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# Nexus between agriculture productivity and carbon emissions a moderating role of transportation; evidence from China

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This research investigates the nexus existing between agricultural productivity and CO2 emissions under the moderating effect of transportation within the context of China. The data for this study are drawn from the World Bank and cover the period 1991–2019. The data is analyzed using an autoregressive distributed lag approach (ARDL). Agricultural productivity is measured in terms of crop and livestock production. The goal of this research is to make some contributions, as crop production has a negative impact on carbon dioxide emissions in the long and short run. Carbon dioxide emissions are positively influenced by livestock production in the long run, but negatively in the short run. As for the moderation effect, the results indicate that transportation significantly impacts agricultural productivity and CO2 in both the long and short term. The study provides in-depth insights to policy makers for designing more suitable policies regarding the necessity of decreasing CO2 emissions. In addition to discussing the crucial implications, future directions are also discussed.

#### KEYWORDS

CO2 emission, transportation, ARDL, agriculture, productivity

## 1 Introduction

In China's economic development, the agriculture sector plays a vital role. As per, Zheng et al. (2019), China is one of the most growing economies in the world. China is dominant in producing vegetables, meat and different kinds of cereals. Further, China is in the first position regarding the largest population ranking. Thus, it is crucial to understand how agricultural activity affects CO2 emissions and also how transportation moderates this relationship. The main objective of this study is to determine how China's agricultural sector is affecting the environmental ecosystem.

Further, the economic development and climate change have been in line for the last two decades. As a result of economic growth, carbon dioxide emissions contribute to the worldwide climate crisis, such as floods, storms, extreme temperatures, melting glaciers

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and rising sea levels (Fei, et al., 2011). One of the greatest threats fronted by humanity on this globe is climate change (Lu et al., 2018). In many parts of the world, rising global average surface temperatures are melting glaciers and altering precipitation, severely eroding regional water supply advantages (Nie et al., 2021). In recent decades, many experimental studies have proclaimed that climate change and global warming are the causes of environmental deterioration and the researchers are highlighting the significance of sustainable environment (Lu et al., 2018).

The sustainable environment denotes securing the climate for posterity without compromising the present speed of economic flourishment. Sustainable progression is essential to form this globe into a livable space for not only the current generation but also for posterity. Minimizing carbon discharges is the major target to achieve the sustainable evolution (Barroso, 2020). Many analysts have examined the relationship between climate and sustainability, while many examined other variables that may affect this relationship from this perspective. One of the key variables in evaluating the relationship between environment and growth (Nathaniel et al., 2021), is energy consumption as it is the primary contributor to CO2 emissions.

As all economic sectors are accountable for their growth, so all have some primary or secondary influence on carbon dioxide emissions, and likely its accurate for the agricultural sector (Khan et al., 2021). The agricultural sector accounts for 14%-30% of global GHG emissions because of its reliance on fossil fuels (Zhang et al., 2020). Indeed, the use of gasoline-powered farm equipment, pumping water for irrigation, indoor livestock care, and the use of nitrogen-rich fertilizers all contribute to agriculture's extraordinary greenhouse gas emissions. According to the Food and Agriculture Organization of the United Nations (FAO), agricultural sector CO2 emissions will likely to decrease by almost 80%-88% between now and 2020 (Zhang et al., 2020). Indeed, it can be attained by replacing the agronomics sector's layout and alternating the energy mix utilized in the agricultural zone by using sustainable sources. This also highlights the significance of the agricultural sector that it is a dominant root of earnings, especially in growing countries (Jebli et al., 2020). Further, agriculture is also in charge of supplying food to masses of humans all over the world. Chien et al. (2022) stated that agronomy could have a constructive or obstructive influence on the standard of the environment. Thus, through energy, and utilization, agriculture can influence the environment adversely.

One of the major causes behind CO2 emissions is energy consumption which is increasing due to the utilization of machinery in production and transport activities, agricultural igniting procedure, soared demand for unprocessed materials, raised use of land along with dangerous cooling and heating mechanisms. Therefore, environmental sustainability is the need of the hour. Thus, now a days, biological farming is getting attention as it also enhances ecological standards by reducing the part of bug spray and reduces the amount of high-energy feed (Chien et al., 2022; Zhou et al., 2022) Therefore, agricultural activity need to be based on green sustainable methods in order to reduce CO2 emissions. In this research, the main focus is on CO2 emissions due to agricultural activities. The main motivation of this research is based on the campaigns about green agricultural practices, climate change awareness efforts, and efforts for reducing CO2 emissions due to agricultural processes. Although past studies have investigated the link between CO2 emissions and agriculture but they fail to consider the moderating effect of transportation. The contributions of this study are manifold, first, this study aims to examine do agriculture activities impact on CO2 emissions under the moderating effect of transportation which will help stakeholders and policy makers in improving the agriculture sector by designing appropriate policies. Second, this study will provide in-depth insights to researchers and practitioners about how livestock and crop production can be enhanced. Third, the findings of this research will provide crucial strategies which other countries can follow to achieve agricultural sustainability along with a decrease in CO2 emissions.

The necessity to reduce global warming and CO2 emissions has received much attention from all countries across the globe. Therefore, the government and policy makers has called for empirical studies and practical measures to achieve sustainable environment. This issue of sustainability is the main priority for environmentalists, researchers, policy makers and government. However, it seems nearly impossible to achieve the targeted goals because of the increase in economic growth that degrades the environment due to various activities like agriculture, forestry and manufacturing products. In view of past studies, the existing research on environmental quality has considered a number of key variables that can influence the quality of the environment, most notably urbanization, globalization, tourism, industrialization, direct expenditures, literacy, public expenses, and inclusive finance (Usman et al., 2022). However, there is a dearth of literature about the moderating role of transportation. Therefore, this research mainly focuses on providing new perspective on the existing environment literature. This research seeks to provide answers to following key research questions: 1) Is there any effect of agricultural activities on environmental degradation in China? 2) What sort of moderating effect do transportation has on the relationship between agriculture processes and CO2 emissions ? 3) What is the role of transportation sector in increasing CO2 emissions in China ? In this way this research aims to recommend policymakers about pragmatic initiatives needed in the agricultural sector of China.

## 1.2 Significance of the study

This study will pursue three precise objectives to fill the existing research gaps in the literature. The first goal is to evaluate

the role of transportation in figuring out the carbon dioxide emissions of the transport sector. The second objective is to empirically examine the effect of agricultural productivity on carbon dioxide emissions. The study's third and last goal is to calculate the transportation sector's emissions of CO2. In this paper, we explicitly include transportation in imagining the relationship with carbon emissions.

# 2 Literature review

In the past, several experimental studies have documented the relationship between agricultural productivity and emissions of carbon dioxide, and these studies have been discussed below. However, literature has shown a dearth of studies taking transportation as the moderator. It is generally accepted i.e. there is a relationship between agricultural productivity,  $CO_2$ discharge with the subsequent temperature change.

As per literature, the agriculture accounts for a quarter to a third of worldwide CO2 emissions (World Bank, 2013; Pickson et al., 2020). Agricultural activities account for about one-tenth to 12th percentage of total global emissions. Meanwhile, land use and land cover converted to agriculture account for about twelvetwenty % of worldwide carbon discharges (Villoria & Nelson, 2019). Agriculture's share of worldwide carbon dioxide emissions is relatively smaller than that of the thermodynamic industry. To decrease carbon dioxide emissions due to agricultural activity, there is a high demand to introduce low-carbon farming methods that encourage economic development and safeguard the environment, (Dufour et al., 2009; Zhou et al., 2022; Jiang et al., 2020; Koondhar et al., 2020).

In another study, Reynolds et al. (2015) determined the link between agronomical product yield and CO2 emissions for South Asia and sub-Saharan Africa. The model estimates confirm a link between agricultural yield and CO2 emissions. Likewise Wang H. et al. (2020) studied the effect of crops, crop byproducts, and harvesting procedures on CO2 discharges. This research hypothesizes that harvest residues either raise CO2 discharges or degrade environmental quality. Similarly a study found that the effects of imitated CO2 emissions effects agriculture production and household well-being (Edoja et al., 2016). The simulation results of this study admitted the negative correlation between CO2 emissions and agricultural productivity. The relationship between climate change and the production of agriculture, and the difference in agricultural production to global warming was found smaller than the response of production to CO2 fertilization are determinant by (Nwaka et al., 2020).

Since a few decades, China has been gradually improving as a country. Several agricultural machinery subsidies tend to promote agricultural progression in the Chinese Government. As global warming becomes more serious, actual CO2 emissions have become a key research field in recent years (Shin et al., 2014, Zeng et al., 2019; Zhu et al., 2021). Through photosynthesis

(plants) agriculture contributes to reduce CO2 emissions on one hand, while on the one hand, it adds to its metabolism and endurance from the energy-related CO2 discharges that are unavoidable in the production process because input elements lead to increased CO2 emissions. A study by Yang et al. (2020a) discussed the energy linked CO2 emissions due to using coal and electricity. Another study highlighted that CO2 emissions are linked to the utilization of energy per unit (Chi et al., 2021) and it is also found that CO2 emissions has a strong relationship with the gross domestic product (Wang R. et al., 2020; Yan et al., 2020; Aslam et al., 2021). Considering these facts, based on total factor output and factor replacement, the data envelopment analysis (DEA) method is broadly applied to measure environmental and energy performance, especially carbon emission performance.

Agricultural production extensively uses machinery and transportation that preoccupies bio-fuels and releases carbon emissions (Sardar, 2022). Transport and transport exercise in the sector of agriculture, such as elevating crops, animal husbandry, forest ranging, fishing, sources of pollution of the environment leads to the emission of CO2 (Gomez et al., 2020). Machines used in agriculture, for instance land tilling, yielding crops, and groundwater pumping, emit CO2 (Rahman et al., 2021). Transport of agricultural products, livestock and fishing, forest timber, etc. Are primarily done using bio-fuel-based modes of transport, causing pollution through carbon emissions (Zhan et al., 2018). Two types of emissions are seen in agricultural production processes (Yang et al., 2018). This includes direct and indirect discharges of CO2 gases. Direct carbon emissions arise from the use of fossil fuels in various agricultural and transportation activities (Bhatti et al., 2021). While the indirect carbon emissions are due to the various processes used in agricultural activities. The carbon emissions that are embodied are larger than those produced in course of production of agriculture (Niu et al., 2020; Khursheed et al., 2021). In addition, emissions of CO2 released during international and domestic transport of agricultural activities are an important part of CO2 emissions (Wang et al., 2019).

In this research, transport competitiveness adjustment is used as a moderator to determine changes in agricultural trends. This suggests that the high competitiveness of the transport sector plays a value-adding role for the agricultural sector in reducing CO2 emissions in the transport sector. This research has the theoretical underpinning of the environmental Kuznets curve (EKC). This theory is selected because it is used in several past empirical studies. This theory is also validated by several past researchers (Hanif, 2018; Sharma et al., 2021). This research using the theoretical foundation of EKC proposes that agricultural productivity effects on CO2 emissions and the transportation positively moderates this relationship. Based on the literature reviewed, we propose the following hypothesis;

H1: A positive relationship exists between agricultural productivity and CO2 emissions.

H2: Transportation moderates the relationship between agricultural productivity and CO2 emissions.

TABLE 1 Variables and definitions.

Symbol	Definitions	Sources
Co2	CO2 emissions (kt)	World Bank
LP	Livestock production index (2014–2016 = 100)	World Bank
СР	Crop production index (2014–2016 = 100)	World Bank
ТР	Transport services (% of commercial service imports)	World Bank
	Symbol Co2 LP CP TP	SymbolDefinitionsCo2CO2 emissions (kt)LPLivestock production index (2014-2016 = 100)CPCrop production index (2014-2016 = 100)TPTransport services (% of commercial service imports)

TABLE 2 Descriptive statistics.

Variable	Obs	bs Mean Std. Dev		Min	Max	
ID	30	1	0	1	1	
YEAR	30	2004.5	8.803	1990	2019	
CO2	29	303448.28	305289.98	-100000	1000000	
LP	30	75.61	21.91	31.22	100.89	
СР	30	74.322	20.711	42.3	107.9	
ТР	30	33.996	13.193	18.382	78.896	
I.LP	30	2339.989	432.955	1603.142	3081.996	
I.CP	30	2323.566	421.832	1486.414	3337.309	



# 3 Methodology and data

## 3.1 Data source

The purpose of the study described above is to identify whether transportation has a moderating effect on agricultural productivity and carbon emissions. In order to test the relationship between study variables, the ARDL method was applied to time series data spanning 1991 to 2019.



World Development Indicators (http://data.worldbank.org) provided the data sets of the selected variable for this study in order to accomplish the study objectives. Here, CO2 emissions represent a dependent variable, and livestock production represents an independent variable. Table 1 provides a comprehensive overview of the variables, their definitions, and symbols, as well as the source of the data and the descriptive analysis. Kilotons are used to measure CO2 emissions. Based on 2014–2016 = 100, the livestock and crop production indices are calculated. From Figure 1 to Figure 3, it is illustrated that there has been a trend in the variables, LP, CO2, CP, and TP in China during the period 1990 to 2019.

Figure 2 shows the trend in variables (i.e., CO2, LP, CP, and TP) as a function of time. As shown in Figure 4 and Table 1 contain all the details regarding the variables and sources of the data in regard to the description of the variables.

## 3.2 Empirical model

Most observed and hypothetical studies consider the agricultural and transport sectors the most important factors



Graphical representation of CP over time.



affecting CO2 emissions (Ullah et al., 2020). An important source of income, agriculture, has contributed to increased environmental pollution. As the agricultural sector subsidizes to economic development, it is also responsible for the emission of CO2 and environmental deprivation from land use, deforestation and livestock use of machinery, fertilizers, stump burning and fossil fuels. An analysis of the impact of AP on the environment is conducted using Borlaug's hypothesis (Angalsen et al., 2001). This hypothesis suggests that the early stages of AP reduce eco-friendly value. As a result of agricultural productivity, environmental value is enhanced through increased demand for goods and services produced per environmental regulations. In general, the econometric model of our study can be characterized as follows:

$$Co2, t = \beta 0 + \beta 1AP + \beta 2 TP + \varepsilon$$
(1)

Where CO2t represents CO2 emissions, APt represents agricultural productivity, t denotes time series and  $\varepsilon$  is the error term. The estimate of  $\beta 1$  is likely to lead to the conclusion that agriculture productivity reduces environmental pollution by reducing the number of dirty activities in the economy (Ullah et al., 2022).

Based on the findings of this study, it is suggested that Transportation (TP) might act as a moderating factor in the case of China since it directly affects CO2. Consequently, this study seeks to discover the role of TP in moderating the effect of LP on CP and CO2 emissions. An interaction variable was presented by (Cohen et al., 2014) to check the moderating effects of the interaction variables in this setting. According to (Chen and Myagmarsuren, 2013), as a second step, we construct two models to verify moderating factors' effects. First, we added a proxy for transportation (lnTP) to Equation 2 in order to estimate the main effect as presented below:

$$\ln Co2(t) = \beta 0 + \beta 1(\ln LP) + \beta 2(\ln CP) + \beta 3(\ln TP) + \varepsilon$$
(2)

Added interaction variables to Eq. 2 as an independent variable in the second model after which we get new Eq. 3 to evaluate transportation's moderating effect.

$$\begin{split} \ln Co2\left(t\right) &= \beta 0 + \beta 1\left(\ln LPt\right) + \beta 2\left(\ln CPt\right) + \beta 3\left(\ln LPt*\ln TPt\right) \\ &+ \beta 4\left(\ln CPt*\ln TPt\right) + \varepsilon \end{split}$$

An interaction variable will be considered moderating if it shows statistically significant relationships with the other variables, according to Cohen et al. (2014). The coefficients should also be statistically significant, thus confirming that transportation plays a moderating role in our study. Thus, TP is an important moderating variable in statistical methodology since it affects the direct relationship between CO2 emissions and the regressors (LP and CP).

## 3.3 Methods

Whenever a long-term relationship is to be estimated, it is necessary to determine the order of integration by testing the unit root of each variable. Appropriate methods for the study are determined by factors such as integration order or stationarity characteristics. In the results and discussion section, we present the results of the analyses of Dickey and Fuller (1979), Dickey and Fuller (1981) and Phillips and Perron (1988) using the ADF and PP tests, respectively. In order to answer research questions empirically, we consider the order in which our study variables are integrated. For the examination of asymmetry relationships among fundamental variables, we used recently advanced econometric methodology, namely, the autoregressive

distributed lag (ARDL) bounds-testing approach to cointegration, presented by (Pesaran et al., 2001) for symmetric co-integration, and the ARDL bounds-testing approach. A variety of techniques have been used to investigate long-run associations between variables in literature in the related field (Engle and Granger, 1987; Johansen, 1991), but as indicated in a recent study (Liu et al., 2020) and based on the following superior characteristics, this technique has been selected: The use of ARDL models is recommended only when the underlying variables have mixed integration orders of I (0), and I (1), and none of the series have been integrated at the second level. Alternatively, other conventional co-integration methods are limited to series in the I (0) and I (1) states (Pesaran et al., 2001; Satti et al., 2014). The second benefit of the ARDL framework is its ability to provide efficient results, as it is free of serial correlations and endogeneity issues, as well as when endogenous explanations are present (Liu et al., 2020). Lastly, both techniques produce solid results, even when the sample size is small (Hsueh et al., 2013).

#### 3.3.1 The linear ARDL bounds test to the Cointegration framework

Agriculturalization leads to a shift from green to blue economic growth. We can estimate CO2 emissions in the long run using Eq. 4. We will then assemble our model into an errorcorrection format, which will enable us to assess agricultural productivity over the short and long term using the same equation. According to (Pesaran et al., 2001), the authors describe the ARDL bounds testing approach for exploring long-run and short-run linear relationships in Eq. 4.

$$\Delta CO2, t = a_0 + \sum_{n=1}^{p} \pi \Delta CO2, t - 1 + \sum_{i=0}^{p} \psi \Delta AP, t - 1$$
  
+ 
$$\sum_{n=1}^{p} \mu i \Delta TPt - 1 + \dot{\omega} 1CO2, t - 1 + \dot{\omega} 2AP, t - 1$$
  
+ 
$$\dot{\omega} 3TP, t - 1CO2 + \varepsilon t$$
(4)

Calculating lags in the short and long run requires consideration of several factors: 1) the first difference operator, 2) the intercept or continuous parameter, 3) the optimal number of lags, 4) and 5) the short and long-run coefficients. An alternative hypothesis of linear co-integration among variables (H0:  $\gamma 1 = \gamma 2 = \gamma 3 = \gamma 4 = 0$ ) is compared with the null hypothesis of no co-integration among the underlying variables (H0:  $\gamma 1 = \gamma 2 = \gamma 3 = \gamma 4 \neq 0$ ). Testing for the null hypothesis of no co-integration among the underlying variables is conducted by applying the ARDL bounds approach. These hypotheses are tested based on the nonstandard F-test proposed by (Pesaran et al., 2001), famously known as FPSS. The authors provide critical bound values at different levels of significance. A null hypothesis that no co-integration exists is rejected if the calculated value of the test statistics is higher than the upper

Variables	CO2	LP	СР	ТР	I.LP	I.CP
CO2	1.000					
LP	0.921	1.000				
	(0.000)					
СР	0.975	0.963	1.000			
	(0.000)	(0.000)				
TP	-0.650	-0.825	-0.769	1.000		
	(0.000)	(0.000)	(0.000)			
I.TP	0.290	0.309	0.202	0.154	1.000	
	(0.120)	(0.096)	(0.285)	(0.415)		
I.CP	0.169	-0.003	0.023	0.544	0.827	1.000
	(0.373)	(0.989)	(0.906)	(0.002)	(0.000)	

TABLE 3 Pairwise correlations.

bound's critical value. The null hypothesis is accepted if the test statistics decrease below the inferior bound critical value. We could conduct another co-integration test if the test statistics fall between the upper and lower bound critical values. Additionally, ARDL assumes that all variables explain the dependent variable in an asymmetric manner.

## 4 Empirical results and discussion

All variables in the study are described in Table 2, including mean and standard deviation, maximum and minimum values, and *p*-values for Cramer von Mises, Shapiro-Wilk, and anderson Darling tests. As a result, Co2 and both interaction variables of AP have significantly higher means. In both the interaction terms of AP and the standard deviation of Co2 there is a high level of volatility compared to the rest of the variables.

The results in Table 3 indicate that TP correlates negatively with CO2, LP, and CP. On the other hand, it has a positive correlation with the other variables. The moderating term (I. LP, CP) correlates positively with the other variables, except for the correlation of I. LP with LP.

We must ensure that our variables are stationary when using time series data. This is because estimations based on nonstationary data can be misleading. Therefore, before we perform long-run estimations (through ARDL), we apply the unit root test to ensure that variables involved are stationary. Table 4 presents the unit root test results as described by (Ng and Perron, 2001).

In Table 5, it is stated that the ARDL bounds test could only be applied to variables with mixed integration orders I (0) or I (1). We used the ADF test, developed by (Dickey and Fuller, 1978; Dickey and Fuller, 1981), as well as the PP test, developed by (PHILLIPS and PERRON, 1988) to determine the stationary properties of the variables; the results are presented in Table 5. Based on this, both LP, I. LP, the

#### TABLE 4 Unit root testing.

Variables	Augmented fuller	dickey-	Phillips-perron		
	I (0)	I (1)	I (0)	I (1)	
CO2	-2.303	-4.151***	-3.314	-6.854***	
LP	-5.515***	-	-2.765*	-	
СР	-0.092	-6.000***	0.309	-7.846 ***	
ТР	-3.181**	-	-4.639***	-	
I.LP	-1.953	-3.986***	-1.736	-4.274***	
I.CP	-2.551	-4.783***	-3.081***	-	

Note: \*\*\*p < 0.01; \*\*p < 0.05; and \*p < 0.1.

interactive term (i.e. the interaction variable that results from multiplying the TP and I. LP in order to examine the moderating effect of TP), CO2, and CP are non-stationary at the level, however, as per ADF, they are stationary when the first difference is taken. ADF results are also confirmed by the PP test. At both the level and the first difference, the TP and LP are found to be stationary. The results obtained from unit roots are supported by both tests, demonstrating their robustness.

Based on the results of the linear ARDL bound test on the stationarity of the variables, first, we applied the co-integration test using the linear ARDL bound test, which is shown in Table 5. In all models from Equations (1)–(3), ARDL F-statistics are greater than the upper bond critical values given by (Pesaran et al., 2001) at all significance levels 1%, 5%, and 10%. In the case of China, the co-integration between the AP, the Co2, the TP, and the interactive term was established over the period of study. A diagnostic and stability test was performed to ensure the robustness of the results; as a result, ARDL bounds test of (Pesaran et al., 2001) proved to be robust, reliable, and useful for the formulation of policy recommendations. This study also demonstrates a strong long-term co-integration among variables (significant F-statistics) found in the linear ARDL model (Table 5).

Also, we apply some robust analysis to the diagnostic test, and the results are also provided at the bottom of Table 5. It is demonstrated that the residuals are normally distributed in the BJarque-Bera test, BD-Watson test, and BAmsey's RESET test

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that the data is homoscedastic under the given model, whereas BD-Watson test reveals no autocorrelation. Finally, the BAreush Pagan Godfrey test demonstrates that data is homoscedastic within the given model.

ARDL model is implemented in a suitable manner using the cumulative sum of the square of recursive residuals (CUSUMsq) tests, as Brown 1976) suggested. As shown in Figure 5, the CUSUMsq test graphs lie within the red colored critical bounds at a 5% confidence interval. The blue line in the middle of the graph represents the measurements of the cumulative sum of the squares of the residuals. According to the CUSUMsq graphs, our model appears to be well-stable.

Using ARDL approach, Table 6 provides the results of short-run and long-run estimations. Carbon dioxide emissions (CO2) in panel 1) are positively and statistically significantly related to livestock productivity and transportation, while negatively and statistically significantly related to crop productivity. In the short run, the coefficient of LP is 32907.8, while in the long run, the coefficient is 4829.8. This indicates that a 1% increase in LP will result in a 98% increase in carbon emissions per capita.

Table 6, also provides the results of the estimation with interaction variables (see panel b). The analysis results are still significant after the inclusion of interaction variables, except livestock productivity (LP). The coefficient of crop productivity is significant but its sign is negative ( $\beta$  = -13890.14, p < 0.05). Further, when interaction terms (variables) are included in the analysis, LP and CP have a greater impact on carbon emissions than before. The main difference between model 1) and model 2) is that the inverted U-shaped relationship has disappeared and the interaction variables (lnLP x TP and CP x TP) have become statistically significant. It is evident that Transportation acts as a moderator in the relationship between Agriculture Productivity (AP) and Carbon Dioxide (CO2). Nasir and Rehman found similar results as described in Table 6. Overall, the long-run results suggest that transportation contributes significantly to CO2 emissions as a moderator.

In the second portion of Table 6, the short-run estimates are presented for both cases: the main effect (without an interaction term) and the main effect with an interaction or moderating effect. Crop productivity error correction terms are statistically significant at 1% and have a negative coefficient.

TABLE	5	Linear	ARDL	bounds	test	to	co-integration.	

Estimation method **Diagnostic test** ARDL Bounds Test JB LM BPG RR **F**-Statistics Lag Length CO2t = LP, CP, TP(1,0,2,0) 0.0174 0.236 0.083 0.072 0.326 CO2t = LP, TP I. LP(1,0,2,2)0.0022 1.993 0.003 0.008 0.454 CO2t = CP, TP, I. CP (1,2,1,0)0.0087 0.601 0.050 0.038 0.967

Note: (PBG, represents the *p*-values of the Heteroskedasticity Test, while BPG, and RR, represent the *p*-values of Breusch-Pagan-Godfrey tests. The Jarque Bera test *p*-values are depicted in Jarque Bera.



TABLE 6 Results of ARDL Short run and long run analysis.

a) Without	interaction effe	ct		b) With interaction effect			
Coeff.	Std. Error	t stat.	Prob	Coeff.	Std. Error	t stat.	Prob
Long-run (De	p. Variable = CO <sub>2</sub> )			Long-run (dej	p. Variable = CO <sub>2</sub> )		
32907.83	9712.71	3.39	0.003	4829.807	3586.442	1.35	0.192
-16985.18	9618.306	-1.77	0.092	-13890.14	6211.071	-2.24	0.037
-32363.84	9606.89	3.337	0.003	-27851.88	13094.96	-2.13	0.047
-	-	-	-	514.3898	164.1147	3.13	0.005
-	-	-	-	994.7256	211.9986	4.69	0.000
0.1850	0.1561	1.1850	0.2476	3.1016	0.8624	3.5961	0.0369
Short-run (De	p. variable = $CO_2$ )			Short-run (De	p. variable = $CO_2$ )		
-71822.82	40539.45	-1.77	0.091	28160.59	24043.95	1.17	0.255
-0.3391	0.31781	-1.07	0.296	-96055.72	38909.91	-2.47	0.023
-	-	-	-	-40386.38	19275.09	-2.10	0.050
-	-	-	-	959.0669	370.319	2.59	0.018
-	-	-	-	61383.84	49203.56	1.25	0.228
-6.461	2.769	-2.33	0.004	-1.0689	0.4779	-2.23	0.035
0.7521				0.8177			
0.6409				0.7409			
1.707				3.0399			
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To determine the robustness of the model, the pairwise Granger causality test is estimated between two variables simultaneously, which elaborates the directional linkages between them. In Table 7, we demonstrate the results of the pairwise Granger causality analysis. The estimations of the pairwise Granger causality shows unidirectional causality between LnLP to LnCO2, LnLP to LnCP, ln (LP\*TP) to LnCO2, Ln (CP\*TP) to LnCO2, lnLP to Ln (CP\*TP) and LnTP to Ln (CP\*TP).

# **5** Discussion

China is one of those countries which are progressively improving its agricultural methods for achieving environmental sustainability. Further, China produces energy from coal, a nonrenewable source, this research recommends using a renewable source to control CO2 emissions. Further, as per Abdoli et al. (2018) latest biofuels, including biogas and other agricultural

Variables	$\Delta \ln CO_2$	ΔLΡ	Δln CP	ΔLn TP	ΔLn (LP*TP)	Δln (CP*TP)
$\Delta \ln CO_2$	_	12.214*** (0.0005)	12.419*** (0.0007)	0.027 (0.868)	12.198*** (0.0007)	11.464*** (0.0005)
Δln LP	2.971* (0.0951)	-	7.878*** (0.0050)	0.821 (0.3647)	6.821*** (0.0095)	7.342*** (0.0067)
Δln CP	1.748 (0.2863)	0.020 (0.8858)	-	0.000 (0.9921)	0.102 (0.8934)	0.017 (0.6944)
Δln TP	1.031 (0.4065]	0.238 (0.6251]	0.002 (0.9617]	-	0.706 (0.4519]	0.446 (0.8197)
Δln (LP*TP)	0.045 (0.9502)	0.088 (0.5666)	0.008 (0.9271)	0.723 (0.3948)	-	0.118 (0.6419)
$\Delta ln$ (CP×FP)	2.380 (0.1810)	7.817*** (0.0065)	6.277*** (0.0060)	1.302 (0.2629)	7.146*** (0.0069)	-

TABLE 7 Granger Causality/Block Exogeneity Wald test.

Null hypothesis, no causality; represents to p-value; \*, \*\* and \*\*\* indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance.

deposits such as hazelnut, wheatgrass etc, are the key source of renewable energy in the agriculture sector. Therefore, the increase in global warming due to CO2 emissions is one of the most investigated research topics. Although several studies have analyzed the factors leading to pollution, in this research a new comprehensive framework is developed and tested on Chinese economy. The findings of this study reveal a significant relationship between agriculture and CO2 emissions under the moderating effects of transportation. Thus, this study recommends that the government of China should organize trainings for farmers regarding the latest harvesting techniques. This study's results give policymakers direction to focus more on research and development activities. This study also has a few limitations, including limited inclusion of variables and sample size. Thus, future researchers can increase the variables with a huge sample to analyze this key relationship. As the effects of agricultural productivity on CO2 may differ among different economies. Further, all categories of green activities can reduce the level of CO2 emissions as the energy generally used in the agriculture sector is highly dependent on fossil fuels. Therefore, the agriculture sector of China should increase the photosynthesis process to increase the oxygen supply for the environmental sustainability. Thus, organic farming will not only positively affect human health but also help environmental sustainability. This study also deserve consideration from policy makers in China for designing policies regarding the significance of transportation in understanding the relationship between agricultural activities and CO2 emissions. Additionally, the policy makers should design policies to create the awareness about the necessity of decreasing CO2 emissions through the understanding the importance agriculture processes. Thus, it is crucial to develop the rural areas focused on modern and green agriculture policies. Therefore, this study will help policy makers in designing more suitable policies for reducing the emissions of CO2 considering the characteristics of that country.

# 6 Conclusion

In this study, the impact of agricultural activity on CO2 emissions is investigated under the moderating effects of transportation. For the

empirical results, we have used very widely applicable econometric methodology, ARDL applied on a data from 1991 to 2019. For the presentation of agricultural productivity, crop and livestock production are used. The findings revealed that the crop production negatively affects carbon dioxide emissions in the long and short run. While livestock production positively affects the carbon dioxide emissions and negatively in the short run, the moderator (transportation) shares a negative relationship with the dependent variable, that is CO2. Therefore, both hypotheses are accepted. As a result, the Granger Causality test confirms that agricultural productivity contributes to CO2 emissions in a bidirectional fashion, as opposed to the one-way causality between transportation and CO2, which does not show a causal relationship with CO2. Hence, the findings of this study reveal a significant relationship between agriculture and CO2 emissions under the moderating effects of transportation.

In case of with moderation effect, the results reveal a significant and positive moderation effect of transportation on the relationship between agricultural productivity and CO2 in the long and short run. This result is consistent with past studies (Adams et al., 2020; Kocak et al., 2020). Thus, the results highlight the significant role of agricultural productivity, and transportation in understanding the environmental degradation due to CO2 and the research objectives are achieved. The study concludes with highlighting significant role of agriculture and transportation in understating the control on CO2 emissions. Further, the study also provides empirical implications, as the moderation of transportation confirms its effect on the relationship between agricultural activity and CO2 emissions. Therefore, this study recommends that government should strengthen the control of transportation and should regulate the use of green agricultural methods. Further, if the grip on transportation is strengthened then CO2 emissions will be reduced leading to achieve environmental sustainable goals. In the presence of strict government regulations, green agricultural practices should be adopted and resultantly, the CO2 emissions will be decreased. This study gives a new perspective to researchers and practitioners for understanding the significance of reducing CO2 emissions by considering the role of agriculture sector along with transportation sector. Thus, this study recommends that China should adopt organic farming techniques and the latest technological and innovative farming techniques and the farmers should be introduced to new farming techniques.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

DW wrote the paper draft and collected the data. RH helped in formatting and also managed statistical issues. IA ensured grammar checks and overall structure of the paper.

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# **Conflict of interest**

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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