms that there is heterogeneity in the data. It suggests that the panel data constants are heterogeneous, and the slopes differ across cross-sections. It also suggests that relationships of economic variables can be distinct in different countries. So, assumption of homogeneity in model estimation can provide ambiguous and biased results (Alam et al. 2018).

Table 4: Slope homogeneity test by Pesaran and Yamagata

Test-statistics	Value	P-value
$\tilde{\Delta}_{SH}$	46.371	0.00***
$\tilde{\Delta}_{ASH}$ (adjusted)	53.081	0.00***
Note: *** indicates significant at 1% level.		

Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

The presence of dependence and panel data heterogeneity requires the second-generation unit root tests and the panel cointegration method of DCCE MG for the estimations. Order of integration has been confirmed to avoid spurious regression estimations (Ulucak and Bilgill, 2018). Therefore, CADF and CIPS have been used. Table 5 shows the CADF test results. Stated statistics of unit roots are for logged values except agriculture value added and rural population.

Table 5: CADF unit root tests

Variables	Level		First difference		Order
	Intercept	Intercept and trend	Intercept	Intercept and trend	
$ln\_CarbonFP_{(i,t)}$	-1.994**	-2.048			I(0)
$ln\_GDP_{(i,t)}$	-2.131***	-2.619***			I(0)
$ln\_GDP^2_{(i,t)}$	-2.113***	-2.559**			I(0)
$AgriVA_{(i,t)}$	-2.475***	-2.813***			I(0)
$ln\_AgriExp_{(i,t)}$	-2.204***	-2.652***			I(0)
$ln\_Fer_{(i,t)}$	-1.824	-2.423	-4.693***	-4.830***	I(1)
$ln\_Trac_{(i,t)}$	-2.214***	-2.700***			I(0)
$RuralPop_{(i,t)}$	-2.359***	-2.665***			I(0)

Note: H_0: All series are non-stationary.
*** and ** imply significant at 1%, and 5% level respectively.
Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

Result confirms that carbon footprint, GDP per capita, GDP per capita square, agriculture value added, agriculture exports, tractors and rural population indicators are level stationary as p-values of test statistics reject null hypothesis of unit root for all indicators. So, order of integration for all these indicators is zero i.e. I(0). Only fertilizers variable is first difference stationary as p-values of statistics accept null hypothesis of unit root at level and reject at first difference. So, order of integration for fertilizers indicator is one i.e. I(1).

Table 6 displays the results of CIPS tests at level and at first difference. Stated unit root statistics are for logged values except agriculture value added and rural population. Result confirms that carbon footprint, agriculture value added, agriculture exports, fertilizers, tractors, and rural population indicators are level stationary as p-values of test statistics reject null hypothesis of unit root for all indicators. So, order of integration for all these indicators is zero i.e. I(0). Indicators GDP per capita and GDP per capita square are first difference stationary as p-values of test statistics accept null hypothesis of unit root at level and reject at first difference. So, order of integration for GDP per capita and GDP per capita square is one i.e. I(1).

Table 6: CIPS panel unit root tests

Variables	Level		First difference		Order
	Intercept	Intercept and trend	Intercept	Intercept and trend	
$ln\_CarbonFP_{(i,t)}$	-2.337***	-2.363			I(0)
$ln\_GDP_{(i,t)}$	-1.638	-2.287	-4.264***	-4.612***	I(1)
$ln\_GDP^2_{(i,t)}$	-1.634	-2.260	-4.161***	-4.547***	I(1)
$AgriVA_{(i,t)}$	-2.545***	-2.769***			I(0)
$ln\_AgriExp_{(i,t)}$	-2.570***	-2.991***			I(0)
$ln\_Fer_{(i,t)}$	-2.239***	-2.871***			I(0)
$ln\_Trac_{(i,t)}$	-2.456***	-2.789***			I(0)
$RuralPop_{(i,t)}$	-1.561***	-2.354			I(0)

Note: H_0: Homogeneous non-stationary.
*** indicates significant at 1% level.
Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

Here, results of CIPS are important as compared to the estimates of CADF, because it provides more consistent results in case of CD and panel data slope heterogeneity. Results of CIPS tests provides mixed order for integration for indicators and requires application of Westerlund's (2007) panel cointegration tests to ensure long run association between indicators.

Statistics of cointegration tests are shown in Table 7 for carbon footprint models. Statistics G_t and P_t provide evidence of cointegration between carbon footprint and its determinants for all models of Westerlund i.e., without intercept, with intercept, and with intercept and trend. So, confirmation of cointegration suggests that there exists long run association between carbon footprint, GDP per capita, GDP per capita square, agriculture value added, agriculture exports and fertilizers.

Table 7: Westerlund's panel cointegration tests

Specification	Statistic	Statistics	Z-value	P-value
without intercept	G_t	-2.623	-3.123	0.001***
	G_a	-8.021	3.609	1.000
	P_t	-18.216	-3.385	0.000***
	P_a	-7.106	0.871	0.808
with intercept	G_t	-2.872	-1.776	0.038**
	G_a	-8.576	5.809	1.000
	P_t	-19.552	-1.660	0.049**
	P_a	-7.756	3.196	0.999
with intercept and trend	G_t	-3.343	-2.666	0.004***
	G_a	-9.474	7.947	1.000
	P_t	-22.133	-1.291	0.098*
	P_a	-9.613	5.033	1.000

Note: H_0: No integration.
***, ** and * mean significant at 1%, 5% and 10% level.

Source: Author's calculations using the dataset from FAOUN, WDI and GFN.

Table 8 shows the correlation between carbon footprint indicator and other variables. Correlation estimates confirm that carbon footprint has positive association with indicators of GDP per capita, agriculture exports, tractors, and fertilizers; and negative association with indicators of GDP per capita square, agriculture value added and rural population.

Table 8: Correlation between $ln\_CarbonFP_{(i,t)}$ variable and other indicators

Variable	Measure
$ln\_GDP_{(i,t)}$	0.5620
$ln\_GDP^2_{(i,t)}$	-0.5461
$AgriVA_{(i,t)}$	-0.5377
$ln\_AgriExp_{(i,t)}$	0.7720
$ln\_Fer_{(i,t)}$	0.4468
$ln\_Trac_{(i,t)}$	0.5672
$RuralPop_{(i,t)}$	-0.5090

Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

Ratification of cointegration between variables allow estimation of long run relationship with the help of DCCE MG. Table 9 reports heterogeneous parameter estimates by using DCCE MG approach. Results of estimations include estimated coefficients, their P-values and post estimation tests of DCCE MG models (model I to V). Estimation of different models with DCCE MG technique confirms long run relationship between variables.

Coefficient of GDP per capita is statistically significant and its positive sign in estimated models shows that carbon footprint increases with increase in GDP per capita. Coefficient of GDP per capita square is also statistically significant, but its sign is negative in all models. This implies that carbon footprint increases with increase in countries' income in the developing phase of economic growth (GDP per capita), but later it begins to decrease in the developed period, confirming the EKC hypothesis (Grossman and Krueger, 1995).

Coefficient of agriculture value added is also significant and negative, which suggests inverse relationship between carbon footprint and agriculture value added. This inverse relationship indicates agricultural development decreases carbon footprint accordance with Balogh and Jambor (2017) and Balogh (2019). Improved technologies due to agriculture growth provide grounds for negative relationship between carbon footprint and agriculture development. Therefore, it helps to lower resource usage and environmental pollution through environment-friendly technologies and methods (Munasinghe, 1999). Agricultural exports coefficient is also significant, but it is positive, which means agricultural exports brings increase in carbon footprint. Therefore, results are in line with Ang (2009), Chebbi et al. (2011), Balogh and Jambor (2017) and Balogh (2019) declare that agricultural export quantity burdens environment by increasing carbon footprint in exporting country.

Agriculture sector production variable tractor does not affect carbon footprint, but coefficient of fertilizers is statistically significant and positive. So, results of models only confirm the fertilizers as significant determinant of carbon footprint from the selected agricultural sector inputs. Therefore, agricultural production heavily based on fertilizer increases carbon footprint, which certifies production-based emission approach (Foley et al., 2011; Grace et al., 2014; Henders et al., 2015; Balogh, 2019). Moreover, the carbon footprint does not depend on the share of rural population or urban population in the total population of country, which is contrary to the results of Sethi (2017) and Balogh (2019).

Table 9 also reports results of F tests and CD tests by Pesaran (2015) for all estimated models. F test estimates the overall significance of econometric model. Reported F-statistics and their respective P-values for all estimated models reject the null hypothesis 'estimated model is statistically insignificant' and accept the alternative hypothesis 'estimated model is statistically significant'. CD-statistics of all estimated models and their respective P-values do not reject the null hypothesis of weak CD against the strong cross-sectional dependency in the variables. CD test results guarantee that there is a presence of weak cross-sectional dependency in the data, which will not persist in the long run.

Additionally, Table 9 also provides the estimate of turning point of GDP per capita of sample countries, where carbon footprint is at a maximum level. Turning point estimate of GDP per capita is approximately US$ 39940 for selected countries. Carbon footprint declines when the value of GDP per capita becomes US$ 39940 or greater. Therefore, the relationship between carbon footprint and GDP per capita follows the pattern of inverted U-shaped curve.

Table 9: Heterogeneous parameter estimates by using DCCE MG

Variables	Functional forms (dependent variable: $ln\_CarbonFP_{(i,t)}$)				
	I	II	III	IV	V
$ln\_GDP_{(i,t)}$	17.50 (0.000)***	13.45 (0.002)***	15.29 (0.013)**	8.831 (0.028)**	17.82 (0.029)**
$ln\_GDP^2_{(i,t)}$	-0.774 (0.001)***	-0.614 (0.008)***	-0.777 (0.025)**	-0.428 (0.072)*	-0.959 (0.041)**
$AgriVA_{(i,t)}$	-0.027 (0.023)**	-0.035 (0.001)***	-0.346 (0.006)***	-0.020 (0.025)**	-0.038 (0.001)***
$ln\_AgriExp_{(i,t)}$		0.053 (0.012)**	0.052 (0.050)**		0.055 (0.036)**
$ln\_Fer_{(i,t)}$			0.046 (0.024)***		0.041 (0.028)**
$ln\_Trac_{(i,t)}$			2.265 (0.563)	9.848 (0.363)	5.512 (0.454)
$RuralPop_{(i,t)}$				-0.006 (0.766)	0.004 (0.882)
Constant	-0.093 (0.022)**	-0.097 (0.019)**	-0.141 (0.058)*	-0.052 (0.516)	-0.088 (0.370)
$l.ln\_CarbonFP_{(i,t)}$	0.023 (0.008)***	0.025 (0.008)***	0.079 (0.038)**	0.224 (0.000)***	0.066 (0.079)*
Post Estimation Tests					
F- Statistics	7.500 (0.000)***	3.220 (0.000)***	1.330 (0.000)***	5.120 (0.000)***	1.990 (0.000)***
CD- Statistics (Pesaran, 2015)	1.170 (0.240)	-0.250 (0.804)	-0.570 (0.572)	-1.560 (0.118)	-1.310 (0.121)
Inflection point on EKC					

Turning Point[2]	39940$	$\tau^3 = \exp\left(\frac{-\widehat{\omega}_1}{2\widehat{\omega}_2}\right)$	$\widehat{\omega}_1$= 8.90 $\widehat{\omega}_2$= -0.42

Note: P-values of test statistics of DCCE MG estimators are in the parenthesis.
***, ** and * suggest significant at 1%, 5% and 10% level.
Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

Lastly, the findings of Dumitrescu-Hurlin panel causality tests given in the Table 10 confirms that GDP per capita, GDP per capita square, agriculture value added, agricultural exports and fertilizers have acausal relationship with the carbon footprint in selected economies. Table contains statistics and P-values of Dumitrescu-Hurlin causality tests.

Table 10: Dumitrescu-Hurlin panel causality tests

Null hypothesis	W-bar	Z-bar	P-value	Remarks
$ln\_GDP_{(i,t)}$ does not cause $ln\_CarbonFP_{(i,t)}$	2.88	9.98	0.00***	It does Granger-cause
$ln\_GDP^2_{(i,t)}$ does not cause $ln\_CarbonFP_{(i,t)}$	2.80	9.51	0.00***	It does Granger-cause
$AgriVA_{(i,t)}$ does not cause $ln\_CarbonFP_{(i,t)}$	2.84	9.76	0.00***	It does Granger-cause
$ln\_AgriExp_{(i,t)}$ does not cause $ln\_CarbonFP_{(i,t)}$	2.22	6.45	0.00***	It does Granger-cause
$ln\_Fer_{(i,t)}$ does not cause $ln\_CarbonFP_{(i,t)}$	3.47	13.09	0.00***	It does Granger-cause

Note: Statistics and P-values of Dumitrescu-Hurlin causality test results are reported.
*** suggests significant at 1% level.
Source: Authors' calculations using the dataset from FAOUN, WDI and GFN.

6. Conclusion

Macroeconomic analysis of agriculture sector inputs and outputs in the study contributes to the existing literature by evaluating agriculture-specific determinants of carbon footprint. The study investigates the relationship between agriculture sector indicators and carbon footprint by using panel econometrics. This study finds that carbon footprint depends on economic development of countries and confirm EKC hypothesis. Therefore, early stage of economic growth and development upsurge carbon footprint and damages environment, then later, after a turning point, carbon footprint decrease and environmental quality increases.

[2] Turning point is based on the DCCE MG specification:

$$\begin{aligned} ln\_CarbonFP_{(i,t)} &= \omega_{0(i)} + \omega_{1(i)} ln\_CarbonFP_{(i,t-1)} + \omega_{2(i)} ln\_GDPpC_{(i,t)} + \omega_{3(i)}\, ln\_GDPpC^2_{(i,t)} + \omega_{4(i)} AgriVA_{(i,t)} \\ &+ \omega_{5(i)} ln\_AgriExp_{(i,t)} + \omega_{6(i)} ln\_Fer_{(i,t)} + \sum (d_{(i)} z_{(i,s)}) + e_{(i,t)} \end{aligned}$$

[3] Estimation formula by Stern (2004).

The study finds that there is a long run relationship between agriculture value added and carbon footprint. Rise in value addition of agricultural sector in country reduces carbon footprint. Therefore, agriculture sector expansion by employing environment friendly methods and technologies decreases carbon footprint in countries. Furthermore, the positive relationship between carbon footprint and agricultural exports proves that there exists a long run relationship between agriculture sector exports and carbon footprint. It implies that agricultural exports encourage the carbon footprint growth by stimulating the production and transport of agricultural commodities. Finally, the current study also assures that there exists a long run relationship between high scale of agricultural production and carbon footprint. Carbon footprint has positive relationship with high scale of agricultural production, which supports the concept of production-based emission. This relationship underlines that too much use of fertilizers in agriculture sector fosters the carbon footprint growth and damages natural environment of countries.

The conclusion of the current study has some strong implications for policy formulation by suggesting that in agricultural production processes, innovative techniques should be introduced that could ensure less environmental damage and bring considerable decrease in carbon footprint. Departments related to agriculture sector must promote research and development culture for innovative solutions to the current issues in production practices. Furthermore, trade sector must devise policies to incentivize green agricultural exports. Finally, such production techniques must be adopted which are environment friendly and may contribute to reducing carbon footprint i.e. the use of organic fertilizers may provide eco-friendly agriculture.

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Appendix

Table A: List of sample countries

Sustainable Agriculture Index (for high-income countries)			
1. Austria	79.9	2. Denmark	79.6
3. Israel	78.3	4. Germany	78.0
5. Poland	78.0	6. Netherlands	77.1
7. Belgium	74.6	8. Czech Republic	74.5
9. Australia	73.4	10. Japan	73.4
11. South Korea	73.4	12. Canada	73.0
13. Sweden	72.7	14. France	71.0
15. Italy	70.2	16. Portugal	69.7
17. Estonia	69.6	18. United States	68.6
19. Argentina	66.9	20. Spain	66.6
21. Lithuania	66.5	22. Croatia	66.3
22. Greece	65.1	24. Slovenia	63.0
25. United Kingdom	61.5	26. United Arab Emirates	56.9
27. Slovakia	54.6	28. Latvia	53.7
29. Luxembourg	53.6	30. Saudi Arabia	52.4
Sustainable Agriculture Index (for middle-income countries)			
31. Colombia	76.5	32. Cote d'Ivoire	73.9
33. Zambia	72.7	34. Cameroon	72.2
35. Tunisia	70.1	34. Mexico	61.3
37. Turkey	68.3	38. Romania	68.0
39. Kenya	66.6	40. Nigeria	66.6
31. India	65.5	42. Lebanon	65.1
43. Brazil	64.2	44. Jordan	64.0
45. Indonesia	61.1	46. China	60.7
47. Ghana	57.4	48. Russian Federation	53.9
49. South Africa	52.4		
Sustainable Agriculture Index (for low-income countries)			
50. Rwanda	71.0	51. Tanzania	70.5
52. Zimbabwe	70.5	53. Uganda	68.9
54. Mozambique	68.4	55. Burkina Faso	67.5
56. Ethiopia	66.6		

Note: Index values are ranked: zero to hundred, while hundred is maximum sustainability value and best progress to meet societal, economic, and environmental main indicators of performance.

Source: Economist Intelligence Unit, Food Sustainability Index 2018

Table B: Indicators selected for the estimation

Sr. no.	Indicator (unit)	Abbreviation and Description
1	Carbon Footprint (Global hectors)	CarbonFP: It evaluates CO_2 emissions related with use of fossil fuel. In the ecological footprint[4] estimates, emission quantities are estimated into biologically productive areas required for absorbing this CO_2 emission. The carbon footprint is considered in the ecological footprint because it is a rival user of bio productive space. Increasing CO_2 concentrations in the atmosphere represent an increase of ecological debt. It is generally quantified in global hectares.
2	GDP per Capita (Constant 2010 US$)	GDPpC: GDP (gross domestic product) per capita is the GDP divided by midyear value of population. It is total of values added by all producers in the country and taxes on product, excluding subsidies not included in the value of products.
3	Agriculture Value Added (Percentage of GDP)	ln_AgriVA: Agriculture value added is measured as percentage of GDP of country. Value added of agriculture is the net output value of sector after totaling all final outputs and deducting intermediate inputs.
4	Agricultural Exports (1000 US$)	ln_AgriExp: Agricultural exports indicator measures value of agriculture sector exports in thousand US dollars.
5	Tractors (Per 100 sq. km of arable land)	Trac: Tractors are the indicator of machinery employed in agricultural sector. This indicator measures tractors per 100 square km of arable land.
6	Fertilizers (Kg per hectare of arable land)	Fer: Fertilizer indicator measures utilization of fertilizers in kilograms per hectare of arable land of agriculture sector.
7	Rural Population (Percentage of total population)	RuralPop: Rural population is percentage of total population who lives in rural parts of country.

Note: Current study uses natural log of indicators of Carbon Footprints, GDP per Capita, Agricultural Exports, Tractors, and Fertilizers in the estimations.

Source: FAOUN, WDI and GFN.

[4] It is an estimate of area consists of water and biologically productive land, which a population, individual, or action requires to create the natural resources it utilizes and to take in the waste it creates, employing resource management practices and existing technology. It is estimated in global hectares. Nation's Footprint include sea and land from all other countries. It normally mentions Ecological Footprint of consumption.