RESEARCH ARTICLE

Looking back over the past two decades on the nexus between air pollution, energy consumption, and agricultural productivity in China: a qualitative analysis based on the ARDL bounds testing model

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Abstract

Increasing population and food demand has led to steadily declining resources as a result of over-exploitation and fossil fuel consumption that cause air contamination and reduce soil fertility. Therefore, this study aimed to investigate the correlation between air pollution, energy consumption, and the contribution of agriculture to national GDP. Secondary study data covering two decades were collected from different sources, and an autoregressive distributed lag (ARDL) bounds testing model was employed to determine long-run and short-run correlations. First, the unit root test was used to determine the stationarity of variables, and results showed that variables were integrated at level, ARDL co-integration equation estimation, which rejected the null hypothesis at less than 5% significance level. Further, based on the results of the ARDL bounds testing model, F-statistic values exceeded the upper bound value. This entire model was adjusted at a speed of -2.364 towards long-run equilibrium. In addition, CUSUM test and CUSUMSQ test results confirmed the goodness of fit of this model. In light of the resulting policy implications, the Chinese government may consider measures to improve the agricultural industry to meet the food demand for the fast-growing population while maintaining a healthy environment and safeguarding the available limited resources for future generations.

Keywords Agricultural productivity · Fertilizer · Energy consumption · Carbon emission

Introduction

The agricultural sector of China is considered the backbone of the national economy and is critical for global sustainability. China's agricultural development is of particular concern in the face of a burgeoning demand (Yu and Wu 2018). The most crucial and controversial topic is how China can best provide the food resources to meet the demands of a growing population. China has long been struggling to find an answer to this question, as resources and arable land have been shrinking due to overpopulation and urbanization. Along with the benefits of rapid economic growth and urbanization, new challenges have emerged for agriculture and rural society, including food security, food production and pollution. With the surge in food demand and declining natural resource availability, it is necessary to increase agricultural productivity and employment of labor, as well as a greater contribution to agricultural sector development (Rehman et al. 2019).

China has already executed brilliant work in supplying food to approximately 22% of the world's population from the limited available arable land, despite biophysical and environmental limitations such as uneven distribution of water resource assets (Liu et al. 2010). At the same time, China's farms have had major effects on ecosystems, and farmers have adopted innovative agro-based techniques to improve soil fertility, water resources, fertilizer applications and energy consumption. These agricultural practices have led to grave environmental pollution and over-

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exploitation of resources, resulting in serious ecological problems such as soil, water, and air pollution from over-utilization of fertilizer applications and soil erosion from land conversion and deforestation. China's agricultural industry has undergone significant change, including institutional modifications, structural changes to policies, and adoption of advanced technologies (Jin et al. 2010). Evidence illustrates that the widespread institutional change during the period of 1979−1984, including de-collectivization and land reform involving the redistribution of land equally to all rural households, was a major driver of the growth in agriculture (McMillan et al. 1989; Lin and Liu 2000). Huang et al (1986) described the adoption of modern agro-based technology as the most important factor for the increased production during this period.

In many ways, the increasing worldwide demand for agricultural products is at odds with the goal of environmental security, and this is especially true for China's agricultural industry (Huang and Rozelle 1996). The success in achieving food security has had consequences on the environment, affecting soil fertility, suitable water for irrigation resources, and biodiversity (Huang and Rozelle 1996; Norse and Ju 2015). In developing economies, a significant portion of greenhouse gas (GHG) emissions comprise CO2, and this results in environmental degradation; emissions and air pollution together contribute a substantial share of pollutants in total GHG emissions. Because of the swiftly rising population, the increasing demand of consumption of energy, financial growth and products of agricultural causes to increase air pollution owing time span (Khan et al. 2011; Kulak et al. 2013; Ahmada et al. 2016; Khan et al. 2018). By the rapidly rising population, worldwide agricultural productivity has been enhanced from the mid-twentieth century. The doubling of the global demand for food threatens to deplete agricultural resources and sustainable environments. The agricultural industry is considered the leading contributor of greenhouse gases to the environment due to the utilization of energy in the form of fossil fuels to increase agricultural productivity (Burney et al. 2010; Li et al. 2014; Liu et al. 2016). The agriculture sector is massively dependent on weather conditions such as variations in temperature and rainfall as well as floods, which cause agricultural productivity to decline, and consequently increases food insecurity, product prices, and other factors that subsequently reduce economic growth (Saidi and Mbarek 2016; Ben Jebli and Ben Youssef 2017). Globally, the agriculture sector contributes 20% of total global carbon emissions, 70% of methane, and 90% of nitrogen (Rehman et al. 2019). Nevertheless, the agriculture industry plays an important role in the development and growth of any country's economy.

Literature review

In this section, we present a review of the literature to gain a clear understanding of the correlation between variables. We divided the review into subsections as given below.

Air pollution and energy consumption

According to a basic understanding of the relationship between air pollution and energy consumption, it would seem to be mathematically straightforward to assume that greater energy consumption leads to higher levels of air pollution. However, a review of the literature revealed that air pollution and energy consumption do not run in parallel. In some developing countries, trends in air pollution parallel both economic development and energy consumption, such as that seen in China (Zoundi 2017; Dong et al. 2018b). Accelerated development and adaptation of modern technologies leads to higher consumption of energy, and contributes to pollutant levels (Dong et al. 2018a). The rapid rise in energy consumption has led to tremendous changes in the environment, especially climate change caused by increased carbon emissions from the burning of fossil fuels (Pata 2018; Shuai et al. 2018). According to Dong et al. (2017), replacing fossil fuel with renewable energy to reduce carbon emissions is the best solution for cleaner energy consumption. Thus, in the context of global warming, renewable energy has emerged as a valuable alternative to fossil fuel and is widely recognized as a means to balance development and a healthy environment (Bhattacharya et al. 2017; Sarkodie and Strezov 2019). Many researchers have investigated the correlation between carbon emissions from different sources with energy consumption, and the results of earlier work confirmed the short-run and long-run nexus of air pollution and energy consumption (Zoundi 2017). Sinaga et al. (2018) studied the long-run correlation of hydropower energy with economic growth and carbon emissions in Malaysia. Many researchers have estimated the environmental Kuznets curve (EKC) for different countries for different time spans, using both panel and time-series data. A number of scientists have already confirmed a cointegration and causality connection among carbon emissions, energy consumption and economic growth, and EKC, including Richmond and Kaufmann (2006), Ang (2007), Soytas and Sari (2009), Acaravci and Ozturk (2010), Apergis and Payne (2009), Ozturk (2010), Shahbaz et al. (2014), Wang et al. (2016), Koondhar et al. (2018), Wang et al. (2018), Rehman et al. (2019), and Shahbaz and Sinha 2019). Yuan (2015) found a bidirectional nexus between carbon emissions and energy consumption required to increase economic development and confirmed the existence of short-run and long-run causality. In a previous study, we investigated the long-run and short-run correlation between air pollution, energy

consumption, and economic growth in China and the USA. Because both countries are the superpowers, we conducted a comparative analysis with regard to the development of a green environment. The results revealed a parallel upward trend in China between the environment and GDP, while in the USA, the GDP curve showed upward movement but the environment curve showed a downward trend. However, China's speed of adjustment towards long-run equilibrium in short-run adjustment was much faster (Koondhar et al. 2018). Wang et al. (2011) used panel data for 28 provinces in China from 1995 to 2007 and estimated a causal correlation between CO2, energy consumption, and economic growth. They found a bidirectional association between carbon emissions and energy consumption and between energy consumption and economic growth, and confirmed a long-run causal correlation between carbon emissions and energy consumption. Similar results were confirmed by Zaman et al. (2012), Li et al. (2014), Rafindadi et al. (2014), Farhani and Ozturk (2015), Lorente and Álvarez-Herranz (2016), and Bakhsh et al. (2017).

Energy consumption and agricultural productivity

Because of the large amount of the consumption of fossil gasoline energy, the agricultural industry accounts for approximately 14−30% of global GHG emissions. Agriculture consumes both direct and indirect energy: directly through consumption of fuel such as diesel, natural gas, biogas and electricity for operating agricultural machinery, for example, water for irrigation and livestock grazing, and indirectly through the overuse of fertilizer and pesticide, causing contamination of the air (Hitaj and Suttles 2016; Rehman et al. 2019). The use of modern agricultural machinery or over-fertilization in order to increase productivity to meet the food demand. Therefore, agriculture is considered an energy-consuming industry and a large contributor to climate change from energy-related emissions. A conceivable upcoming modification in energy could lead the agricultural sector to carbon emissions (Hitaj and Suttles 2016). An earlier report by the UN Food and Agriculture Organization (FAO) estimated that the agricultural sector had significant potential to reduce hazardous emissions by eliminating 80–88% of new CO2 emissions (Reynolds and Wenzlau 2012). Concerning carbon emission in specific cases, unwanted activities regarding the environment are mainly responsible for air contamination. In energy generation, financial endeavors entail the combustion of energy for local manufacturing and transportation industries, which causes increased GHG emissions (Nasir and Rehman 2011). Many researchers have investigated the correlation between energy consumption and agricultural productivity and production efficiency. Karkacier et al. (2006) analyzed the effect of energy use in agriculture and estimated a strong

correlation between energy consumption and agricultural efficiency. Moghaddasi and Pour (2016) investigated energy consumption in Iranian agriculture and found a negative and significant correlation in the long term. Fuglie et al. (2007) confirmed the short-run and long-run correlation between agriculture and energy consumption in the United States. Chen et al. (2018) conducted a study on factor productivity growth in Chinese agriculture and showed that the primary cause of reduced productivity over time by regional disparities. A recent study by Chandio et al. (2018) analyzed the nexus of energy consumption and agricultural growth in Pakistan over the period 1984–2016 by applying the autoregressive distributed lag (ARDL) bounds testing model. Their significant findings revealed that agricultural productivity is reduced in the long- and short-run by gas and energy consumption. Other scholars have also investigated the correlation of energy consumption and economic growth with agricultural productivity and confirmed the existence of long-run and short-run associations (Binh 2011; Ahmed and Zeshan 2014; Guan et al. 2015; Nadeem and Munir 2016; Tang et al. 2016).

Air pollution and agricultural productivity

The connection between air pollution and agricultural economic growth and food production has adverse effects, because in order to increase production to meet food demand, farmers use more fertilizer and pesticide applications and adopt modern agro-based technologies that consume fossil fuel energy such as diesel and natural gas, which all release contaminants into the air. With the effects of air pollution on food production and the reduced resources available to meet the level of demand for food and nutrition, the loss of food grain production brings economic loss as well (Burney and Ramanathan 2014; Huo et al. 2014; Wei et al. 2014). In the past, the unofficial policy of "pollute first" and then "clean up" was at the heart of the poor environmental processes in China's agricultural industry (Liu et al. 2010), and finding a balancing between the agricultural environment and its correlation with food security is a huge challenge for China. Many researchers have sought to develop productive and environmentally friendly approaches for the sustainable production of food (Burney et al. 2010; Liu et al. 2016). Various works in the literature have revealed a correlation between CO2 emissions and environmental changes on the one hand and agricultural productivity on the other. The agricultural industry is an important source of carbon emissions, and at the same time is extremely vulnerable to the effects of climate change. In general, compared with thermodynamics industries, agriculture's contribution to carbon emissions is lower. Nevertheless, efforts to reduce CO2 emissions within the agricultural

sector are critical to expand the practice of low-carbon agriculture for economic growth and for environmental sustainability (Fan et al. 2015; Nayak et al. 2015; Fais et al. 2016). Increased agricultural activity causes increased CO2 discharge for food production (Johnson et al. 2007). As the world's largest agricultural producer, China's increased agricultural productivity has been accompanied by increases in carbon emissions, from 46.33 million tons in 1994 to 85.75 million tons in 2011 (Li et al. 2014). Agriculture is life-sustaining for those developing countries with massive populations, and thus they must be self-sufficient in delivering the supply of food (Timmer 2000). Greater efforts are needed to increase agricultural productivity through the use of modern agro-based technologies such as high-yield and disease-resistant crop varieties and land management, and motivating farmers to switch from traditional methods of farming to more advanced agrarian techniques. Chavunduka and Bromley (2013) highlighted the need for regulatory measures to ensure industry compliance in order to solve problems associated with the rising food demand. Because of increased food production and the need to adopt modern agro-based technologies, and in light of the increased air pollution from fossil fuel consumption associated with increased agricultural productivity, the issue of CO2 emissions from agriculture is a hot topic for China's governmental policymakers, and efforts to identify carbon emission determinants to replace pollution emitters with environmentally friendly agricultural methods. Li et al. (2014) used the Logarithmic Mean Divisa Index (LMDI) as a decomposition index and estimated the decomposition of China's CO2 emissions from agriculture for a data set spanning the period from 1994 to 2011. Their major findings confirmed that economic development was adversely affected by CO2 emissions associated with agricultural productivity. Another study illustrated similar results (2014; Asumadu-Sarkodie and Owusu 2016). Based on the literature and the objectives of this study, the following hypotheses were formulated.

Hypothesis

H$_1$: It may be possible that the ARDL co-integration equation estimation shows the long-run or short-run causality trending significantly towards agricultural economic growth as a cause of air pollution, crop area, total food grains, and greater use of fertilizer applications and energy consumption.

H$_2$: A one-way or two-way causal connection may be shown from agricultural economic growth, energy consumption, and food production as causes of air pollution in the short-run or long-run axis.

H$_3$: It may be possible that agricultural productivity does Granger cause or does not Granger cause air pollution and energy consumption.

Theoretical framework and literature assessment

Before going for further investigation, we first want to clarify the scope of the agricultural condition nexus and discussions around this subject. In Fig. 1, the rationales and correlations of variables are displayed in different aspects. In this article, we dissect two essential questions brought up earlier regarding the structure of the agricultural condition nexus, in which we start with factors affecting the agricultural industry in China (left). We then show how agriculture is influenced by environmental factors such as land management, water, and soil fertility (middle). Finally, we discuss policy implications for reducing air pollution and increasing agricultural industry production while at the same time sustaining the available resources.

The literature shows that only a few researchers have investigated the relevance of CO2 emissions and air pollution and their nexus with consumption of energy resources, financial development, agricultural growth, economic development, and renewable waste. These studies were conducted in various countries with different variables using different models to estimate their correlation. Nevertheless, the results of responsive literature stretched the indecisive and the provocative conclusion of each study from time to time. The fundamental changes between this research and previous literature selected variables to achieve the main objective is to know the correlation of air pollution with energy consumption and agricultural GDP, data of different time span, analytical equations, and model for estimation of the association. In an earlier work, we investigated the nexus of energy consumption, air pollution, and economic growth in China and the USA. However, we did not include agricultural economic growth. In the present study, we chose to examine the nexus between air pollution, energy consumption and agricultural development, as this has not been reported in previous literature for this study area. Another purpose in conducting this research is that agriculture in China supports approximately 22% of the world's population, and the country's limited resources and increasing food demand causes the over-exploitation of land resources. Therefore, in this study, we want to investigate whether China's agriculture trajectory runs in parallel with air pollution and energy consumption in long-run or short-run association, and whether it is able to supply the food demand within the framework of a healthy and sustainable environment.
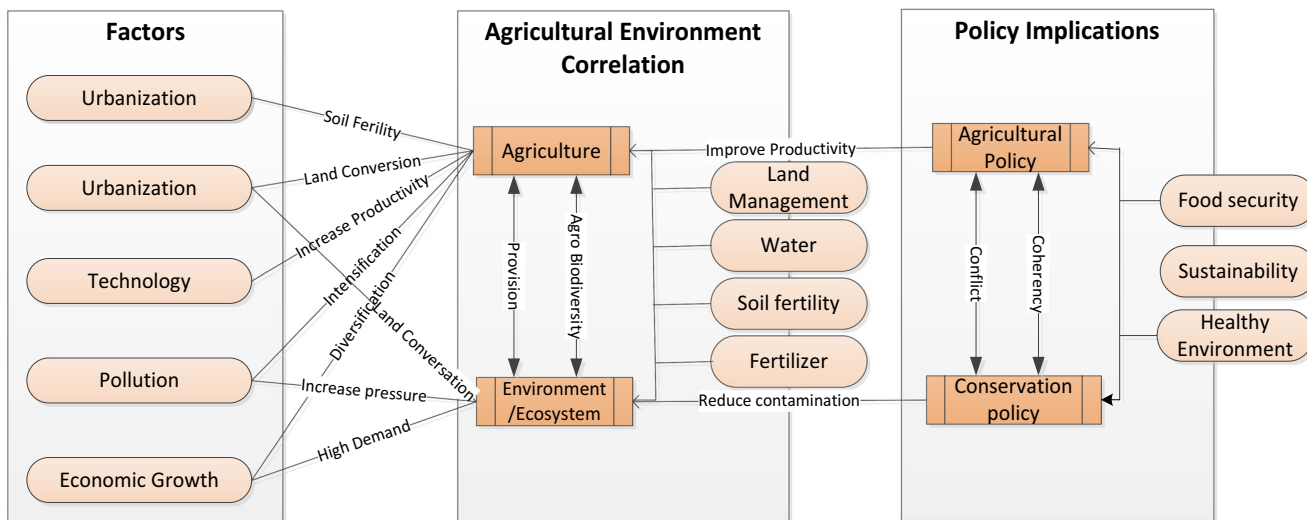
Fig. 1 Theoretical analysis (Yu and Wu 2018)

Methodology

Data collection

Time-series data for this study were collected from census data published by the World Bank and the Chinese National Bureau of Statistics for the period 1998−2018. The multivariate framework includes the agricultural GDP (LnAGDP) in constant US$2000, crop area (LnCA) in millions of hectares, energy consumption (LnEC) in a kilogram of oil equivalent per capital, consumption of fertilizer (LnUF) kg per hectare, total food grains implies with (LnTFG) measured in tonnes and carbon and methane emissions denoting to air pollution (LnAP) in kg tone. Furthermore, selected desired variables for this study can be seen in Table 1.

Model specification

For this study, the ARDL model was used for analysis to estimate the air pollution caused by the consumption of energy to increase agriculture production in China,

Table 1 Explanation of variables

Abbreviation	Variable	Explanation
LnAGDP	Agricultural GDP	Current US$
LnCA	Crop area	Million hectares
LnEC	Energy consumption	Kg of oil equivalent/capita
LnUF	Use of fertilizers	Kg per hectares
LnTFG	Total food grain production	Tons
LnAP	Air pollution	Metric tons per capita

Data source: secondary data gathered from GoCN and World Bank

looking back over the past two decades. Following the EKC hypothesis equation developed by Ang (2007) and similarly estimated by other researchers (Lean and Smyth 2010; Sugiawan and Managi 2016; Shahbaz and Sinha 2019).

$$AP_{it} = \alpha_i + \beta_1 AGDP_{it} + \beta_2 AGDP_{it}^2 + \beta_3 CA_{it} + \beta_4 EC_{it}$$
$$+ \beta_5 TFG_{it} + \beta_6 UF_{it} + \varepsilon_{it} \quad (1)$$

By employing the logarithm in Eq. 2, it is rewritten as follows:

$$LnAP_{it} = \alpha_i + \beta_1 LnAGDP_{it} + \beta_2 LnAGDP_{it}^2 + \beta_3 LnCA_{it}$$
$$+ \beta_4 LnEC_{it} + \beta_5 LnTFG_{it} + \beta_6 LnUF_{it} + \varepsilon_{it} \quad (2)$$

where AP represents air pollution, AGDP and $(AGDP)^2$, respectively, represent agricultural GDP, CA refers to crop area, EC is energy consumption in agriculture, UF is the designated fertilizer usage in the agricultural sector, TFG represents total food grain production and its square term, i indicates cross-section, t represents the time period, and the error term is denoted by ε $v_t$vt for the error term. β_4 predicts confidence that the growth of energy consumption is likely to aggravate air pollution. The EKC hypothesis indicates that β_1 is desirable, but β_2, β_3, β_5, and β_6 are expected to be undesirable. However, this study estimated that the equation with $(AGDP)^2$ is probably not suitable. If the EKC hypothesis does not provision in the paper or through the co-integration among desired variables in Eq. 1, it is difficult to determine, formerly including CA, EC, UF, TFG does not appropriate. Therefore, to identify whether, comprising CA, EC, UF, TFG are appropriate or inappropriate, and then test the rationality of the EKC hypothesis, in this work Eq. 2 in the form is given below:

$$LnAP_t = \beta_0 + \beta_1 LnAGDP + (LnAGDP)^2 + V_1 \quad (3)$$

If the EKC hypothesis for LnAGDP is undesirable, which meaning that the co-integration indicates the byzantine correlation, then $(AGDP)^2$ will not be consider as desirable variable.

For the stationarity of the variables, the unit root test was employed, following the techniques reported by of Dickey and Fuller (1979), Phillips and Perron (1988), and Perron 1990). The aim of the unit root test is to test the null hypothesis, and there are two excessive or surplus hypotheses. One is that the series does not have a unit root with a linear time trend, and the second is that the series has a nonzero mean and a stable trend with no time trend. The unit root equation is given below.

$$\Delta T_i = \delta_0 + \delta_1 T_{t-1} + \sum_{i=1}^{Z} \alpha_i \Delta T_{t-1} + \nu_t \quad (4)$$

where T proves the unit root test, Δ reflects the first difference, t represents the time span, z indicates the optimal lag order, and V is the white noise residuals. In the unit root test, ADF provides the cumulative distribution. The Phillip and Perron (PP) test equation is given below.

$$\Delta T_i + \varphi_0 + \rho^* T_{i-t} + \nu_t \quad (5)$$

The correlation co-integration test was employed as follows:

$$\delta_1 AP_{2i-1} - (\delta_1 CA_{t-1} + \delta_2 EC_{t-1} + \delta_3 UF_{t-1} \quad (6)$$
$$+ \delta_4 TFG_{t-1} + \delta_5 AGDP_{t-1}$$
$$+ \delta_6 AGDP_{t-1}^2 + V_{2t}) = 0$$

where the signs δ_1, δ_2, δ_3, δ_4, δ_5, δ_6 are consistent with the long-run co-integration correlation.

The ARDL model was introduced by Pesaran and Shin (1998) for analysis of long- and short-run correlations, it was further developed by Pesaran et al. 2001). Narayan (2004) similarly used this model to check the long-run and short-run nexus between selected variables. The integration order was distributed among the variables at I(0) or I(1) separately from the incidence of I(2). Here, we distinctly proved the long-run and short-run models in checking the correlations between variables. Many other scholars have established and used the co-integration hypothesis. These include an approach proposed by Engle and Granger (1987), the maximum likelihood co-integration by Johansen and Juselius (1990), and the recently introduced ARDL approach by Pesaran et al. (2001). The ARDL for the co-integration estimation has numerous advantages over substitutions. Pesaran and Smith (1998) exposed some compensations of the ARDL bounds testing model. The basic and positive fact of

ARDL is that it is not necessary to integrate the variables in order. Halicioglu (2009), Ghosh (2010) and Iwata et al. (2010) examined the co-integration correlation between carbon emissions and economic development with other variables for a single country. In the present study, we followed the same analytical technique in order to estimate the short-run and long-run causality among selected variables for China. The ARDL model is shown in Eq. 7.

$$\Delta lnAP_t = \alpha_0 + \sum_{i=1}^{z} \varepsilon_{3i} \Delta lnEN_{t-i} + \sum_{i=1}^{z} \rho_{4i} \Delta lnUF_{t-i}$$
$$+ \sum_{i=1}^{z} \omega_{5i} \Delta lnTFG_{t-i} + \sum_{i-1}^{z} \sigma_{6i} \Delta lnAGDP_{t-i}$$
$$+ \vartheta_1 lnAGDP_{t-1}^2 + \vartheta_2 lnCA_{t-1} + \vartheta_3 lnEC_{t-1}$$
$$+ \vartheta_4 lnUF_{t-1} + \vartheta_5 TFG_{t-1} + \vartheta_6 lnAGDP_{t-1}$$
$$+ \varepsilon_t \quad (7)$$

where α_0 represents the intercept of the constant, Δ represents the difference operator, Z is the lag order, β, γ, ε, ρ, ω, and σ is the short-run coefficient, and ε_t the sign of the error term. The ARDL bounds testing approach is directly analyzed using EViews version 9.0, and the OLS first has not been estimated. The null hypothesis of no co-integration of any long-run relationship, H0 $\vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 = 0$ tested beside the alternative H1: $\vartheta_1 \neq \vartheta_2 \neq \vartheta_3 \neq \vartheta_4 \neq \vartheta_5 \neq \vartheta_6 = 0$. We estimated the value of the F-statistic to confirm the long-run association among the desired variables. The results for the F-statistic are calculated following Pesaran (2001) grounded theory for critical value. In attendance the two sets of critical values proposed for level of significance by time lag and without time lag, where I(0) stands for level and I(0) stands for first difference, we also identify the lower bound and upper bound critical values (LBV and UBV). This provides a band covering all possible classifications of the variables co-integrated at a level I(0) and I(0). If the estimated value of the F-statistic proposed is greater than UBV, the null hypothesis can probably be rejected and the alternative hypothesis accepted, and if the F-statistic value is below the critical value of LBV, then the null hypothesis is accepted and the alternative hypothesis will be rejected, and probably remain among the critical value of LBV and UBV, meaning the results can be indecisive. Therefore, the lag order of the variables is likely to be selected on the basis of the Schwartz-Bayesian criterion (SBC), Hannan Quinn criterion (HQC) and Akaike information criterion (AIC). The SBC is obvious through the lowermost possible lag order, though the AIC is equipped to select the uppermost lag order. The long-run nexus among variables possibly analyzed subsequent the assortment of the ARDL model based on the AIC, HQC, and SBC. After a long-run relationship is confirmed, then the error

correction model (ECM) can be analyzed by following Eq. 8.

$$\Delta lnAP_t = \delta_0 + \sum_{i=1}^{z} \delta_{1i} \Delta lnAGDP^2_{t-i} + \sum_{i=1}^{z} \delta_{2i} \Delta lnCA_{t-i}$$
$$+ \sum_{i=1}^{z} \delta_{3i} \Delta lnEC_{t-i} + \sum_{i=1}^{z} \delta_{4i} \Delta lnUF_{t-i}$$
$$+ \sum_{i=1}^{z} \delta_{5i} \Delta lnTFG_{t-1} + \sum_{i=1}^{z} \delta_{6i} \Delta lnAGDP_{t-i}$$
$$+ \theta ECM_{i-1} + V_t \qquad (8)$$

The error correction term (ECT) identifies the speed of adjustment, and depicts how the variables run towards the equilibrium through short-run time adjustment, and it must have a negative sign of the coefficient along with statistically significant value. Diagnostic and stability tests are conducted to ensure the goodness of fit model. These tests were analyzed to clearly understand the causal correlation, functional form, normality and heteroscedasticity. In addition, analyzing the stability of the short-run, we estimate the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMQ). Consequently, constancy tests such as the CUSUM and CUSUMQ are evaluated to confirm the goodness of fit and the stability of the model.

Analysis and results

A basic test in time-series analysis is the unit root test to determine the stationarity of the variables at level or first difference; all the variables have stationarity at an identical difference level. Consequently, the process should be integrated variables, and the acceptable value for bounds testing should be level or at first difference. In this research, we followed the ADF and PP sub-tests of the unit root test established by Dickey and Fuller (1979) and Phillips and Perron (1988), respectively. Both tests similarly used the unit root test for substitution of stationary. The results in Table 2 show that in ADF, the lnAGF test

shows stationarity at first difference at a 5% level of significance, while lnUF shows stationarity of first difference at 1% significance, and all other variables demonstrate stationarity at the first difference level with 1% significance. In the PP test, lnAP confirms stationarity at the first difference with 5% significance, while lnCA and lnUF maintains stationarity at the first difference with 10% significance. All other variables demonstrate that there is stationarity at the first difference level with 1% significance. The results of the unit root test show that all the variables are integrated at the first order, i.e. I(1), which indicates that the ARDL bounds testing approach can be employed. The above results are supported by earlier research. For example, Rehman (2019) analyzed the correlation of CO2 emissions and agricultural productivity in Pakistan and found a positive correlation among variables by rejecting the null hypothesis. Mardani et al. (2018) also demonstrated that the same variables rejected the null hypothesis at a 5% significance level.

Co-integration test

For the statistical model, the co-integration technique was employed, and the value of the F-statistic and W-statistic was used for the upper bound of statistics at the desired significance value. The F-statistics do not accept the null hypothesis, nor do they have any co-integration the between desired variables. The results of the co-integration equation show that the lower-bound value (LBV) I(0) and upper-bound value (UBV) I(1) are significant at the 1%, 5% and 10% levels (Table 3). The results were confirmed on the basis of the Pesaran et al. (2001) table and exceeded the upper bound value, while the critical values of (LBV) and (UVB) were 3.538 and 4.428, respectively, which were recorded at the 5% significance level (Table 3). The same results were found in earlier work by Ben Jebli and

Table 2 Unit root test results

Variables	ADF test				PP test			
	Level	Trend & Intr	First level	Trend & Intr	Level	Trend & Intr	First level	Trend & Intr
lnAGDP	0.572	−0.765	−4.356***	−4.324***	1.852	0.125	−3.761**	−3.124**
(lnAGDP)^2	2.142	−0.364	−5.076***	−4.875***	1.297	−3.251**	−4.872***	−4.536**
lnAP	−1.302	−2.132	−4.256***	−4.017**	2.978	−0.214	−5.462**	−5.934***
lnEC	−1.724	−2.211	−4.876***	−4.507**	0.916	−0.282	−5.263***	−4.572**
lnCA	1.124	−.0851	−5.609***	−4.980**	1.876	0.252	−3.081*	−3.152**
lnTFG	1.018	−0.425	−4.352**	−5.342***	1.564	−1.289	−4.265**	−4.016**
lnUF	−1.087	−2.321	−3.871*	−3.346*	0.652	−0.123	−3.124**	−3.045**

*Null hypothesis rejected at 10% significance level; **null hypotheses rejected at 5% significance level; ***null hypotheses rejected at 1% significance level. Above results analyzed by EViews 9.0 student version

Table 3 Results of autoregressive distribution lag bounds testing approach

Variables	F-statistic	P-value
$H_{AGDP}(AGDP^2/AP, EC, CP, TFG, UF)$	9.104	***
Critical bound value	**I(0)**	**I(1)**
10%	2.081	3.000
5%	2.394	3.380
1%	3.065	4.153

***Null hypotheses rejected at the 1% significance level. Above results analyzed by EViews 9.0 student version

Ben Youssef (2017), Khan et al. (2018), and Koondhar et al. (2018). Furthermore, if the critical value of the F-statistic is greater than the UVB and is significant at a 1% significance level, this indicates that there is co-integration among our study variables, and the null hypothesis can be rejected. Now, if we call H0:$\vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 = 0$, then it can be rewritten as:

$$D(AGDP) = -0.096 - 0.093*D(AGDP(-1)) - 1.146*D(AP(-1))$$

$$+ 1.677*D(EC(-1)) + 1.227*D(CA(-1))$$

$$+ 0.135*D(TFG(-1)) - 0.766*D(UF(-1))$$

$$-1.161*AGDP(-1) + 0.011*AP(-1)$$

$$-1.627*EC(-1) + 0.196*CA(-1)$$

$$+ 0.282*TFG(-1) + 1.466*UF(-1)$$

In addition, to further investigate the stability of the variables, we performed a co-integration test using trace and maximum eigenvalue (max-eigen) statistics with a critical value, and the results are presented in Table 4. The results indicate that in trace statistics, cons≤0 cons≤1 cons≤2 are significant at the 1% level, only cons≤3 is significant at the 5% level, and others are nonsignificant. In max-eigen statistics, cons≤0 and

cons≤1 are significant at the 1% level, and cons≤2 and cons≤3 are significant at the 5% level. This indicates that the null hypothesis was rejected at the 5% and 1% significance levels. The probability value was measured based on the MacKinnon-Haug-Michelis (1999) p-values. Awad (2017) found that the results of EKC have a U-shaped curve, and similar results were reported earlier by Ozcan (2013), Koondhar et al. (2018), and Rehman et al. 2019).

To further investigate the correlation among the desired variables, we analyzed the long-run and short-run Granger causality test to ascertain the precise implications of robust policies (Table 5. The results revealed that agricultural economic growth ($AGDP_t$) Granger causes air pollution (AP_t) both in long-run and short-run causality. Further, the Granger causality test confirmed the existence of EKC, based on the literature related to this study (see e.g. Shahbaz et al. 2012 for Pakistan, Shahbaz et al. 2013 for South Africa, Shahbaz et al. 2014 for Tunisia, Shahbaz, Bhattacharya et al. 2017 for Australia, and Jalil and Mahmud 2009; Kang et al. 2016; Li et al. 2016; and Stern 2017 for China).

For the secondary investigation of the relationship among energy, air pollution and agricultural GDP, a special lag order selection equation was required. Therefore, we investigated the ARDL long-run and short-run coefficient nexus between selected variables. The key technique for this system was to employ an unrestricted error correction model. The description of this model is to disorder the causality in order. Therefore, it is necessary to use the proper selection of lag order for the variables based on time span. The best order can be found based on the values of the AIC, HQC and HBC. The results of AIC, SC and HQC can be seen in Fig. 2, with the appropriate lag order of the derail variables for the ARDL model (1, 1, 0, 1) designated for auxiliary analysis. Various techniques have been similarly used by other researchers with the different variables and different objectives, and are discussed in the literature (Halicioglu 2009; Hatemi and Hacker 2009; Yildirim and Aslan 2012; Koondhar et al. 2018).

Table 6 presents the results of the short-run correlation among our desired variables based on the ARDL bounds testing approach. The results show that the Lagrange multiplier (LM)

Table 4 Results of co-integration test for ARDL model

Null hypothesis	Trace statistics	P-value	Null hypothesis	Max-eigen statistics	P-value
$Coin \leq 0*$	207.814*	0.000***	$Coin \leq 0$	74.303*	0.000***
$Coin \leq 1*$	133.512*	0.000***	$Coin \leq 1$	58.057*	0.000***
$Coin \leq 2*$	75.454*	0.000***	$Coin \leq 2$	33.413*	0.007**
$Coin \leq 3*$	42.041*	0.001**	$Coin \leq 3$	28.881*	0.003**
$Coin \leq 4$	13.160	0.109	$Coin \leq 4$	10.469	0.183
$Coin \leq 5$	2.6913	0.101	$Coin \leq 5$	2.6913	0.101

**Null hypotheses rejected at 5% significance level; ***null hypotheses rejected at 1% significance level. Above results analyzed by EViews 9.0 student version

Table 5 Pairwise Granger causality test

Null hypothesis	F-Statistic	Sign value
Long-run causality		
$AGDP_t$ does not Granger cause AP_t	2.383	0.129
AP_t does not Granger cause $AGDP_t$	1.795	0.202
$AGDP_t^2$ does not Granger cause AP_t	4.543	0.030
AP_t does not Granger cause $AGDP_t^2$	2.265	0.141
Short-run causality		
$\nabla AGDP_t$ does not Granger cause ∇AP_t	2.580	0.111
∇AP_t does not Granger cause $\nabla AGDP_t$	1.770	0.206
$\nabla AGDP_t^2$ does not Granger cause ∇AP_t	4.129	0.039
∇AP_t does not Granger cause $\nabla AGDP_t^2$	1.891	0.188

approach tests the causal correlation as well. The results demonstrate the X2 circulation towards one degree of freedom, which means that the autoregression exists in the residuals of the applied models. Therefore, the mis-specification by the Ramsey RESET test that is similarly dispersed by the solitary degree of freedom confirms that the applied replication is a proper fit. The replication is also examined by the normality test.

The results of $AGDP^2$, EC, TFG and UF do not show short-run causality with agricultural growth in China. Therefore, we accept rather than reject the null hypothesis, and an alternative hypothesis is rejected. Cropland shows a positive and significant correlation with agricultural GDP, which means that the null hypothesis is rejected at 10% significance level, and the alternative hypothesis is accepted. Dantama (2012) used the same ARDL bounds testing model to investigate the nexus between CO2 and economic growth, and his research found that the soul variables had a long-run relationship.

Additionally, Rehman et al. 2019) investigated CO2, energy consumption, and agricultural productivity, and found positive and significant causality between the selected variables. The results indicated that a 1% increase in cropland caused an increase in agricultural GDP. When air pollution rejects the null hypothesis rather than accepting the null hypothesis at a 5% significance level by the negative sign of the coefficient, this means that agricultural GDP can be increased by reducing air pollution. For this system overall, we can say that the entire system is adjusted at a speed of 2.364% towards the long-run equilibrium.

The correlation among the desired variables was estimated using EViews 10.0, and the results can be seen in Fig. 3. Data for this study cover the years 1998–2018. In 1998, the cropland and pollution were lower as compared with the contribution of agricultural to GDP. While farmland increased gradually with increasing fertilizer consumption and increased pollution in agriculture, the contribution of agriculture to GDP decreased owing to the increase in the other variables. The peak fertilizer consumption was recorded in 2015, after which governmental initiatives led to a decrease to some extent in 2016–2018. It is clear that the increase in pollution in 2017 and 2018 was greater than the contribution of agricultural GDP to national GDP. In early literature, some researches were conducted to test EKC for different objectives (Kaika and Zervas 2013; Al-Mulali et al. 2015; Stern 2018).

To confirm the goodness of fit and stability of the model for the short-run and long-run coefficients, the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) statistical techniques were employed for further analysis. The CUSUM and CUSUMSQ plots presented Fig. 4 clearly show that both plots collapse between two lines with a significance level of 5%, which means that our selected variables for this study rejected the null hypothesis and instead accepted the alternative hypothesis. The literature shows that a number of researchers have also used CUSUM and CUSUMSQ tests for checking both model stability and goodness of fit (Ploberger and Krämer 1992; Xiao and Phillips 2002; Lee et al. 2003; Westerlund 2005; Afzal et al. 2010; Huang et al. 2011; Seker et al. 2015; Koondhar et al. 2018; Rehman et al. 2019).
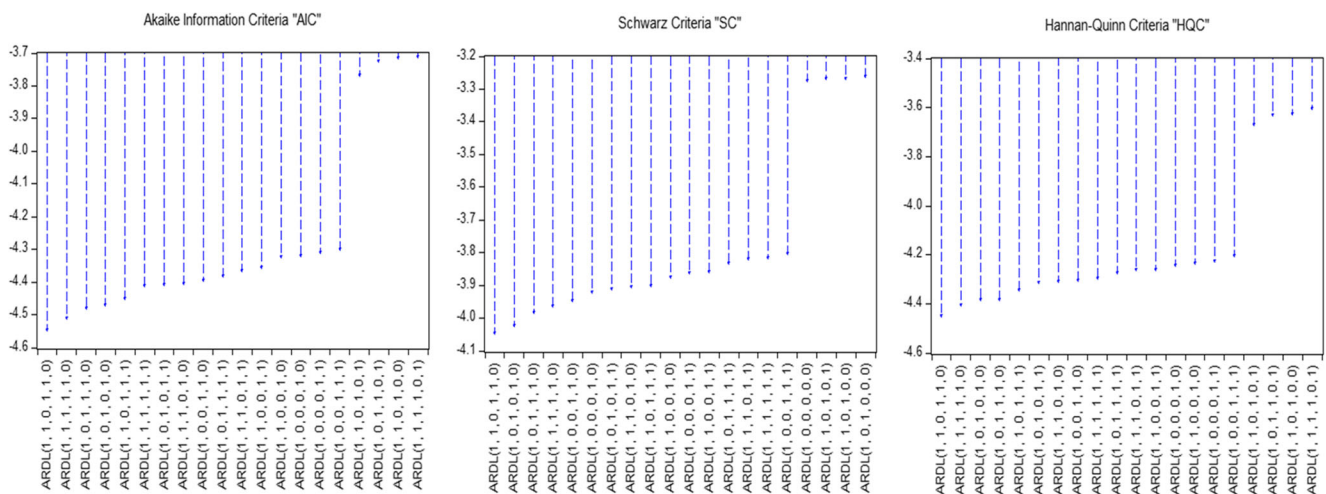
Fig. 2 Lag selection approach for our desired variables by AIC, SC and HQC

Table 6 Short-run and long-run coefficient analyzed by ARDL

Variables	Coefficient	Std error	t-test	P-value
C	−0.045720	0.017820	−2.565739	0.028**
D[AGDP(-1)]	0.038879	0.262572	0.148071	0.885
D[AGDP^2(-1)]	−2.166992	1.030528	−0.724389	0.045
D[CA(-1)]	1.269446	0.674972	1.880739	0.089*
D[EC(-1)]	0.040489	0.390128	0.103783	0.919
D[TFG(-1)]	−0.319296	0.192958	−1.654739	0.129
D[UF(-1)]	−0.269956	0.283907	−0.950863	0.364
ECT(-1)	−2.364078	0.921602	−1.890345	0.048**
R^2		0.548	F-stat	3.567
Adjust R^2		0.232	D.W. stat	1.682
Prob F-Stat		0.000	L.M.	
RESEM		1.652***	Hetro….	2.429***

*Null hypothesis rejected at 10% significance level, **null hypotheses rejected at 5% significance level, ***null hypotheses rejected at 1% significance level. Above results analyzed by EViews 9.0 student version

Conclusion and policy implications

Agriculture is considered China's most important sector in terms of its contribution to national GDP and in meeting the food needs of one-third of the world's population. The rapid increase in population has led to steadily declining resources in order to meet the food demand of the growing population. The problem of limited resources in turn has led to overuse of fertilizers and modern agro-based technology that consumes high levels of energy and causes air pollution. Therefore, in this study, we aimed to explore the nexus between air pollution energy consumption and the contribution of agricultural to

GDP, to determine whether a causal relationship existed between air pollution and agricultural development. Secondary time-series data for the past two decades were collected from World Bank indicators and statistics bureau of China. Empirical results estimated using an ARDL bounds testing model to determine the long-run and short-run co-integration basic unit root test, and co-integration tests were employed. The results of the unit root test show that lnAFG, lnUF, lnAP and lnCA rejected the null hypothesis and accepted the alternative hypothesis at a significance level of >5%, indicating that all variables were integrated at level and first difference.

The results of the co-integration equation upper bound value (UBV) and lower bound value (LBV) were significant at 1% and 5%, which means that there is co-integration causality between air pollution, energy consumption and agricultural GDP. For a clear understanding of the estimation model, suitable lag order (1,1,0,1) was selected based on the values of AIC, HQC and SBC. For the short-run analysis, consequences of the desired variable distribution towards one degree of freedom, acquires the autoregression exists in the residuals of the applied models. Therefore, the mis-specification by Ramsey's RESET test show that the similarly dispersed by the solitary degree of freedom confirms that the applied replication is a proper fit. In addition, some variables rejected the null hypothesis and accepted the alternative hypothesis with a significance level of less than 5% in the ARDL model. This means that short-run causality is available between variables, and also shows that the speed of long-run equilibrium association adjustment of air pollution, energy consumption to agricultural productivity in a short period of time. Constructed by EKC equation correlation of soul variables were estimated and found that in 1998, cropland was limited and the population was lower, but the contribution of
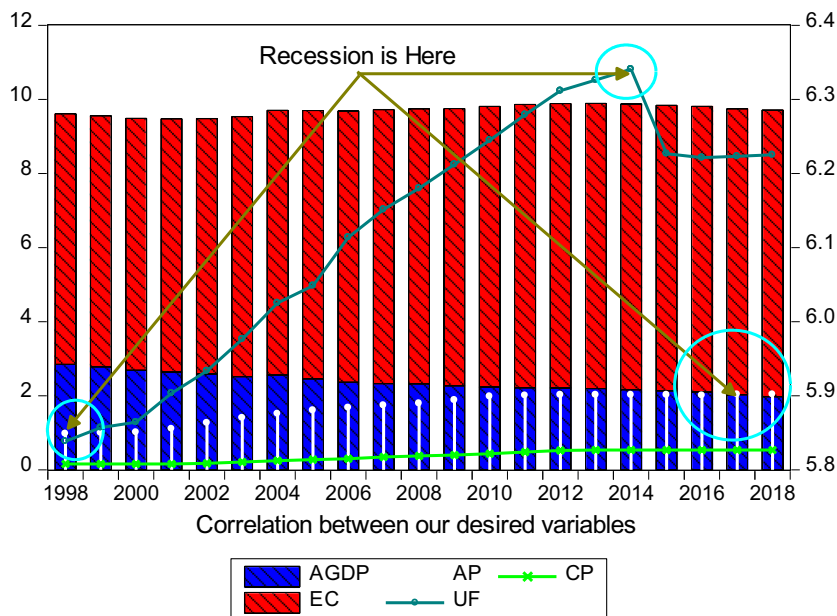
Fig. 3 Nexus between desired variables
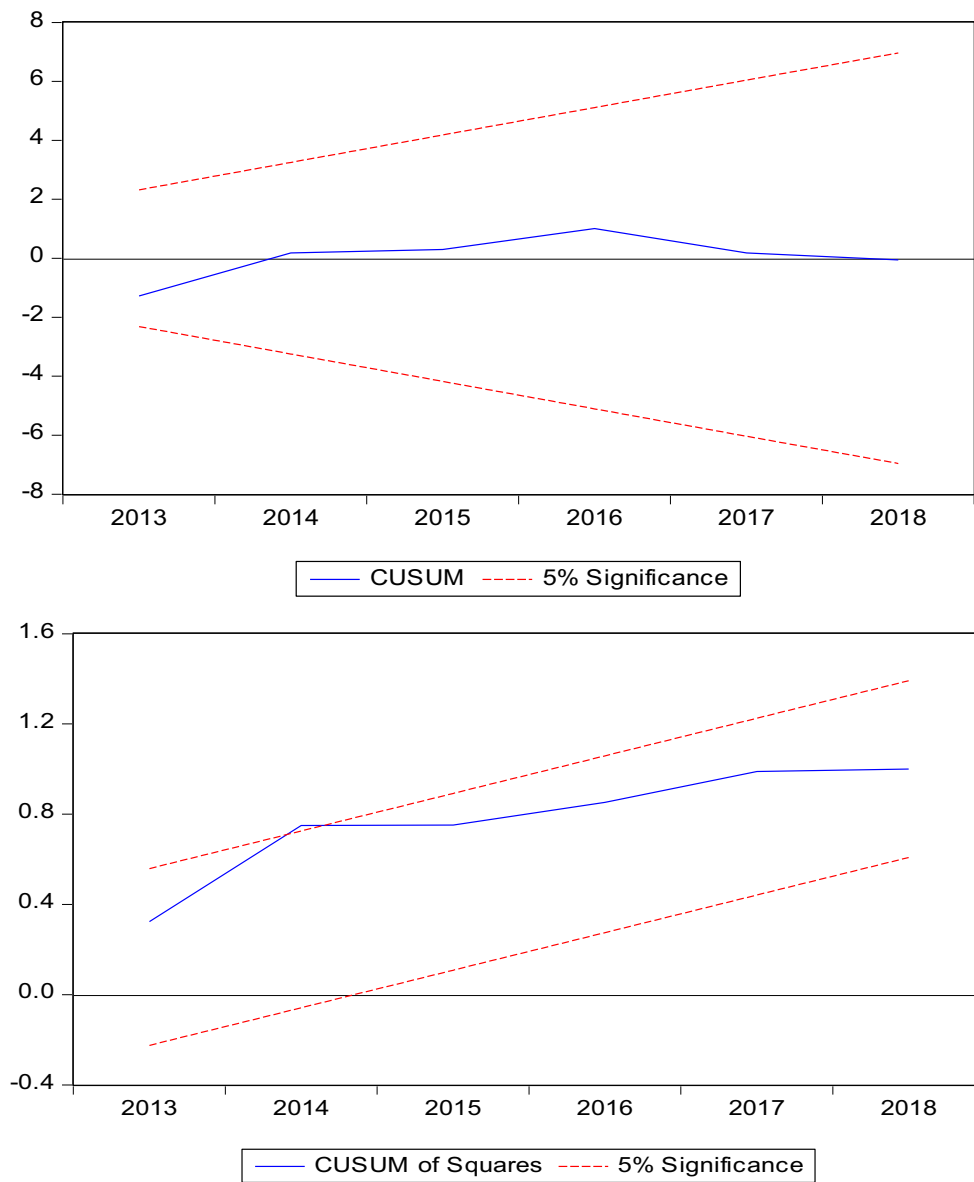
Fig. 4 Plot of the CUSUM (cumulative sum) of recursive residuals and CUSUMSQ (cumulative sum of squares) of recursive residuals

agriculture to national GDP was much higher than in 2018, and agriculture did not lead to contaminated air. The results of Granger causality test also confirmed the existence of EKC. Within the time span, the population increased and demand for food also increased. In order to supply the food demand, over-fertilization and new agro-based technologies were adopted, which consumed more fuel and caused air pollution, which reduced the agricultural contribution to national GDP by the time lag. To confirm the goodness of fit and stability of the model for the coefficient of short-run and long-run, the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) statistical techniques were employed for further analysis. Clearly, in two different plots what the common found in both plots CUSUM and CUSUMSQ collapsed in between

two lines with a significance level of 5%, which means that our selected variables for this study rejected the null hypothesis and accepted the alternative hypothesis. The null hypothesis indicates that there is a long-run and short-run association running from air pollution and energy consumption towards agricultural productivity.

Policies for this study were measured based on the results. New policies to be considered include switching from chemical fertilizer and pesticide to organic fertilizer and biological pest control applications, adopting renewable energy technologies to replace fossil fuels, such as solar energy, wind turbine, and biomass, and genetically modified high pest-resistant crops along with climate-favorable varieties of cereal crops for higher yield to meet the food demand while sustaining a healthy

environment. The implementation of these measures would not only increase the contribution of agriculture to national GDP, but also reduce air pollution through the adoption of modern technologies based on an environmentally friendly approach.
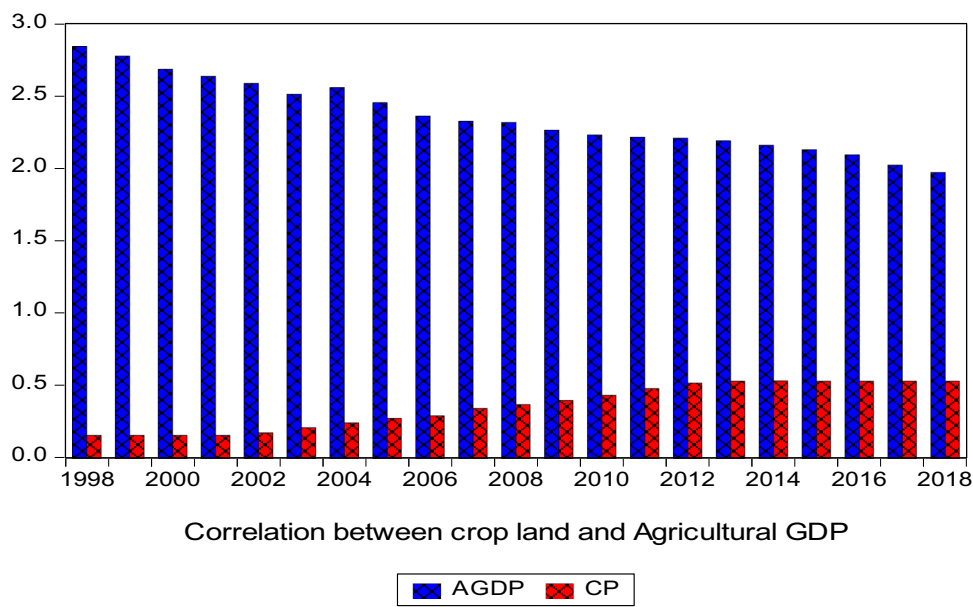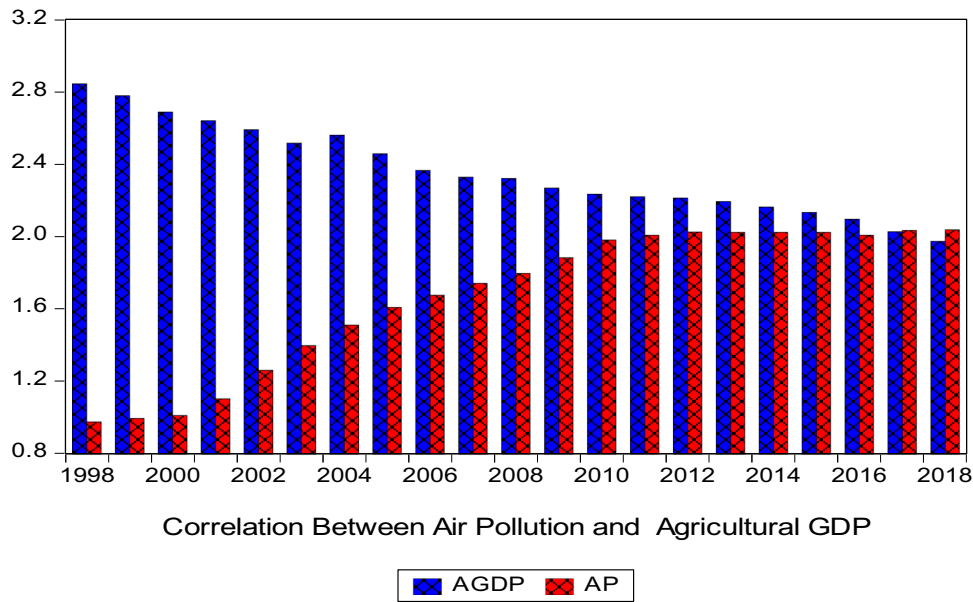
Author contributions All authors made significant contributions to the study conception and design. The generation of ideas, collection of data, and analysis was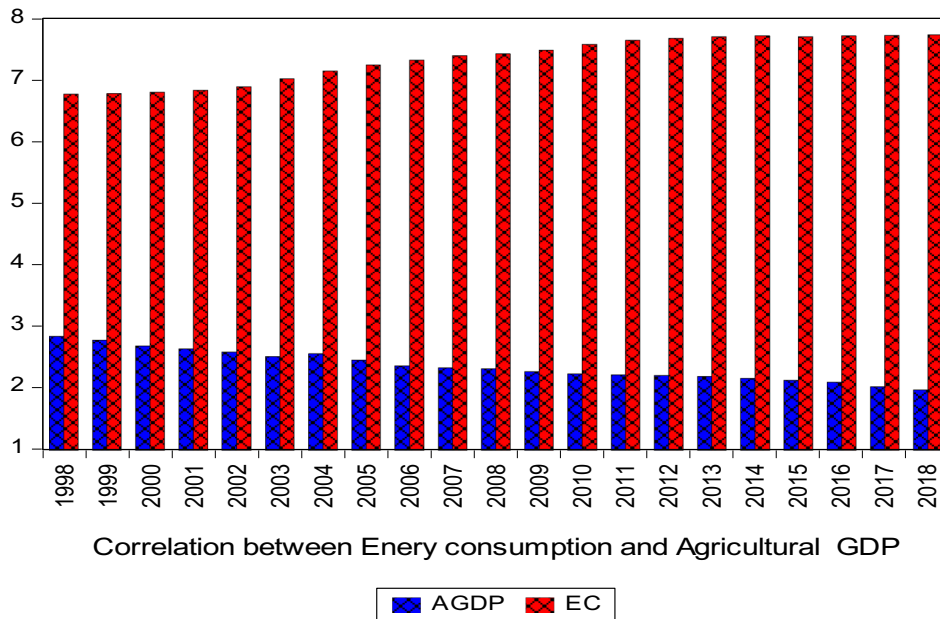 performed by Houjian Li, Huiling Wang, and Sanchir Bold. The first draft was completed by Mansoor Ahmed Koondhar, and all authors were involved in providing feedback and critical revision of the manuscript. The whole work was carried out under the supervision of Prof Dr. Rong Kong, who approved the final version of the manuscript.

Compliance with ethical standards

Conflict of interest   All authors declare that they have no conflict of interest.

Appendix

Correlation Between Air Pollution and Agricultural GDP

Correlation between crop land and Agricultural GDP

Correlation between Enery consumption and Agricultural GDP

AGDP   EC

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