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Research article

Fertilizer use and agricultural practices in the paradox of maize crop production and environmental sustainability

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A R T I C L E I N F O

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A B S T R A C T

The enduring existence of pollution presents a substantial danger to human health, natural systems, and social welfare. Human activities mostly generate greenhouse gas emissions, namely carbon dioxide, which negatively impacts the environment. This study used annual datasets to examine the association between maize crop production, maize yield, fertilizer consumption, agricultural land use, and environmental quality in China. In order to identify the positive and negative shocks with the assessment of short- and long-run dynamics, the study used an asymmetric Nonlinear Autoregressive Distributed Lag (NARDL) approach. A Robust Least Squares method was also used to locate the parameters nexus in order to assess the series' robustness. Results from the long-run interaction indicate that the maize crop production and agricultural land use has a positive impact on CO_2 emissions with probability values of (0.000), (0.000), and (0.001), (0.780), respectively, via both positive and negative interruptions. Additionally, maize yield exposed a detrimental effect on environmental quality. Results of the robust least squares analysis showed that maize crop production, fertilizer consumption, and agricultural land use had a positive influence on environmental quality, with probability values of (0.000), (0.004), and (0.949), respectively. However, there is an unfavourable relationship between variable maize yields and CO_2 emissions. China should play a significant role in seeking to reduce carbon dioxide emissions and adopt the beneficial policies necessary to ensure the environment's long-term sustainability, since these emissions are now a rising issue around the world.

1. Introduction

The demand for food has risen in parallel with the expansion of the world population and advancements in living standards. Food security is a critical concern for countries like China, which has a population of 19 % of the world's total yet only has access to 8 % of the world's arable land. The cultivation of crops has a substantial influence on characteristics such as arable land area, crop density,

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and productivity, all of which are vital for ensuring access to nutritious meals. The farming area is determined by multiplying the planted area by the planting density. In order to address the growing demand for crop production, it is necessary to fulfil one or more prerequisites. Furthermore, to enhance agricultural productivity, it is vital to augment planting intensity [1–3]. There is strong evidence that changes in the climate have a substantial impact on the productivity of crops. However, precisely determining the specific climatic conditions that have the greatest impact on food production in a particular geographic region may be a challenging task. Prior to developing adaptation methods for agricultural output in light of global warming, it is essential to first identify the key environmental factors that restrict the potential productivity of crops [4–6]. The possible increase in the incidence of severe heat events might be associated with rising temperatures. Rising temperatures lead to faster crop growth, which in turn shortens the growing season by reducing the time available for growth and grain filling. It offers evidence that prolonging the agricultural growing season is essential for reducing the adverse effects of environmental degradation [7,8].

China imports and consumes a larger quantity of grain than any other country. The rise in individual meat and animal product consumption is primarily responsible for the rising demand for maize as livestock feed. Therefore, China's maize output has a substantial impact on worldwide supply and demand. So it is imperative for economists and policymakers at both national and international levels to acquire a greater awareness of the influence of global warming on China's maize output. Additionally, it has been the subject of several study investigations [9–11]. China is among the nation's most vulnerable to the environment because of its massive population, expansive landmass, complex meteorological conditions, and delicate natural environment. Throughout the entire period, there have been significant variations in precipitation changes across different regions, with the total rate of rise in the country

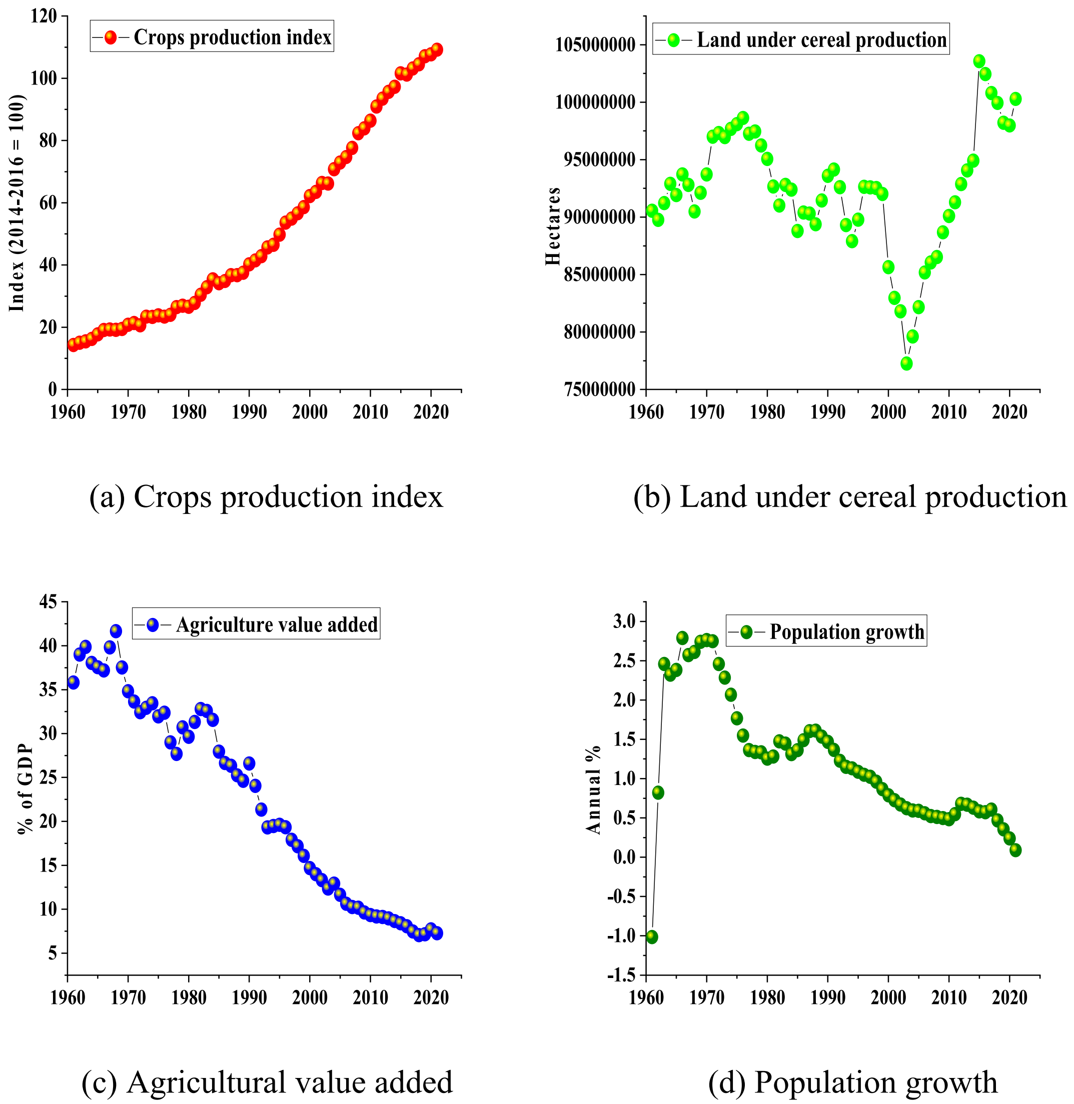


Fig. 1. Historical trends of (a) crops production index, (b) land under cereal production, (c) agricultural value added, and (d) Population growth in China (1960–2020).

surpassing the global average. Climate change has had a considerable impact on China's agricultural productivity, presenting a danger to global food security. Crop potential for production can be analysed to determine the primary constraints to agricultural output, and an assessment of such patterns and the factors influencing crop production potential in conjunction with climate change may directly indicate the extent of collaboration as well as variations among crop production prospective and temperatures, light, and water resources [12,13]. The occurrence of weather changes is now attributed to global warming, which is generally acknowledged as a significant environmental danger. This issue has garnered attention from scientists, governments, and the general public. Given the probable influence of climate change on the agricultural industry, scientists have shown enduring interest in the consequences of changing weather patterns on crop production. Climate change and altered precipitation patterns are causing an increase in the frequency and intensity of severe weather occurrences. According to Rosenzweig et al. (2014) [14], Zampieri et al. (2017) [15], Sui et al. (2018) [16], and Zampieri et al. (2019) [17], the most prevalent forms of severe weather include heat waves, floods, and droughts.

China's agriculture sector has played an integral part in the nation's economic development for many years. The most serious question is whether China will be able to feed its massive population. As the country's population and economy develop, this issue will remain a source of contention. Agriculture and rural society face new possibilities and hazards as a consequence of the present fast economic expansion and urbanization process [18]. Agriculture is vital to the economy of the entire country. Increases in agricultural production and output are well recognized to considerably benefit a country's economic growth. The provision of raw materials to other businesses is one way agricultural growth improves the economy [19]. Contrarily, climate has a significant influence on agricultural production. Rising global temperatures have a negative influence on agriculture and crops since many plant species are temperature sensitive. Food security and systems for producing maize are both negatively impacted by climate change-related extreme weather events [20]. The agricultural sector is disproportionately impacted by the consequences of accelerated global warming. Climate change might potentially impact the production and yields of food crops. Optimal weather conditions are necessary to enhance the output of food crops. Climate change factors such as changing weather patterns and greenhouse gases like carbon dioxide have had a substantial influence on agricultural productivity. The growth of the economy is influenced by many aspects, including agriculture output, commodity price, and farmer income [21,22]. One of the biggest threats to human welfare is global warming, the environmental effect of rising carbon emissions. China has emerged as the leading economy in terms of carbon emissions, therefore guaranteeing a forthcoming surge in emissions levels. In recent years, China's food production industry has seen substantial progress due to technological advances. The advancement in agricultural commodities has great significance for the future of both agriculture and human civilization. These inputs have a significant impact on the increase of greenhouse gas emissions in both the upstream and downstream stages of the industrial process. The agriculture sector's substantial dependence on fossil fuels, exacerbated by advancements in technology and ways of irrigation, has led to a marked increase in carbon emissions. There has been an increase in the occurrence of straw combustion as a result of the transition away from straw as the primary energy source in rural households. Fig. 1 depicts the chronological progression of the crops production index, land use for cereal production, agricultural value added, and population growth in China. As a consequence, the emission of greenhouse gases (GHGs) has significantly risen, leading to the escalation of smog and air pollution. These factors have adverse impacts on human health. The present study constitutes a unique and original extrapolation to the existing literature by examining the distinct impacts of maize crop production, agricultural land usage, and fertilizer use on the environment. According to our present knowledge, there are not many existing studies that have adequately explained the intricate connection between maize crop production, agricultural land usage, and their influence on the environmental quality. The investigation used yearly datasets to investigate the association between maize crop production, agricultural land usage, maize yields, fertilizer consumption, and carbon emissions in China. The study used an asymmetric Nonlinear Autoregressive Distributed Lag (NARDL) technique to investigate the influence of various factors on the environmental quality. In addition, a Robust Least Squares approach was used to find the variable nexus and evaluate the robustness of the series.

2. Literature review

In this part, we will look at the previous studies that uncover the influence of CO_2 emission on the agricultural productivity. Limiting the negative impacts of carbon emission is a crucial concern in the national development policies. Over the last decade, there has been much discussion over the detrimental effects of economic advancement on the environment.

In recent decades, improved crop varieties, usage of fertilizers, farm management and irrigation have all led to the better crop yields. Increasing temperatures, on the other hand, shorten the growing season for crops, potentially leading to poorer yields and more variability if no management changes are undertaken [23]. There is an intrinsic connection between environmental health and agriculture. Greenhouse gas emissions are rising as a result of agricultural activity. Enhanced oversight of livestock production, rice cultivation, and fertilizer use might potentially mitigate greenhouse gas emissions linked to agriculture [24]. One may argue that a thriving economy requires an efficient environment. Reductions in CO_2 emissions have been utilized in many studies as a measure of environmental health. Significant increases in greenhouse gas emissions, especially carbon dioxide emissions, are necessary for economic development activities linked to environmental deterioration. Given that carbon dioxide emissions are seen as a serious danger to human survival, several countries have committed to reducing pollution while maintaining economic progress. Recent decades have seen a great deal of investigation on the EKC hypothesis from both ecological and economic angles [25–27]. Meeting the food needs of a growing population, however, means paying greater consideration than previously to issues related to agricultural output production and the impacts it has on land, air, water, and biodiversity. García-González et al. (2018) [28] discovered that soil functions as a substantial carbon sink, capable of storing three times as much carbon than plants can and twice as much as the atmosphere. The assumption that growing amounts of anthropogenic and neurogenic greenhouse gas emissions are responsible for climatic changes and increased global warming is widely accepted by scientists. Climate change will have an influence on businesses that depend on the weather, such as agriculture and forestry. Producer and consumer welfare, agricultural commodity prices, output, demand, trade, and regional competitiveness are all potentially impacted by global warming [29]. Food poverty is exacerbated because maize production is more complex to climatic change than any other crop in the entire country. The ability of farmers to acclimatize to climate change must be strengthened if it is possible to maintain a consistent food supply that can fulfil local demand. Environmental changes have been shown to expose an adversative impression on developing-country food security and production [10,30]. The decrease in CO_2 emissions connected with agriculture is a complex issue that involves both technical and societal factors. Subsequently, agricultural activities are a significant source of greenhouse gas emissions. Changes in land use and the implementation of agricultural mechanization might potentially impact both energy consumption and the release of CO_2 emission. Investigations have shown an interaction between changes in crop production and land utilization, which might potentially be mitigated by advancements in technology. Input prices and revenues have a more significant impact on agricultural production choices than technology constraints. The possibility of farmers participating in high-income agricultural activities is connected to the net profit they get from their agricultural output [31–33].

Agriculture employs over one-third of the world population, with Asia accounting for half of that figure. As a consequence, agriculture maintains its worldwide dominance and critical role in the global economy, especially in developing countries. Groundwater pollution, habitat damage, resource depletion, and forest loss are just a few of the global environmental challenges that need more agricultural investment [34]. The social and economic repercussions of decreased agricultural CO_2 emissions are significant. Agricultural activities are the primary contributor of carbon dioxide emissions. The pollution level generated by agriculture and the extent of automation in the sector may vary significantly. Recent evidence indicates that variations in agricultural productivity and cropland are the primary cause of the recent worldwide rise in agricultural CO_2 emissions. Furthermore, it is expected that technological advancements will substantially decrease agricultural CO_2 emissions in the future. When making decisions on agricultural output, producers must consider not just limitations on resources, but also the expenses of inputs and the income generated [35–37]. Although carbon dioxide emissions contribute significantly to GHGs emissions, the erosion of ecological sustainability is the extreme danger to the world's supportable expansion and must be included into any assessment of environmental concerns. Conversely, CO_2 emissions are not always a reliable predictor of environmental damage. Carbon dioxide emissions from mining, petroleum, soil, and forests, for example, could not be considered accurate indicators of resource depletion. As a result, a large indicator is required to combat ecological deterioration and ensure sustainable development [38,39].

The agriculture sector will be the primary recipient of the majority of adverse consequences resulting from warming temperatures. Agriculture's role in creating jobs and ensuring food security is particularly important in emerging economies. With increasing temperatures, agriculture faces heightened vulnerability. Climate and weather fluctuations exert a substantial influence on agricultural output and farming practices. The volatility of meteorological patterns presents a substantial apprehension for the sustainability of economies heavily reliant on agriculture, since it performs an essential part in sustaining livelihoods and guaranteeing food security [40–42]. On one side of the discussion, the global economy has undergone significant industrialization and urbanization in recent decades. Locals, on the other hand, have been vociferous in their support for efficient agricultural expansion in the face of rising global food demand due to periodic droughts and severe weather. Agriculture and industry are competing to reduce carbon emissions, which is driving market growth. Estimating the links between agriculture and environmental quality, as well as those between industry and carbon emissions, is critical for understanding how both sectors contribute to the occurrences of global warming [43,44]. Climate change is harming emerging economies quicker than developed ones, particularly those that rely heavily on agriculture. This might be because wealthy countries can respond quickly to climate concerns and mitigate their effect. Agriculture, on the other hand, is critical

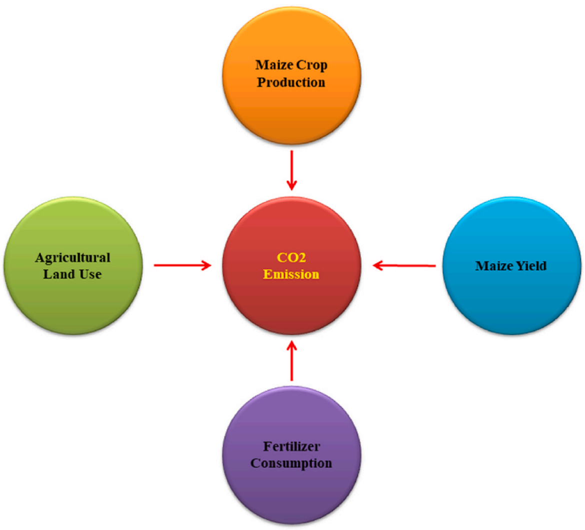


Fig. 2. Influence mechanism to CO_2 emission.

to the economy of growing countries such as China because of the employment and export money it creates. Both Nhamo et al. (2019) [45] and Anderson et al. (2020) [46] conclude that emerging economies are more sensitive to climate change challenges since agriculture is so important to their economies.

3. Methodology of the study

The primary objective of this investigation was to determine the interaction between maize crop production, maize yield, fertilizer consumption, agricultural land use, and environmental degradation in China. This was accomplished by utilising the yearly time sequence data that was obtained from the two primary sources, World Development Indicators (https://data.worldbank.org/) and Our World in Data (https://ourworldindata.org/). Major considerations in the study include the maize crop production, maize yield, fertilizer consumption, agricultural land use, and annual CO_2 emission. The effect process of the CO_2 emission and other factors is being shown by Fig. 2.

3.1. Model specification for the variables

To check the influence of maize crop production, maize yields, agricultural land use and fertilizer consumption to environmental degradation, following model can be stated as:

$$\text{Annual Carbon Dioxide Emission}_t = f\begin{pmatrix} \text{Maize Crop Production}_t, \text{Maize Yield}_t, \\ \text{Fertilizer Consumption}_t, \text{Agricultural Land Use}_t \end{pmatrix} \tag{1}$$

The primary equation (1) may be expanded upon as follows:

$$ACO2e_t = f(MP_t, MY_t, FC_t, AL_t) \tag{2}$$

The variables in equation (2) can be explained as follows: $ACO2e_t$ represents the yearly carbon dioxide emission, MP_t denotes the maize crop output, MY_t represents the maize yields, FC_t indicates the fertilizer consumption and AL_t represents the agricultural land usage. Further, equation (2) can be written as:

$$ACO2e_t = \xi_0 + \xi_1 MP_t + \xi_2 MY_t + \xi_3 FC_t + \xi_4 AL_t + \varepsilon_t \tag{3}$$

Whereas the coefficients ξ_1 through ξ_4 in Equation (3) represent the long-term effects, t is used to determine the amount of time that has passed, and ε_t is used to characterize the error term. In general, the equation exposes the logarithmic formulation for all variables, including maize crop production, maize yields, agricultural land use, fertilizer consumption and annual CO_2 emission.

3.2. Econometric strategy with asymmetric technique

The present investigation used the asymmetric (NARDL) strategy to investigate the interaction between the parameters by examining their positive and negative shocks. The ARDL technique was originally presented by Pesaran et al. (2001) [47] to inspect the interaction of variables. To explain the NARDL approach, we need to first build the autoregressive distributed lag model for the variables in term to error correction form, which may be described as:

$$\begin{aligned}\Delta ACO2e_{\,t} = {} & \tau_0 + \sum_{a=1}^{a} \tau_1 \Delta ACO2e_{\,t-a} + \sum_{a=0}^{a} \tau_2 \Delta MP_{t-a} + \sum_{a=0}^{a} \tau_3 \Delta MY_{t-a} + \sum_{a=0}^{a} \tau_4 \Delta FC_{t-a} + \sum_{a=0}^{a} \tau_5 \Delta AL_{t-a} + \eta_1 ACO2e_{\,t-1} + \eta_2 MP_{t-1} \\ & + \eta_3 MY_{t-1} + \eta_4 FC_{t-1} + \eta_5 AL_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

The dynamic linkage for the variables is presented in equation (4). Further, equation (4) can be stated in error correction form as follows:

$$\Delta ACO2e_{\,t} = \theta_0 + \sum_{a=1}^{a} \theta_1 \Delta ACO2e_{\,t-a} + \sum_{a=0}^{a} \theta_2 \Delta MP_{t-a} + \sum_{a=0}^{a} \theta_3 \Delta MY_{t-a} + \sum_{a=0}^{a} \theta_4 \Delta FC_{t-a} + \sum_{a=0}^{a} \theta_5 \Delta AL_{t-a} + \beta_0 ECT_{\,t-1} + \varepsilon_t \tag{5}$$

In equations (4) and (5), $\tau_1 - \tau_5$ and $\theta_1 - \theta_5$ represent short-term coefficients, $\eta_1 - \eta_5$ represents long-term coefficients, and ε_t represents the residual term. Furthermore, it outperforms other standards since it concentrates on a more manageable subset of fundamental demands while rewarding its contributions. Meanwhile, Pesaran et al. (2001) argue that the (F-test) may be used to check the accuracy of long-term forecasts as well as the specific consequences of such predictions on the provided parameters. Once coexistence has been established, the long-term pliability is determined using η_2-η_5, and then this value is regularized using η_1. In contrast to the outcomes of the Shin et al. (2014) [48], maize crops production, maize yield, fertilizer consumption, agricultural land positive and negative effects with the decomposition of $\left(MP_a^+; MY_a^+; FC_a^+; AL_a^+\right)$ and can be written as:

$$\left(MP_a^+ = \sum_{a=1}^{a} \Delta MP_a^+ = \sum_{a=1}^{a} \max\left(\Delta MP_a^+, 0\right); MY_a^+ = \sum_{a=1}^{a} \Delta MY_a^+ = \sum_{a=1}^{a} \max\left(\Delta MY_a^+, 0\right); FC_a^+ = \sum_{a=1}^{a} \Delta FC_a^+ = \sum_{a=1}^{a} \max\left(\Delta FC_a^+, 0\right); AL_a^+ = \sum_{a=1}^{a} \Delta AL_a^+ = \sum_{a=1}^{a} \max\left(\Delta AL_a^+, 0\right)\right) \tag{6}$$

For the negative shocks ($MP_a^-; MY_a^-; FC_a^-; AL_a^-$);

$$\left(MP_a^- = \sum_{a=1}^{a} \Delta MP_a^- = \sum_{a=1}^{a} \min\left(\Delta MP_a^-, 0\right); MY_a^- = \sum_{a=1}^{a} \Delta MY_a^- = \sum_{a=1}^{a} \min\left(\Delta MY_a^-, 0\right); FC_a^- = \sum_{a=1}^{a} \Delta FC_a^- = \sum_{a=1}^{a} \min\left(\Delta FC_a^-, 0\right); AL_a^- = \sum_{a=1}^{a} \Delta AL_a^- = \sum_{a=1}^{a} \min\left(\Delta AL_a^-, 0\right)\right) \tag{7}$$

Equations (6) and (7) reflect the impacts of both positive and negative shocks on maize production, maize yield, fertilizer use, and agricultural land use. Thus, the model's asymmetrical appearance can be described in equation (8) and stated as follows:

$$\Delta ACO2e_t = \phi_0 + \sum_{a=1}^{a} \phi_1 \Delta ACO2e_{t-a} + \sum_{a=0}^{a} \phi_2 \Delta MP_{t-a}^+ + \sum_{a=0}^{a} \phi_3 \Delta MP_{t-a}^- + \sum_{a=0}^{a} \phi_4 \Delta MY_{t-a}^+ + \sum_{a=0}^{a} \phi_5 \Delta MY_{t-a}^- + \sum_{a=0}^{a} \phi_6 \Delta FC_{t-a}^+ + \sum_{a=0}^{a} \phi_7 \Delta FC_{t-a}^- + \sum_{a=0}^{a} \phi_8 \Delta AL_{t-a}^+ + \sum_{a=0}^{a} \phi_9 \Delta AL_{t-a}^- + \vartheta_1 ACO2e_{t-1} + \vartheta_2 MP_{t-1}^+ + \vartheta_3 MP_{t-1}^- + \vartheta_4 MY_{t-1}^+ + \vartheta_5 MY_{t-1}^- + \vartheta_6 FC_{t-1}^+ + \vartheta_7 FC_{t-1}^- + \vartheta_8 AL_{t-1}^+ + \vartheta_9 AL_{t-1}^- + \varepsilon_t \tag{8}$$

However, we may use the following assumptions to illustrate the error-correction model exploration as:

$$\Delta ACO2e_t = \phi_0 + \sum_{a=1}^{a} \phi_1 \Delta ACO2e_{t-a} + \sum_{a=0}^{a} \phi_2 \Delta MP_{t-a}^+ + \sum_{a=0}^{a} \phi_3 \Delta MP_{t-a}^- + \sum_{a=0}^{a} \phi_4 \Delta MY_{t-a}^+ + \sum_{a=0}^{a} \phi_5 \Delta MY_{t-a}^- + \sum_{a=0}^{a} \phi_6 \Delta FC_{t-a}^+ + \sum_{a=0}^{a} \phi_7 \Delta FC_{t-a}^- + \sum_{a=0}^{a} \phi_8 \Delta AL_{t-a}^+ + \sum_{a=0}^{a} \phi_9 \Delta AL_{t-a}^- + \lambda ECT_{t-1} + \varepsilon_t \tag{9}$$

The error correction models for the variables maize crop production, maize yield, fertilizer consumption, and agricultural land use are shown in equation (9).

4. Empirical findings and discussion

The results of summary statistics between variables are shown in Table 1. The estimate of Skewness test reveals that all parameters are negative with the exception of ACO_2e. Furthermore, observations from Kurtosis also show that all variables are platyphosic. In order to emphasize how significant the data is, the J-Bera metrics could further corroborate the aforementioned normal distribution. Moreover, findings of the correlation matrix reported in Table 2 for the variables, indicating that each variable is interrelated.

4.1. Stationarity test among variables

We validated stationarity among the parameters by using unit root testing mainly described as the DFGLS [49], P–P [50] and the ADF [51]. To improve the variables' validity, the order of inclusion is crucial for the choosing of the regression estimator applied to the task of estimating longevity of coefficients. The main drawback of these two initial inquiries is that they do not consider possibilities for data consolidation. Table 3 summarizes the estimates for all the unit root tests, which is necessary for transforming non-declarative time series data into a fixed format and reducing the complexity of imitation assessment. We found that by the utilization of these

Table 1
Descriptive analysis.

	ACO2e	MP	MY	FC	AL
Mean	21.944	18.459	1.441	17.168	19.956
Median	21.934	18.470	1.546	17.486	20.074
Maximum	23.163	19.423	1.843	17.877	20.085
Minimum	20.510	17.284	0.654	15.579	17.750
Std. D.	0.812	0.612	0.334	0.669	0.331
Skew.	0.011	−0.097	−0.791	−0.940	−5.833
Kurtosis	1.755	2.065	2.478	2.699	39.269
Jarque-Bera	3.355	1.972	6.013	7.859	3145.110
Probability	0.186	0.372	0.049	0.019	0.000

Table 2
Correlation matrix.

	ACO2e	MP	MY	FC	AL
ACO2e	1.000	0.984	0.938	0.926	0.086
MP	0.984	1.000	0.962	0.936	0.082
MY	0.938	0.962	1.000	0.979	0.163
FC	0.926	0.936	0.979	1.000	0.211
AL	0.086	0.082	0.163	0.211	1.000

Table 3
Stationarity testing via unit roots.

DF-GLS unit root test conducted at the level					
	ACO2e	MP	MY	FC	AL
(Statistical test results and p-values)	1.046 (0.300)	0.759 (0.451)	0.513 (0.610)	0.250 (0.803)	−1.123 (0.266)
DF-GLS unit root test conducted at the first difference					
(Statistical test results and p-values)	−3.503*** (0.001)	−3.739*** (0.000)	−7.927*** (0.000)	−6.030*** (0.000)	−0.961** (0.040)
P–P unit root test conducted at the level					
(Statistical test results and p-values)	−1.175 (0.678)	−1.141 (0.692)	−2.580 (0.103)	−9.623*** (0.000)	−0.869 (0.789)
P–P unit root test conducted at the first difference					
(Statistical test results and p-values)	−4.727*** (0.000)	−9.896*** (0.000)	−10.348*** (0.000)	−6.227*** (0.000)	−2.921*** (0.009)
ADF unit root test conducted at the level					
(Statistical test results and p-values)	−0.703 (0.836)	−1.720 (0.414)	−3.971*** (0.003)	−4.057*** (0.002)	−0.869 (0.789)
ADF unit root test at conducted the first difference					
(Statistical test results and p-values)	−4.715*** (0.000)	−8.351*** (0.000)	−7.845*** (0.000)	−5.284*** (0.000)	−3.568*** (0.000)

Note: **, *** signifies level of significance at $p < 0.05$ and $p < 0.01$, accordingly.

unit root tests, no variables is get integrated at the second difference.

4.2. Assessment of bounds testing through cointegration

The NARDL approach was used in the study to investigate the variables' connections. The AIC may be used to determine the statistical significance of the F-test obtained from autoregressive distributed lag bounds testing. As showing in Table 4, the result of the F-test, which produces statistically significant estimates, is (10.644).

4.3. Cointegration technique

After confirming the sequence of the test parameters, the interaction between the measurements is considered to be significant. Incorporating the test variables is crucial when the predicted statistical value is equal to or higher than the critical value. The method of J-cointegration may be used to analyse variable procedures. Before using the NARDL approach, we conducted a J-cointegration test to expose the long-term convergence of the model's research parameters [52]. The results explored in Table 5 demonstrate that the statistics from both the trace test and maximum Eigen values, we reject the hypothesis of no cointegration equation at a significance level of 5 %. Due to these accomplishments, every variable has at least one cointegrating equation, signifying that the research variables are cointegrated across long periods of time.

4.4. Findings of asymmetric technique (short and long-run)

Table 6 displays the asymmetric (NARDL) analysis results with short- and long-run estimates. Short-run interactions demonstrate that the variables maize crop production and agricultural land utilization had a negative influence on CO_2 emission for positive and

Table 4
Findings of bounds test to cointegration.

F-statistic Value (10.644) k (8)	At the level of Significance	I(0)	I(1)
	(10 %)	(1.85)	(2.85)
	(5 %)	(2.11)	(3.15)
	(2.5 %)	(2.33)	(3.42)
	(1 %)	(2.62)	(3.77)

Table 5
Cointegration analysis.

Trace Testing			
Hypo-no of CE(s).	(Trace test Stat.)	Critical values at (0.05)	Prob-values
None *	75.468	(69.818)	(0.016)
At most 1	42.925	(47.856)	(0.134)
At most 2	18.586	(29.797)	(0.522)
At most 3	6.018	(15.494)	(0.693)
At most 4	0.335	(3.841)	(0.562)
Maximum Eigenvalue Rank Testing			
Hypo-no of CE(s).	**(Max-Eigen Stat.)**	**Critical values at (0.05)**	**Prob-values**
None	32.542	(33.876)	(0.071)
At most 1	24.339	(27.584)	(0.123)
At most 2	12.567	(21.131)	(0.492)
At most 3	5.683	(14.264)	(0.654)
At most 4	0.335	(3.841)	(0.562)

Table 6
Asymmetric short and long-run.

Short-run evidence				
Variables	Coeff.	S-error	t-Stat.	P-values
C	−0.735	1.305	−0.563	0.576
ACO2e(-1)	0.040	0.063	0.636	0.527
MP_POS	−0.179	0.137	−1.307	0.198
MP_NEG	−0.681***	0.221	−3.081	0.003
MY_POS	0.226	0.208	1.083	0.285
MY_NEG	0.817***	0.332	2.462	0.018
FC_POS	0.016	0.082	0.204	0.839
FC_NEG	−0.111	0.139	−0.796	0.430
AL_POS	−0.563	0.432	−1.303	0.199
AL_NEG	−0.005	0.018	−0.307	0.760
ECT	0.040***	0.003	11.393	0.000
Long-run dynamics				
MP_POS	4.402***	6.039	0.728	0.000
MP_NEG	16.734***	25.796	0.648	0.000
MY_POS	−5.553	9.238	−0.601	0.551
MY_NEG	−20.066	31.397	−0.639	0.526
FC_POS	−0.413	2.262	−0.182	0.855
FC_NEG	2.726**	5.633	0.484	0.030
AL_POS	13.829***	24.904	0.555	0.001
AL_NEG	0.139	0.495	0.281	0.780
C	18.055***	3.722	4.850	0.000
R^2 (0.997)		F-stat. (2261.533)		
Adjusted-R^2 (0.997)		Prob(F-stat.) (0.000)		
Akaike Info Criterion (AIC) (−3.458)		D-Watson stat (1.841)		

Note: **, *** signifies level of significance at $p < 0.05$, $p < 0.01$.

adverse shocks, with coefficients (−0.179), (−0.681), (−0.563), (−0.005) and probabilities of (0.198), (0.003), (0.199), (0.760). Maize yield had an upward trend with CO_2 emissions, with coefficients (0.226), (0.817) and probabilities (0.285), (0.018). Furthermore, fertilizer usage demonstrated a substantial and negative relationship to CO_2 emission through positive and negative shocks.

On the other side, the long-run estimated outcomes show that maize crop production and agricultural land use positively influenced the CO_2 emission in China with coefficients (4.402), (16.734), (13.829), (0.139) and probability values (0.000), (0.000), (0.001), (0.780) respectively via positive and negative shocks. The variables maize yield adversely impacted the environment with coefficients (−5.553), (−20.066) and probabilities are (0.551), (0.526) through the positive and negative shocks. Furthermore, the variable fertilizer consumption demonstrated a positive and negative influence to the environment during positive and negative shocks.

Maize is the most widely cultivated cereal crop globally, and its importance has consistently increased over time. The impacts of global warming on crops throughout the entire growing season are substantial, especially in terms of climate and agronomic control. The impact of increasing temperature on livestock and cereal crop yields creates challenges for assessing present conditions and preparing for the future [53]. In comparison to wheat and rice, maize may be used in more ways. In industrialized countries, it serves several purposes as an industrial and energy crop in addition to its primary usage as animal feed. The demand for maize as feed is rising

Table 7
Results of stability tests.

Tests	F-statistic	Prob.-values
Test of Serial-Correlation (Breusch-Godfrey)	0.916	0.408
Test of Heteroskedasticity (Harvey)	8.403***	0.000
Test of Ramsey -RESET	1.674	0.203

Note: *** signifies level of significance at $p < 0.01$.

rapidly in regions like Asia where economic development has led to a rise in the consumption of food of animal origin [54]. Reduced food supply, agricultural deterioration, and chemical pollution are among challenges posed by global warming, all of which threaten social and economic stability and ultimately human life. Human-caused CO_2 emission and other GHGs are the principal cause of global warming [55,56]. The rising frequency of extreme weather events, such as heat waves, droughts, floods, and biological shocks, is causing growing apprehension about agri-food systems. This issue is not limited to any certain crop. The concurrent disintegration of worldwide food storage facilities and its consequences may arise from severe climatic circumstances affecting global agricultural production [57].

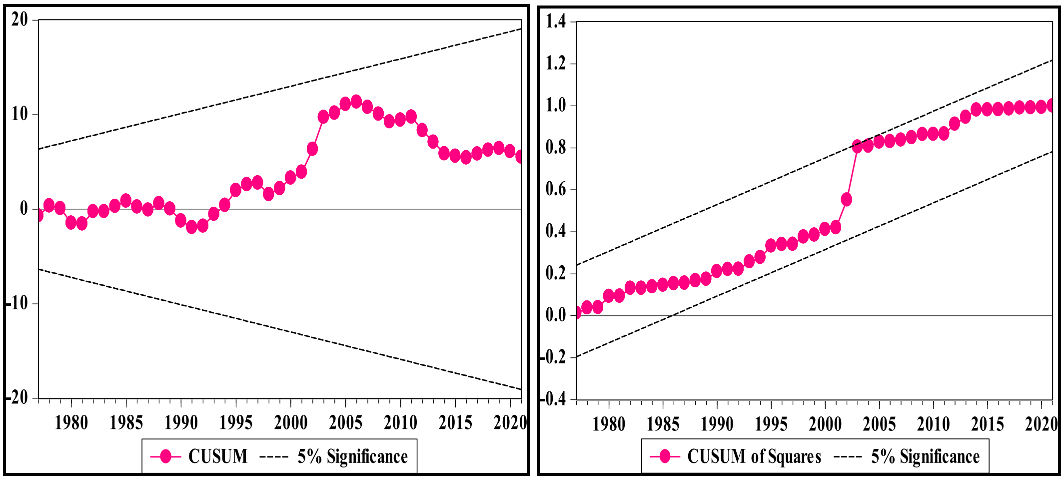
Despite geophysical and ecological limitations, such as the severely disparate allocation of water resources, China has done an amazing job of feeding the world's vast population and arable land. But there is a cost to this. Soil health, water availability, and pollination are just a few examples of the ecological services provided by local ecosystems that farms in China and elsewhere rely on. Overuse of agrochemicals, soil erosion due to land conversion, and deforestation are just a few examples of the ecological problems caused by intensive farming practices [58–60]. In order to sustainably feed the growing global population within the current environmental crisis, it is imperative to use conservation agriculture practices that are environmentally-friendly, resource-efficient, and yield-enhancing [61]. Soil is a limited resource that undergoes continuous replenishment and depletion due to natural and human activity. Degradation has led to a fall in soil production and quality, making it a very urgent environmental and socioeconomic concern. The process of erosion, a natural phenomenon, is responsible for the breakdown of soil and the subsequent deformation of its surface under physical stresses [62]. Moreover, a prominent indicator of land degradation is the progressive depletion of carbon in the soil. The issue of sustainable development, biodiversity conservation, and climate change mitigation is a significant challenge [63]. Addressing the food needs for a growing global population while adopting a circular economy approach in agriculture is a worldwide challenge. The main goal is to grow high-yield maize in unused fields, using a low-yield production technique. In order to enhance system productivity and energy usage efficiency, maintain environmental health, and generate profits, maize fallow systems must include energy conservation, a low carbon footprint, and financially viable short-term crops [64].

The practice of environmentally sustainable agriculture draws on several disciplines. A few examples include the fields of agronomy, livestock science, ecology, hydrology, meteorology, entomology, pathology of plants, and economics. Pollinator-friendly flower management on farms is an area of environmental sustainability in agriculture that has extended a lot of consideration. In the food and agriculture business, information exchange is necessary since there is a lack of integration and consumers who are interested have no ability to access and understand the appropriate scientific material. Reducing greenhouse gas emissions in agricultural and livestock farming is a relatively recent priority that has not been well linked with other environmental concerns [65,66]. Because of the dynamic interplay between climatic change, CO_2 emissions, and agriculture, the negative consequences on one will have a knock-on effect on agricultural output. The beneficial and detrimental effects of precipitation, temperature, and CO_2 emission intensity on crop production during sowing have been shown [67]. A rise in major greenhouse gases in the atmosphere has been connected to resource depletion [68]. Although the scale effect is more applicable to industry, it is also applicable to agricultural growth and overall economic development. For example, there is a moderate demand for agricultural products and the manufacturing process in the early stages of expansion may rely on manpower and animal supplies. Due to the increasing demand for agricultural products driven by economic growth and population growth, farmers are compelled to use mechanized services for production purposes. The rise in CO_2 emissions may be attributed to the growing reliance on mechanized agricultural equipment, which mostly operates on fossil fuels such as kerosene [69,70].

Table 7 also encompasses the results of the stability and diagnostic techniques. Figs. 3 and 4 show the cumulative sum and cumulative sum of squares at a threshold for significance of 5 %, illustrating the differential impact of positive and negative shocks on maize crop production, maize yield, fertilizer use, and agricultural land.

4.5. Outcomes of robust least squares

The robustness of the variables was assessed using the robust least squares technique. The results are presented in Table 8. Table findings uncover that maize crop production, fertilizer consumption and agricultural land positively influenced the CO_2 emission with coefficients (1.521), (0.431), (0.004) with probability values (0.000), (0.004), and (0.949) respectively. Maize yield demonstrated a negative connection with environment having coefficient (−1.248) with probability value (0.001).



(e) Cumulative sum (f) Cumulative sum of squares

Fig. 3. Asymmetric (e) cumulative sum and (f) cumulative sum of squares.

5. Conclusion

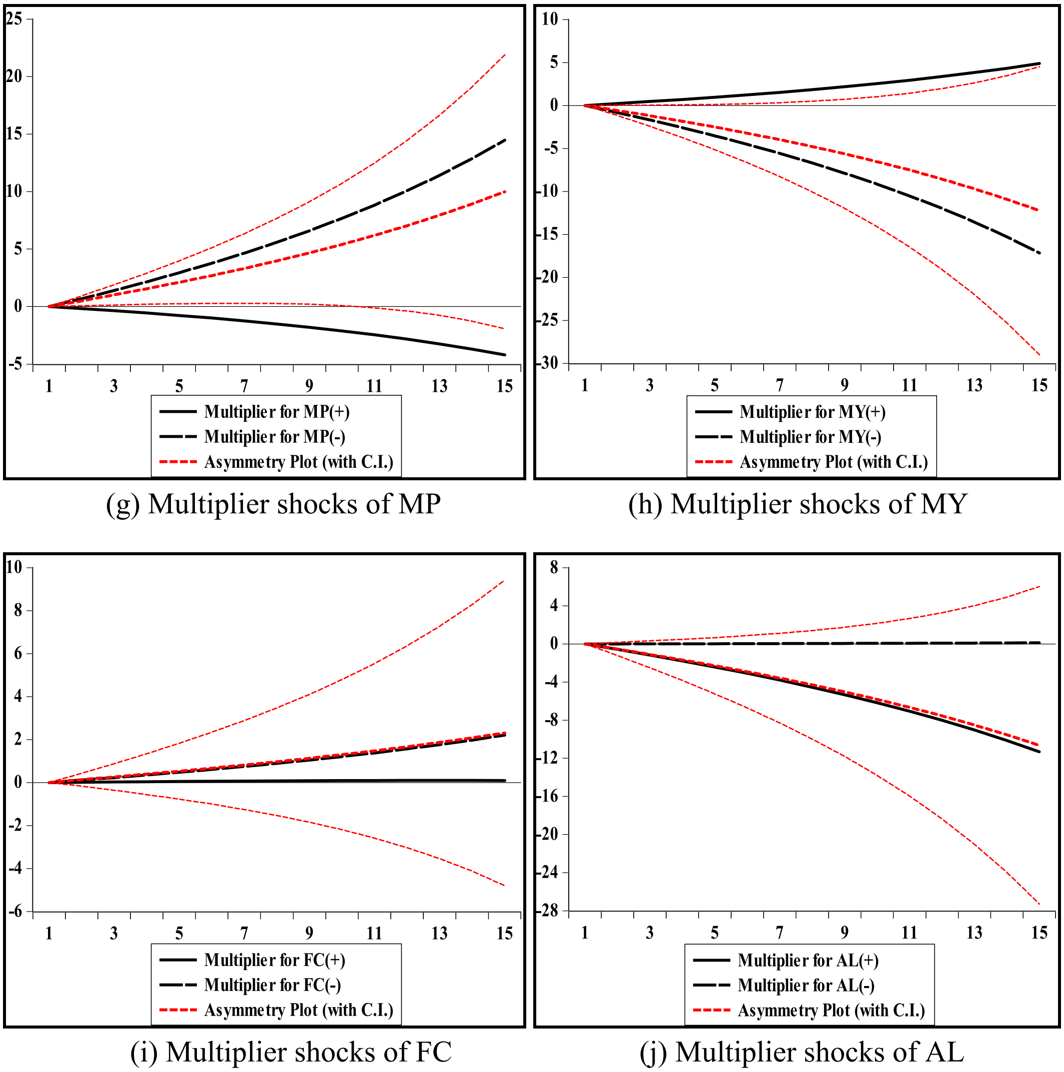
This study was set out to primarily investigate the contribution of maize crop production, maize yield, fertilizer usage, and agricultural land use to environmental deterioration in China using yearly data sets spanning 1970 to 2021. The asymmetrical technique (NARDL) was employed in the study to discover the interactions among parameters in the short and long-run. A robust least squares approach was also used to ensure that the variables are resilient. The results display that maize crop production and agricultural land usage had a positive impact on the environment via asymmetrical positive and negative shocks. The outcomes also reveal that maize yield has an adverse influence on CO_2 emissions in China. Furthermore, the variables fertilizer consumption via positive and negative shock demonstrated a constructive and adverse influence to environmental quality. Similarly, the findings of the robust least squares uncover that maize crop production, fertilizer consumption and agricultural land positively influence the environment, while maize yield adversely impacted the CO_2 emission. Undoubtedly, China is a significant contributor to CO_2 emissions. However, in order to enhance agricultural productivity and attain environmental sustainability, it is imperative to adopt economically beneficial and environmentally conservative procedures and regulations on a worldwide scale to mitigate CO_2 emission.

5.1. Policy implications

The study's findings have significant policy implications as they provide insight on the intricate systems that regulate CO_2 emissions and their impact on trends in agricultural production. The findings of our research highlight the need of giving priority to environmentally sustainable agriculture, since it has substantial policy implications. Further, carbon dioxide emissions are now a growing problem worldwide, China should play a significant role in seeking to reduce these emissions and adopt the good policies necessary to ensure the environment's long-term viability. Beyond climate change, in addition to pollution and the deterioration of biodiversity are also grounds for worry when thinking about environmental sustainability. By concentrating on the negative footprint, it is challenging to cut emissions while neglecting other environmental implications. People all throughout the globe seem to be concerned about global warming. However, there are a variety of reasons why neither developing nor affluent economies are eager to reduce their CO_2 output. Development of a country will be constrained as a means of controlling GHGs emissions. The reduction of GHG emissions has also turned into an activity of reluctant. The massive population of the least developed countries presents another problem. Population-rich nations will consume more carbon emissions. In other words, the increase in population will result in increased GHG emissions. Developing countries are pouring a lot of cash towards enhancing the environment for a sizable populace. In contrast to this, economic analysis may be used to identify several more connections among the output of numerous sectors and the growth of agriculture. These connections can then be used to guide the creation of appropriate plans for a given country's agriculture sector.

5.2. Limitations and future research directions

The study paves the way for additional research on the topic of sustainable agriculture, environmental degradation, and global warming, including (1) studies of links among, financial sector development, technological innovation, and CO_2 emissions; (2) the use of other estimation techniques for discovering the associations among parameters by obtaining bigger data samples or panel data investigations; and (3) the creation of novel strategy recommendations and policy proposals to establish a foundation to boosts the



(g) Multiplier shocks of MP (h) Multiplier shocks of MY

(i) Multiplier shocks of FC (j) Multiplier shocks of AL

Fig. 4. Asymmetric multiplier shocks of (g) MP, (h) MY, (i) FC, and (j) AL variables.

Table 8
Results of robust least squares.

Variables	Coeff.	S-error	z-St.	P-values
MP	1.521***	0.126	12.051	0.000
MY	−1.248***	0.384	−3.249	0.001
FC	0.431***	0.151	2.839	0.004
AL	0.004	0.065	0.063	0.949
C	−11.835***	3.303	−3.583	0.000

Note: The robust statistics of Table 8 includes R^2 (0.869), Rw-squared (0.977), AIC (43.008), Deviance (0.769), 1618.259 (1618.259), Adj-R^2 (0.858), Adjust Rw-squared (0.977), SC (55.869), Scale (0.145), Prob(Rn-squared stat.) (0.000) and Non-robust Statistics includes MD var (21.944), S.E. of regression (0.132), SD dep. Var (0.812) and SS resid (0.828) respectively. *** signifies level of significance at $p < 0.01$.

agricultural production towards the environmental sustainability by decreasing the carbon emissions. In addition, future research may make a significant contribution to the advancement of sustainable development goals and the promotion of an appropriate equilibrium between economic prosperity, sustainable agricultural production and environmental quality by emphasizing the importance of linking research to policy.

Ethics approval

Not applicable.

Data availability statement

The data will be available on reasonable request.

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CRediT authorship contribution statement

Abdul Rehman: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Junguo Hua:** Writing – review & editing, Validation, Resources, Investigation, Funding acquisition. **Stefania Pinzon:** Writing – review & editing, Visualization, Validation, Investigation, Data curation. **Florea Ianc Maria Mirabela:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis, Data curation. **Ciurlău Loredana:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis, Data curation. **Ioana Anda Milin:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis, Data curation.

Declaration of competing interest

All authors declare that they have no known competing financial interests or personal relationships that may have influenced the work presented in this paper.

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