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Shocks in agricultural productivity and CO_2 emissions: new environmental challenges for China in the green economy

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ABSTRACT

The primary motive behind this research is to see the role of China's large agriculture sector in promoting or demoting CO_2 emissions. Therefore, we applied linear and non-linear ARDL models by collecting data over the period 1971–2019 for China. The results of the linear model suggest that livestock production can help to reduce CO_2 emissions both in the short and long run. In the non-linear model, the short-run estimates of livestock production are insignificant, however, in the long run, the positive shock in the livestock production helps to reduce the CO_2 emissions and the negative shock is insignificant. On the other side, an increase in crop production deteriorates the environmental quality in the short run in both linear and non-linear models. In long run, the estimate of crop production in the linear model is insignificant and in the non-linear model, the estimated coefficients of both positive and negative shocks in crop production are negative implying that a positive shock reduces the CO_2 emissions while the negative shock increases the CO_2 emissions.

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1. Introduction

Economic growth and global warming are going side by side for the past several decades. Economic growth is causing greenhouse gas emissions (GHG) which is the main cause of global climate change such as floods, droughts, storms, extreme temperatures, melting glaciers, and rising sea level (Apergis & Ozturk, 2015; Skare et al., 2020; Ullah et al., 2021). According to an estimate, the world's collective GDP was about US$1,423.6 billion in the year 1961 and it soared to about US$75,124 billion in the year 2013 (Shuai et al., 2018). In percentage terms, it was estimated at 8.1% per annum during the years 1961–2013. The driving force behind economic development

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is the massive reliance on energy (Khoshnevis Yazdi & Golestani Dariani, 2019; Usman et al., 2020), obtained from fossil fuels such as coal, oil, and gas which are acting as a catalyst in CO_2 emissions and consequently global warming (Govindaraju and Tang, 2013; Luukkanen et al., 2015; Sueyoshi et al., 2017). In this context, the fifth valuation report issued by the UN Intergovernmental Panel on Climate Change (IPCC) is worth mentioning which verified that GHG emissions and other man-driven activities are the leading cause behind rising global temperature since the last half of the previous century. The report further mentioned that during the period 1880–2012 the average global temperature rose by 0.85 °C and this increase is projected to continue for the next 100 years. Moreover, the period between 1880–2012 was the warmest period during the 1400 years of the world's history (IPCC, 2014).

Sustainable development simply means protecting the environment for future generations without affecting the current pace of economic development. Sustainable development is necessary to make this world a better living place not only for this generation but also upcoming ones and reducing CO_2 emissions is the main goal to attain sustainable development (Lackner et al., 2012; Luo et al., 2017; Magazzino, 2017). To keep this perspective in my mind many researchers have focused on the environment-growth nexus by exerting various other variables that could affect this nexus. Most of the previous studies have included energy consumption as the main variable while estimating the environment-growth nexus and confirmed that energy consumption is the main driver behind CO_2 emissions (Aslam et al., 2021; Magazzino, 2016). However, recently, studies have started to include various other variables that may affect environmental quality and among these, industrialization, globalization, tourism, urbanization, foreign direct investment, education, public expenditures, and financial inclusion are the most noticeable (Ullah et al., 2020; Usman et al., 2021).

Indeed, every sector of the economy is responsible for its growth, thus every sector directly or indirectly affects CO_2 emissions in one or another way and the same is true for the agricultural sector (Ullah et al., 2021). According to Reynolds and Wenzlau (2012), the share of the agricultural sector in global GHG emissions is between 14%–30% due to its dependency on fossil fuels. Certainly, utilizing farm apparatus driven by petrol, propelling water for irrigation, nurturing farm animals in enclosed areas, and employing nitrogen-abundant fertilizers add to agriculture's extraordinary GHG productions. The food and agricultural organization (FAO) of the UN have faith in the agricultural sector that it can reduce its current carbon emissions by almost 80%–88% (Reynolds & Wenzlau, 2012). Surely this can be achieved by changing the structure of the agricultural sector and by transforming the energy mix used in the agricultural sector from non-renewable sources to renewable ones.

The importance of the agricultural sector can be recognized from the fact that it is a major source of income and employment, particularly, in developing economies (Dogan, 2016; Hu et al., 2021; Magazzino et al., 2021; Streimikis & Saraji, 2021; Ullah et al., 2018). Besides, this sector is responsible for providing food to billions of people around the globe. Hence, it has an important part to play in determining the environmental quality of the globe. However, the literature regarding the impact of agricultural productivity on environmental quality is not ample, and the results are

inconclusive. Ullah et al. (2018) stated that agriculture can have either positive or negative impacts on environmental quality. Agriculture can negatively affect the environment via energy consumption which increased because of using machines in the production and transportation procedures, on-farm lighting systems, rise in the demand for raw stuff, increased land use, heating and cooling systems for livestock, and increased utilization of insecticides, chemicals, and fertilizers. Conversely, the positive effects come from the process of photosynthesis which emerges due to increased supply of oxygen in the atmosphere as a result of massive plantation and cropping. Moreover, organic farming can also help to improve the environmental quality by lowering the role of pesticides, fertilizers, and reducing the proportion of consuming high-energy feedstuffs (Lee & Choe, 2019).

As far as the top emitter of GHG emissions is concerned China has surpassed the USA in 2012 and now become the world's leading emitter as per the report of the World Resource Institute (Magazzino et al., 2020; Mele & Magazzino, 2020). Additionally, the UN's food and agricultural organization reported that the Chinese economy is the world's leading economy in terms of agriculture. China predominantly produces meat, vegetables, and cereal grains, whereas, its main import products are feed grains, oilseeds, and cotton. Furthermore, China is the most populous country in the world and its agricultural sector is of prime importance. Hence, analyzing the impact of China's agricultural sector on its environment is vital for the living standard of Chinese people. Investigation of this topic is needed in Chine due to some specific reasons. In the last two decades, China has attained outstanding growth in each sector of the economy. China is producing one-fourth of the grains of the world and feeding one-fifth of the population of the world that is a great achievement in the mission of nutrition security. Moreover, China is leading in the world in the production of fishery products, eggs, poultry, meat, vegetables, fruit, cotton, and cereals. While China produces 55% of agricultural productivity via technology by lowering the pollution. Keeping this thing in mind, in this study, we have analyzed the relationship between agricultural productivity and environmental sustainability in China. China has positive variation in the agricultural sector, so this study scrutinizes the different impacts of agricultural productivity on CO_2 emissions under positive and negative shocks using the NARDL method.

Shocks in agricultural productivity can easily affect CO_2 emissions through different mechanisms. Agricultural productivity is more sensitive to China-specific agricultural practices and policies. Ullah et al. (2021) noted that a positive shock in agricultural productivity is a more dominant impact on CO_2 emissions than a negative shock. Thus, agricultural productivity may influence CO_2 emissions asymmetrically. A positive shock reflects only an increase in agricultural productivity, but a negative shock reflects only declines in agricultural productivity in China. While positive shocks seem to have negative effects on CO_2 emissions, negative shocks have a positive effect. Therefore, an empirical analysis using a nonlinear estimation approach is quite useful for China and other agrarian economies. To the best of our knowledge, this is the first-ever study that has relied on non-linear analysis in this context by collecting data over the period 1971–2019. The methodology adopted for the analysis is linear and non-linear ARDL. The symmetry assumption implies that the positive and

negative changes move in opposite directions with the same magnitude. Conversely, the asymmetry assumption suggests that positive and negative change can move in the same direction with different magnitude. Therefore, the non-linear analysis is more close to reality as it provides us with an opportunity to capture the impact of positive and negative shock in the independent variable, separately, on the dependent variable.

In Sec. 2 literature review is presented. Data and econometric methodology are discussed in Sec. 3 and the results are given in Sec. 4. Lastly, the conclusion is provided in Sec. 5.

2. Literature review

It is widely recognized that there is an association between agricultural productivity, carbon emissions, and the resulting climate change. The agriculture sector contributes to carbon emissions and is susceptible to such emissions (IPCC, 2014). The agricultural sector's contribution to global carbon emissions ranges from one-fourth to one-third (World Bank, 2013). Among these, on-farm activities contribute about 10–12% of total world's emissions; whereas, land-use and land-cover transformed to cropland contribute about 12%–20% of global carbon emissions (World Bank, 2013). The share of the agriculture sector in global CO_2 emissions is comparatively lower than the thermodynamics industry. In order to reduce agriculture-related carbon emissions, the need of the hour is to implement the low-carbon agriculture technique that would not only promote economic development but also protect the environment (Fan et al., 2015; Rehman et al., 2019a; Xiao et al., 2021).

On one side, the agricultural sector is vital for attaining increased economic growth and improved food security of the country. On the other hand, it also generates various social and environmental issues in the economy. A plethora of studies are available that have analyzed various determinants of environmental quality; however, the relationship between agriculture productivity and CO_2 emissions is underexplored. Valin et al. (2013) analyzed the link between crop yield and livestock feed on the emissions of greenhouse gases in the developing economies by employing a partial equilibrium model. They observed that after reducing the yield gaps, 50% and 25% for crops and livestock, respectively, by 2050, there will be an 8% reduction in agriculture-related emissions. Instead of using one single gas as a proxy of environmental degradation, Dufour et al. (2009) combined the data for three leading greenhouse gases, which include CO_2, methane, and nitrous oxide, and used it as a representative of environmental quality. They then applied the autoregressive distributed lag (ARDL) model and estimated the negative association between climate change and agricultural productivity. In numerical terms, they observed that a 100% rise in these gases causes a 22.26% fall in agricultural productivity. However, due to the combination of three gases, the effect of carbon emissions was not clear in this study. For South Asia and sub-Saharan Africa, Reynolds et al. (2015) analyzed the association between agricultural yield and CO_2 emissions. The estimates from the model confirmed that the link between agricultural yield and CO_2 emission is

negative and significant, implying that carbon emissions are detrimental for agricultural productivity in South Asia and Sub-Saharan Africa.

Zhang et al. (2015) investigated the effects of crop harvests, crop remainders, and crop processes on CO_2 emissions. The findings of the study estimated that crop remainders increase the CO_2 emissions or in other words deteriorate environmental quality. Edoja et al. (2016) tried to investigate the impact of simulated carbon emissions on agricultural productivity and the welfare of the household. The simulated findings of the study confirmed that carbon emissions and agricultural productivity are negatively linked to each other. They observed that carbon emissions would lower agricultural productivity in the context of traded and non-traded crops, but the livestock productivity will not be affected. Moreover, they found that increased carbon emissions also affect the welfare of all households; however, the worst affected people are the poor people from the rural areas. Nwaka et al. (2020) estimated the link between global warming and agricultural productivity and found that differences in agricultural yield in response to global warming are lower in magnitude than the yield response CO_2 fertilization.

Rehman et al. (2019b) tried to estimate the impact of agricultural productivity on CO_2 emissions in Pakistan over the period 1987–2019. The study employed the autoregressive distributed lag (ARDL) model as an estimation technique. The findings of the study confirmed that long-run estimated coefficients of cropped area, energy consumption, fertilizers, per capita income, and water availability all are significantly positive, implying that all these factors increase the CO_2 emissions in Pakistan. On the other side, the estimates of improved seeds quality and food grains are negative, suggesting that both these factors reduce the CO_2 emissions. Moreover, from these findings, we deduce that long-run effects are greater in magnitude as compared to the short-run effects, inferring that our results are heterogeneous. Ullah et al. (2021) analyzed the nexus between deagriculturalization, GDP, and environmental quality in Pakistan. They collected data for the period 1975 to 2018 and employed a nonlinear autoregressive distributed lag (NARDL) model to get numerical estimates. Further, to know the causal relationship between the variables, the study applied the Granger causality test. The estimates of the study imply that there exists a negative relationship between agriculturalization and economic growth; whereas, deagriculturalization does not have any noticeable impact on economic growth in the long run. On the other side, agriculturalization and deagriculturalization improve Pakistan's environmental quality. Further, the authors confirmed the presence of asymmetry in the effects of main variables. Finally, the asymmetric causality test confirms that the unidirectional causality is running from agriculturalization to CO_2 emissions and deagriculturalization to CO_2 emissions.

3. Methodology and data

3.1. Methodology

According to most empirical and theoretical studies, agricultural and industrial sectors are the most important determinants of CO_2 emissions (Ullah et al., 2020, 2021). The rise in environmental pollution has been affected by agriculture activities that are

one of the most important sources of income. While the agricultural sector contributes to economic growth, they also encourage CO_2 emissions and cause environmental degradation via deforestation, land use and livestock using fertilizers, machinery, fossil fuel, and burning stubble. Borlaug's hypothesis is used to examine the impact of agricultural productivity on the environment (Angelsen et al., 2001). This hypothesis postulates that at the initial stages agricultural productivity reduces environmental quality, but after some threshold level, agricultural productivity starts promoting environmental quality by enhancing the demand for goods and services produce under environmental regulations. Therefore, the long-run CO_2 emissions are assumed to take the following form:

$$CO_{2,t} = \varphi_0 + \varphi_1 AP_t + \varphi_2 GDP_t + \varphi_3 EC_t + \varphi_4 Trade_t + \varphi_5 Urb_t + \varepsilon_t \tag{1}$$

where $CO_{2,t}$ denotes CO_2 emissions, AP_t denotes agricultural productivity, GDP_t denotes GDP per capita, EC_t denotes energy consumption, $Trade_t$ denotes international trade, Urb_t denotes urban population, and ε_t is the error term. Estimates of φ_1 could be negative and indicates that agricultural productivity reduces environmental pollution by reducing the dirty activities in the economy (Ullah et al., 2021). Agricutrilzation shifts economic growth to green economic growth. Equation (1) gives us the long-run estimates of CO_2 emissions. Next, we are assembling our model into an error-correction format so that we can assess the short-run and long-run effects of agricultural productivity in a single equation. A modelling approach that allows us to estimate the long-run and short-run effects in single step is to estimate the following econometric specification:

$$\begin{aligned}\Delta CO_{2,t} = {} & \alpha_0 + \sum_{i=1}^{p} \pi_i \Delta CO_{2,t-i} + \sum_{i=0}^{p} \psi_i \Delta AP_{t-i} + \sum_{i=0}^{p} \mu_i \Delta GDP_{t-i} + \sum_{i=0}^{p} \theta_i EC_{t-i} \\ & + \sum_{i=0}^{p} \lambda_i Trade_{t-i} + \sum_{i=0}^{p} \rho_i Urb_{t-i} + \omega_1 CO_{2,t-1} + \omega_2 AP_{t-1} + \omega_3 GDP_{t-1} \\ & + \omega_4 EC_{t-1} + \omega_5 Trade_{t-1} + \omega_6 Urb_{t-1} + \lambda.ECM_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

Specification (2) is inferred by the estimates of short-run effects attached to 'Δ' variables, while long-run effects are inferred by the estimates of $\omega_2 - \omega_6$ normalized on ω_1. Such econometric specification has few advantages over other time series methods. This method offers estimates short-run and long-run effects in one step. The unit root testing is not compulsory, because normally time series variables are integrated at different orders i.e., I(0) or I(1), and even a blend of them. However, in other time series techniques variables need to be stationary at the same order of integration (Engle & Granger, 1987). To check the meaningfulness of long-run estimates, Pesaran et al. (2001) recommend two diagnostic tests (F-test and ECM or t-test). Another advantage of this method is that it can provide efficient results in the case of a small sample size (Bahmani-Oskooee et al., 2020). Last but not least, due to the inclusion of short-run dynamic adjustment framework in the model, this technique

can also detect any feedback effect among the variables, thus lessens the risk of multicollinearity and endogeneity (Pesaran et al., 2001). The next step is to modify Eq. (2) so that it can be used to determine the asymmetric effects of agriculture production on CO_2 emissions. To that end, following Shin et al. (2014), AP is separated into two new time-series variables (positive and negative changes) using the partial sum idea as follows:

$$AP^{+}{}_{t} = \sum_{n=1}^{t} \Delta AP^{+}{}_{t} = \sum_{n=1}^{t} \max\ (\Delta AP^{+}{}_{t},\ 0) \tag{3}$$

$$AP^{-}{}_{t} = \sum_{n=1}^{t} \Delta AP^{-}{}_{t} = \sum_{n=1}^{t} \min\ (\Delta AP^{-}{}_{t},\ 0) \tag{4}$$

where the $AP^{+}{}_{t}$ indicates an increase in agricultural productivity variable, while $AP^{-}{}_{t}$ indicates a decrease in agricultural productivity variable. After replacing both these new variables in place of the original variable in Eq. (2) so our extended model is as:

$$\begin{aligned}\Delta CO_{2,t} = {} & \alpha_0 + \sum_{i=1}^{p} \pi_i \Delta CO_{2,t-i} + \sum_{i=0}^{p} \delta_i \Delta AP^{+}{}_{t-i} + \sum_{i=0}^{p} \phi_i \Delta AP^{-}{}_{t-i} \\ & + \sum_{i=0}^{p} \mu_i \Delta GDP_{t-i} + \sum_{i=0}^{p} \theta_i EC_{t-i} + \sum_{i=0}^{p} \lambda_i Trade_{t-i} \sum_{i=0}^{p} \rho_i Urb_{t-i} + \omega_1 CO_{2,t-1} \\ & + \omega_2 AP^{+}{}_{t-1} + \omega_3 AP^{-}{}_{t-1} + \omega_4 GDP_{t-1} + \omega_5 EC_{t-1} + \omega_6 Trade_{t-1} \\ & + \omega_7 Urb_{t-1} + \lambda.ECM_{t-1} + \varepsilon_t\end{aligned} \tag{5}$$

Shin et al. (2014) label models such as Eq. (5) asymmetric time series ARDL model, and nonlinearity creates from the method of the partial sum. They also determine that both models are subject to similar tests, diagnostics, and OLS methods of estimation. The nonlinear model has some extra diagnostics. To test both short and long-run asymmetric hypotheses are confirmed through the Wald test. In the end, we check causality in a non-linear framework by conducting the time series causality test of Hatemi-J (2012).

3.2. Data

This study examines the impact of shocks in agricultural productivity on environmental quality in China for the time period ranging from 1971 to 2019. For that purpose, CO_2 emissions is a dependent variable and livestock production and crop production are independent variables, and GDP per capita, energy use, trade, and urbanization are control variables. Table 1 delivers detailed information regarding definitions and symbols of variables, sources of data, and descriptive analysis. The data for all these variables have been sourced from the World Bank. Data on CO_2 emissions is measured in kilotons. Livestock production index and crop production

Table 1. Variables and definitions.

Variables	symbol	Definitions	Mean	Median	Minimum	Maximum	Minimum	Sources
CO_2 emissions	CO_2	CO_2 emissions (kt)	14.98	15.01	13.68	16.14	13.68	World Bank
Livestock production	LP	Livestock production index (2014–2016 = 100)	52.59	54.53	8.780	103.2	8.780	World Bank
Crop production	CP	Crop production index (2014–2016 = 100)	3.931	3.950	3.101	4.643	3.101	World Bank
GDP per capita	GDP	GDP per capita (constant 2010 US$)	7.123	7.111	5.472	9.017	5.472	World Bank
Energy use	EC	Energy use (kg of oil equivalent per capita)	6.856	6.765	6.142	7.713	6.142	World Bank
Trade	Trade	Trade (% of GDP)	31.71	33.81	4.921	64.47	4.921	World Bank
Urbanization	URB	Urban population (% of total population)	33.78	30.96	17.18	60.30	17.18	World Bank

Source: Wordl Bank.

index are taken at the base of 2014–2016 = 100. GDP per capita is measured at constant 2010 US$. Data on energy use is taken in kg of oil equivalent to per capita. Data on trade is obtained in percent of GDP. Urbanization data is measured as the urban population as percent of the total population. In Table 1, the mean of CO_2, LP, CP, GDP, EC, trade, and URB are 14.98 kt, 52.59, 3.931, 7.123US$, 6.856 kg, 31.71%, and 33.78%, respectively.

4. Empirical results and discussion

In this section, we empirically estimate the livestock production and CO_2, and crop production and CO_2 symmetric ARDL model and the asymmetric NARDL model by examining the shocks of agricultural production on CO_2 emissions over the period 1971–2019. As a preliminary test, since the ARDL and NARDL approaches need the variables to be a mixture of level-stationary and first difference stationary variables, we test for these properties and demonstrate the results with structural break and without structural break unit root statistics in Table 2. From Table 2, it is obvious that some variables are stationary at I(0), and the remaining are stationary at I(1). However, none of the variables is stationary at I(2). From Table 3, Brock-Dechert-Scheinkman (BDS) test reported the nonlinearity in livestock production and crop production variables. Table 4 reports the estimates of long-run and short-run parameters of ARDL and NARDL models.

In the ARDL livestock production model, livestock production is negatively and significantly associated with pollution emissions in the long-run demonstrating that 1 percent increase in livestock results in 0.005 percent decrease in pollution emissions in the long-run. GDP and energy consumption impact is positive on pollution emission and urbanization impact is negative on pollution emissions in the long-run. Coefficient estimates reveal that 1 percent increase in GDP and energy consumption leads to 0.790 percent and 1.026 percent increase in pollution emissions, however, a 1 percent increase in urbanization leads to 0.038 percent reduction in pollution emissions. In contrast, trade has no impact on pollution emissions in the long-run. Livestock production has negative impact on pollution emissions in the short-run. GDP, energy consumption and trade exert a positive impact on pollution emissions but urbanization exerts a negative impact on pollution emissions in the short-run.

Table 2. Unit root testing.

	ADF		DF-GLS			Unit root testing with break		
	I(0)	I(1)	I(0)	I(1)	I(0)	Break date	I(1)	Break date
CO_2	−1.223	−4.420***	−0.240	−2.873***	−3.021	2001	−5.012***	2013
LP	−0.654	−4.656***	−1.123	−3.163***	−3.854	1990	−5.987***	1995
CP	−1.203	−7.321***	−0.878	−1.906*	−2.245	1989	−8.765***	2019
GDP	0.234	−3.023**	−0.102	−3.008***	−1.542	1990	−4.232*	2001
EC	−0.423	−4.775***	0.278	−4.283***	−3.452	2002	−6.565***	2015
Trade	−0.123	−2.654*	−0.242	−4.931***	−1.412	2000	−4.321*	2001
URB	−2.655*		−1.718*		−4.235*	1990		

Note: ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$.
Source: Authors' Calculations.

Table 3. BDS testing.

	LP				CP			
Dimension	BDS Stat	Std. error	z-Stat	Prob.	BDS Stat	Std. error	z-Stat	Prob.
2	0.198***	0.006	31.28	0.000	0.200***	0.006	34.20	0.000
3	0.331***	0.010	32.78	0.000	0.338***	0.009	36.04	0.000
4	0.423***	0.012	34.81	0.000	0.433***	0.011	38.63	0.000
5	0.486***	0.013	38.26	0.000	0.502***	0.012	42.74	0.000
6	0.530***	0.012	42.97	0.000	0.551***	0.011	48.46	0.000

Note: ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$.
Source: Authors' Calculations.

In the NARDL livestock production model, positive shock in livestock production has significant negative impact on pollution emissions in the long-run. Coefficient estimate reveals that 1 percent increase in positive shocks in livestock production results in 0.004 percent decrease in CO_2 emissions. However, the negative shock in livestock production has an insignificant impact on carbon emissions in the long-run. While GDP, energy consumption, and trade exert significant positive impacts on pollution emissions, but urbanization exerts significant negative impact on pollution emissions in long-run. The findings reveal that 1 percent increase in GDP, energy consumption, and urbanization leads to 0.748 percent, 1.068 percent, and 0.003 percent increase in pollution emissions, however, 1 percent increase in urbanization brings 0.036 percent decrease in pollution emissions in the long-run. The short results demonstrate that positive and negative shocks in livestock production have no significant impact on pollution emissions. However, GDP, energy consumption, and trade positively affect pollution emission and urbanization negatively affect pollution emissions in the short-run.

The findings of diagnostic tests for ARDL and NARDL models in case of livestock production reveal that long-run cointegration exists among variables in both models as shown by significant coefficient estimates of F-test and ECM test. The findings of LM test and BPG test confirm that there is no issue of autocorrelation and heteroscedasticity in both models. Ramsey RESET test confirms that models are correctly specified. In the end, the findings of CUSUM and CUSUM-sq test confirm the stability of estimates in the ARDL and NARDL models. In NARDL livestock production model, Wald test confirms the existence of only long-run asymmetries among variables.

The study employed variable-based techniques to check the robustness of findings. So for that reason, crop production is used in empirical analysis. With regard to the

Table 4. ARDL and NARDL estimates of short and long run.

	ARDL-LP		NARDL-LP		ARDL-CP		NARDL-CP	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Short-run								
D(LP)	−0.003**	−2.222						
D(LP_POS)			0.004	0.706				
D(LP_NEG)			−0.049	−0.794				
D(CP)					0.330*	1.727		
D(CP_POS)							0.095	0.390
D(CP_NEG)							1.724**	2.386
D(CP_NEG(−1))							3.273**	1.960
D(GDP)	0.580***	3.931	0.617**	2.530	0.417**	2.314	0.661***	3.449
D(GDP(−1))			−0.376	−1.509				
D(EC)	0.370***	2.724	0.378***	2.641	0.353**	2.492	0.218	1.570
D(EC(−1))	−0.567***	−2.920	−0.505***	−2.716	−0.488**	−2.496	−0.706***	−3.855
D(EC(−2))	0.234	1.494			0.411**	2.449	0.436***	2.848
D(URB)	−0.028***	−3.314	−0.032***	−3.622	−0.018**	−1.996	−0.018**	−2.051
D(TRADE)	0.005***	2.790	0.006***	2.983	0.005***	2.596	0.005***	2.789
D(TRADE(−1))							−0.002	−1.164
Long − run								
LP	−0.005**	−2.347						
LP_POS			−0.004*	−1.696				
LP_NEG			0.037	0.688				
CP					−0.518	−1.013		
CP_POS							−0.553**	−2.093
CP_NEG							−4.505***	−3.447
GDP	0.790***	8.433	0.748***	7.461	0.896***	2.833	0.779***	4.509
EC	1.026***	10.37	1.068***	12.95	0.964***	5.357	0.785***	6.870
URB	−0.038***	−5.374	−0.036***	−5.073	−0.038***	−2.884	−0.021**	−2.447
TRADE	0.002	0.947	0.003***	1.939	0.001	0.536	−0.001	−0.534
C	3.807***	5.382	3.698***	5.420	5.278***	3.899	4.970***	5.358
Diagnostics								
F − test	8.019***		5.767***		3.661*		6.687***	
ECM(−1)	−0.734***	−4.522	−0.902***	−5.690	−0.466***	−3.350	−0.849***	−5.210
LM	1.564		0.124		1.881		1.023	
BPG	1.654		1.754		1.048		1.432	
RESET	0.123		0.987		0.247		0.387	
CUSUM	S		S		S		S	
CUSUM-SQ	S		S		US		S	
Wald-LR			3.955**				2.875*	
Wald-SR			0.654				1.023	

Note: ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$.
Source: Authors' Calculations.

crop production ARDL model, the empirical findings infer that crop production exerts no significant impact on pollution emissions in the long-run due to insignificant coefficient estimates of crop production. GDP and energy production impact is positive on pollution emissions and urbanization impact is negative on pollution emissions in the long-run. The coefficient estimates demonstrate that 1 percent increase in urbanization brings 0.038 percent reduction in pollution emissions and 1 percent upsurge in GDP and energy consumption leads to 0.896 percent and 0.964 percent upsurge in pollution emissions in the long-run. Crop production positively effect pollution emissions in the short-run. In case of control variables, GDP, energy consumption, and trade lead to an upsurge in pollution emissions but urbanization leads to alleviation in pollution emissions in the short-run.

According to NARDL crop production model, positive shock in crop production has a significant and negative impact on pollution emissions in the long-run. The

coefficient estimates infer that 1 percent increase in positive shocks in crop production leads to 0.553 percent reduction in pollution emissions. While findings show that 1 percent decrease in negative shocks in crop production brings 4.505 percent increase in pollution emissions in China in the long-run. In nutshell, the short-run agricultural productivity effects are smaller than the long-run effects on CO_2 emissions. This implies that over the short run, the impact of agricultural production is smaller, but as time goes by, this factor tends to impact more on environmental sustainability in China.

This finding is also consistent with Alhassan et al. (2021), who infers that the agriculture sector can limit greenhouse gasses (GHG) emissions, because of excessive use of renewable energy sources during the production process. Undeniably, many cultivated events, such as irrigation, could be driven by clean energy sources. The findings indicate that Chinese agricultural sector production is adopting eco-friendly technologies by increasing positive externalities and promoting environmental quality. Such as, Bayrakcı and Kocar (2012) pointed out many channels through which renewable energy can be used in the agriculture sector productivity. They indicate that solar energy can be proved vital and useful in heating and cooling the greenhouses, lighting the indoor and outdoor farm facilities, drying the products, irrigating the fields and crops, which in turn reduces the CO_2 emissions.

This finding is congruous with the findings of Lin and Xu (2018), who infers that modern biofuels such as bioethanol and biogas, and numerous agricultural deposits like grain powder, wheatgrass, and hazelnut coverings can be used as important sources of renewable energy in agricultural productivity by reducing the CO_2 emissions. Similarly, another important source of renewable energy viz. geothermal energy that can be used in the agricultural sector, in sheds, in soil enhancement, for heating and cooling in the greenhouses, and to dry agricultural commodities. This means that renewable energy sources proved vital in agricultural productivity as well environmental sustainability in China, this result is also coinciding with those described by Xu and Lin (2017).

All types of green economic activities can cut a significant amount of CO_2 emissions because the energy consumed in the agricultural sector is largely based on fossil fuels which is the main driving force behind GHG emissions (Ullah et al., 2021). Furthermore, the agriculture sector can help the process of photosynthesis to develop due to the extensive amount of standing crops and plantations that promotes the supply of oxygen in the ecosystem, which in turn improves environmental sustainability. Lastly, organic farming in agriculture and livestock is getting popular in China is an important factor not only improving human health but the health of the environment (Lin & Xie, 2016).

GDP and energy consumption impact are significantly positive and urbanization impact is negative on pollution emissions in the long-run. Findings show that 1 percent increase in GDP and energy consumption brings 0.779 percent and 0.785 percent increase in pollution emissions, however, 1 percent increase in urbanization brings 0.021 percent reduction in pollution emissions in the long-run. Positive shocks in crop production have an insignificant impact on pollution emissions but negative shocks in crop production have significant and negative impacts on carbon emissions

in the short-run. GDP and trade have a positive effect on carbon emissions and urbanization has a negative effect on pollution emissions in the short-run. All the findings of diagnostic tests in case of crop production are similar as livestock production models except CUSUM-sq test in the ARDL-CP model. Figure 1 shows the cumulative multipliers for livestock productivity and CO_2 emissions, while Figure 2 shows the cumulative multipliers for crop productivity and CO_2 emissions in China. The graph exhibits that positive and negative shocks in livestock productivity and crop productivity have a different impact on CO_2 emissions in China. Finally, the results of Granger causality are reported in Table 5. To save space, we only discuss the results of Granger causality between agricultural productivity and CO_2 emissions. From Table 5, we gather that one-way causality runs from LP_POS→CO_2 and CP_POS→CO_2 in the base model.

Table 5. Asymmetric causality test results.

Null hypothesis:	F-Stat	Prob.	**Null hypothesis:**	F-Stat	Prob.
LP_POS → CO_2	8.372	0.001	CP_POS → CO_2	3.862	0.029
CO_2 → LP_POS	0.572	0.569	CO_2 → CP_POS	0.262	0.771
LP_NEG → CO_2	0.705	0.500	CP_NEG → CO_2	0.486	0.619
CO_2 → LP_NEG	1.790	0.180	CO_2 → CP_NEG	0.673	0.516
GDP → CO_2	1.227	0.304	GDP → CO_2	1.227	0.304
CO_2 → GDP	0.379	0.687	CO_2 → GDP	0.379	0.687
EC → CO_2	2.313	0.112	EC → CO_2	2.313	0.112
CO_2 → EC	2.179	0.126	CO_2 → EC	2.179	0.126
URB → CO_2	2.751	0.075	URB → CO_2	2.751	0.075
CO_2 → URB	0.194	0.825	CO_2 → URB	0.194	0.825
TRADE → CO_2	4.474	0.017	TRADE → CO_2	4.474	0.017
CO_2 → TRADE	0.291	0.749	CO_2 → TRADE	0.291	0.749
LP_NEG → LP_POS	2.447	0.099	CP_NEG → CP_POS	2.015	0.146
LP_POS → LP_NEG	1.665	0.202	CP_POS → CP_NEG	1.849	0.170
GDP → LP_POS	2.804	0.072	GDP → CP_POS	0.826	0.445
LP_POS → GDP	0.830	0.443	CP_POS → GDP	5.158	0.010
EC → LP_POS	0.441	0.647	EC → CP_POS	0.308	0.737
LP_POS → EC	2.690	0.080	CP_POS → EC	1.937	0.157
URB → LP_POS	2.377	0.106	URB → CP_POS	2.120	0.133
LP_POS → URB	2.371	0.106	CP_POS → URB	2.336	0.109
TRADE → LP_POS	2.387	0.105	TRADE → CP_POS	1.720	0.192
LP_POS → TRADE	0.285	0.754	CP_POS → TRADE	0.184	0.833
GDP → LP_NEG	2.346	0.109	GDP → CP_NEG	1.601	0.214
LP_NEG → GDP	0.082	0.921	CP_NEG → GDP	4.347	0.019
EC → LP_NEG	1.223	0.305	EC → CP_NEG	0.930	0.403
LP_NEG → EC	2.042	0.143	CP_NEG → EC	0.272	0.763
URB → LP_NEG	1.712	0.193	URB → CP_NEG	2.142	0.130
LP_NEG → URB	1.297	0.284	CP_NEG → URB	0.411	0.666
TRADE → LP_NEG	1.652	0.204	TRADE → CP_NEG	0.120	0.888
LP_NEG → TRADE	0.398	0.674	CP_NEG → TRADE	0.816	0.449
EC → GDP	0.153	0.859	EC → GDP	0.153	0.859
GDP → EC	1.853	0.169	GDP → EC	1.853	0.169
URB → GDP	3.231	0.050	URB → GDP	3.231	0.050
GDP → URB	1.363	0.267	GDP → URB	1.363	0.267
TRADE → GDP	2.042	0.143	TRADE → GDP	2.042	0.143
GDP → TRADE	0.044	0.957	GDP → TRADE	0.044	0.957
URB → EC	2.839	0.070	URB → EC	2.839	0.070
EC → URB	0.464	0.632	EC → URB	0.464	0.632
TRADE → EC	3.538	0.038	TRADE → EC	3.538	0.038
EC → TRADE	0.673	0.516	EC → TRADE	0.673	0.516
TRADE → URB	0.089	0.915	TRADE → URB	0.089	0.915
URB → TRADE	3.483	0.040	URB → TRADE	3.483	0.040

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; and $^{*}p < 0.1$.
Source: Authors' Calculations.

5. Conclusion and policy implications

The agriculture sector in China is one of the important contributors to the growth of the Chinese economy. According to Mekouar (2015), China is the leading agricultural economy in the world and it mainly produces meat, vegetables, and cereal grains. Moreover, China ranked number one in the world in terms of population. Therefore, to attain food security in the country, the importance of the agriculture sector has increased manifold. However, such a large agricultural sector can also play its part in disturbing the balance of the ecosystem by infusing the CO_2 emissions in the environment. The primary motive behind this research is to see the role of China's large agriculture sector in promoting or demoting CO_2 emissions. For empirical results, we applied linear and non-linear ARDL models by collecting data over the period 1971–2019. Two proxies i.e., livestock and crop productions are used to represent the agricultural productivity in China.

The results of the linear model suggest that livestock production can help to reduce CO_2 emissions both in the short and long run. In the non-linear model, the short-run estimates of livestock production are insignificant, however, in the long run, the positive shock in the livestock production helps to reduce the CO_2 emissions and the negative shock is insignificant. On the other side, an increase in crop production deteriorates the environmental quality in the short run in both linear and non-linear models. In long run, the estimate of crop production in the linear model is insignificant and in the non-linear, the estimated coefficients of both positive and negative shocks in crop production are negative implying that a positive shock reduces the CO_2 emissions while the negative shock increases the CO_2 emissions. The asymmetric effects between positive and negative shocks in both livestock production and crop production are confirmed only in the long run. Among the control variables, the GDP and energy consumption are exerting a positive impact on CO_2 emissions in all four models, whereas urbanization exerted a negative impact on CO_2 emissions in all four models. The estimated coefficient of trade is significantly positive in only the NARDL-livestock production model and insignificant in all other models.

The findings of this study have some important policy implications. Clearly, in the long run, the response of CO_2 emissions to both livestock and crop productions is asymmetric, hence the policymakers should devise the policies accordingly by keeping in mind both the negative and positive shocks. Although our findings suggest a positive role of agricultural productivity in improving the environmental quality but the magnitude of the positive effects is not large. Because more than 80% of China's energy production is based on coal and other non-renewable energy sources which are the drivers of China's economic and agricultural growth, hence, to control the agricultural-related emissions the country needs to rely more on renewable energy sources. Moreover, China should focus more on organic farming both in terms of crops and livestock that would also help to reduce the emissions in the agriculture sector. Finally, the technological innovation and advancement in the cultivating and harvesting process can help the agriculture sector in China to achieve energy efficiency that is another effective tool to control CO_2 emissions. Awareness of farmers should be increased with education to adopt green production and renewable energy

consumption through enlarged investment in research and development activities. Governments and policymakers should formulate policies that expand agricultural productivity without damaging environmental quality. Policymakers should focus on eco-friendly production to control the agricultural sector's carbon emissions.

This analysis limits in sample and variables in empirical analysis. Our basic focus is to assess the effect of agricultural productivity on CO_2 emissions at the national level but ignoring provincial and cities level empirical dimensions. The impacts of agricultural performance on the environment might differ in diverse provinces and economies. In future studies, provinces-specific factors can be used to interpret the impact of agricultural performance on the environment in China. Furthermore, in future research, authors can explore the threshold asymmetry and see whether this asymmetry holds in the relationship of agriculture, environment, and economic growth.

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