Heliyon 9 (2023) e22982

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Examining the impact of farm management practices on wheat production: Does agricultural investment matter?

Abbas Ali Chandio [a,**], Mohamad Alnafissa [b], Waqar Akram [c,*], Muhammad Usman [d], Mumtaz Ali Joyo [e]

[a] *College of Economics, Sichuan Agricultural University, Chengdu 611130, China*
[b] *Department of Agricultural Economics, College of Food and Agricultural Sciences, King Saud University, Riyadh 11451, Saudi Arabia*
[c] *School of Accounting, Finance, and Economics (SAFE), University of Waikato, Hamilton Campus, New Zealand*
[d] *School of Economics and Management, and Center for Industrial Economics, Wuhan University, Wuha, 430072, China*
[e] *Department of Agricultural Economics, Faculty of Agricultural Social Sciences, Sindh Agriculture University Tandojam, Pakistan*

A R T I C L E I N F O

Keywords:
Agricultural investment
Wheat production
Technology
AMG estimator
China

A B S T R A C T

Over the years, the allocation of public funds toward agriculture has consistently played a pivotal role in facilitating the modernization and commercialization of the agricultural industry. Similarly, the integration of technological breakthroughs plays a pivotal role in guaranteeing the sustainability of food production, not solely for the present populace but also for subsequent generations. The present study examines the impact of public investment in agriculture and farm management practices, specifically focusing on cultivated area, fertilizer use, pesticide application, total agricultural machinery, and rural labour force on wheat production in nine provinces of China. The study encompasses the period from 1995 to 2020. This study employs advanced econometric techniques, such as second-generation unit root procedures (CADF and CIPS) and the Westerlund cointegration method, to investigate the stationarity properties and cointegration of the variables. The findings derived from the AMG and CCEMG methods indicate that public investment plays a statistically significant influence on wheat production. In the context of production-related variables, long-term wheat production is statistically and substantially influenced by the total area under cultivation, fertilizer use, and pesticide application. Besides these results, the Dumitrescu and Hurlin causality test reveals a unidirectional causality from agricultural machinery power consumption to wheat production. Furthermore, bidirectional causality exists between public investment, cultivated area, fertilizer use, labour, and wheat production. These results provide vital implications and valuable insights for policymakers in China, which may furnish novel policymaking options for sustainable food production through strategic investments in research and development, irrigation systems, and technological advancements.

1. Introduction

The achievement of food security is of utmost importance for countries in maintaining sustainable development, as outlined in the

* Corresponding author.
** Corresponding author.
E-mail addresses: alichandio@sicau.edu.cn (A.A. Chandio), malnafissa@ksu.edu.sa (M. Alnafissa), wakram@waikato.ac.nz (W. Akram), usman399jb@gmail.com (M. Usman), majoyo@sau.edu.pk (M.A. Joyo).

https://doi.org/10.1016/j.heliyon.2023.e22982
Received 30 August 2023; Received in revised form 21 November 2023; Accepted 23 November 2023
Available online 28 November 2023
2405-8440/© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Sustainable Development Goals (SDGs). Among these goals, Zero Hunger is identified as the second most critical SDG [1,2]. Over the last four years, the global hunger rate has been on the rise, following a period of decline that lasted for ten years [3]. The World Food Programme (WFP) reports that a global population of around 828 million individuals, constituting approximately 10.35% of the entire population, is confronted with the issue of hunger [4]. Furthermore, the plight of individuals confronted with severe food scarcity has deteriorated further, with the population increasing from 135 million in 2019 to 345 million in 2022. According to recent calculations conducted by the United Nations, the global community is significantly falling short of achieving its SDGs. In coordination with SDG#2, which is to achieve zero starvation, the global population continues to increase despite ample resources and food to sustain even more people [3]. With the current pace, more than 840 million people will face food security by the end of 2030. Under such conditions, food security remains a global issue [5].

China is currently the most populous country in the world and has undergone substantial transformations in terms of its food security and hunger index on a global scale. As an illustration, in the year 2000, almost 16% of the population experienced the condition of undernourishment. This figure subsequently decreased to 8.6% in 2017 and further reduced to 2.5% in 2022. Notwithstanding these advancements, it is noteworthy that a considerable population of 56 million individuals residing in rural regions in China remains below the poverty threshold. Additionally, about 186 million individuals are susceptible to the adverse impacts of natural catastrophes within the country [6].

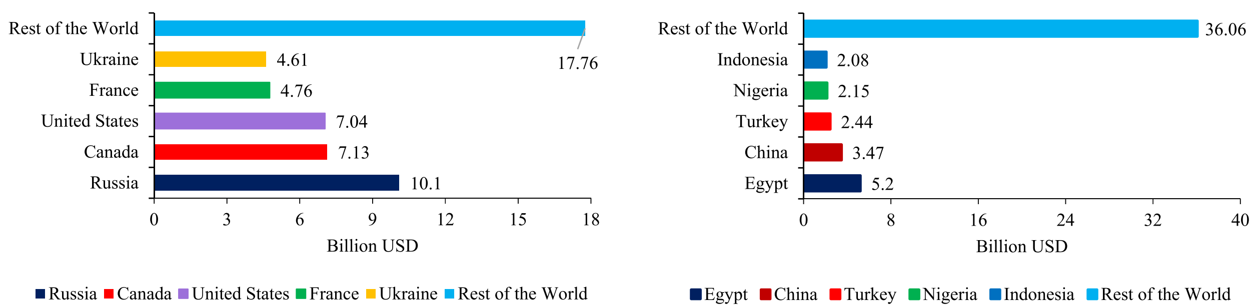
The United Nations [1] suggests that the availability of food to the masses is exacerbated by three primary factors: (i) climatic changes, (ii) humanmade conflicts, and (iii) economic crisis. The world is facing the catastrophic issue of climatic changes and dealing with a conflict between global cereals producers and the resultant increase in food prices [7]. Specifically, the world recently saw a glimpse of a full-fledged conflict between Russia and Ukraine. The tension between both countries severely threatened the sustainability of world food security and affected food prices and the resultant economic predicaments worldwide. If the conditions remain intact, the world may see another food security crisis in the current or following year, as both Russia and Ukraine are among the top five cereal especially wheat-exporting countries. In 2020, both combinedly exported wheat worth 14.61 billion USD (28.47 per cent—19.5% and 8.97%, respectively) out of the global traded value of 51.4 billion USD [8]. Such a high chunk in global wheat export depicts the importance of both countries in meeting and sustaining global food security [9].

China ranks as the second-largest importer of wheat globally, following Egypt. It imports a total value of 3.47 billion, accounting for approximately 6.75% of its wheat imports. These imports primarily originate from Canada, the United States, France, and Australia [8]. According to the data from OEC 2022, the combined import percentage of Russia and Ukraine is 0.353%. The following figures, labelled 1a and 1b, illustrate the relative proportions of the leading five nations in wheat exports and imports. Fig. 2a depicts the distribution of China's wheat imports in 2020 among different countries, while Fig. 2b presents the temporal pattern of these imports. Besides, despite China's limited reliance on the collective wheat production of Russia and Ukraine, it notably expanded its wheat imports from Russia by removing all trade limitations on wheat imports. This decision was made to provide assistance, strengthen bilateral relations, and ensure a stable food supply for the foreseeable future. However, the significant reliance on imported wheat (cereals) in China raises concerns regarding the nation's food security [10]..

China's agricultural industry has consistently received support from the government. This support is driven by the country's commitment to ensuring food security for its rapidly growing population, which currently stands at 1.42 billion. China obtains a substantial portion of its grain supply from its nine provinces. Fig. S1 illustrates the fluctuating path of wheat production in China, with quantities ranging from 2.701 to 20.607 million tonnes in 1995 and subsequently varying between 2.365 and 37.531 million tonnes.

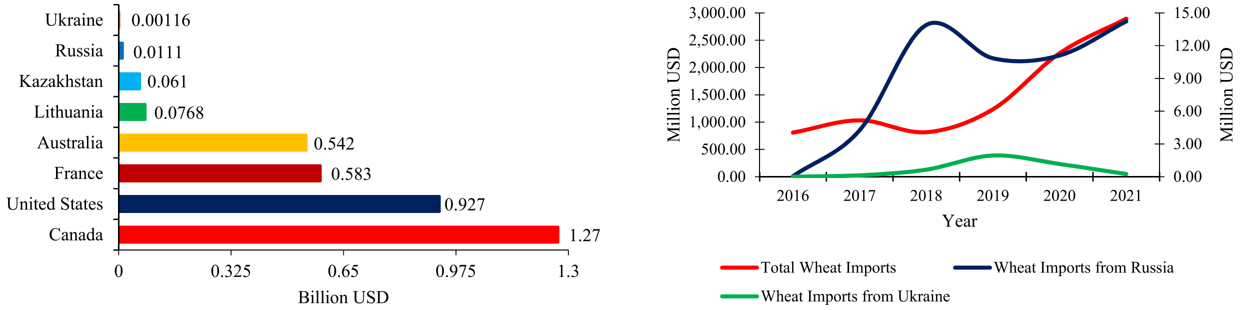
Wheat (*Triticum aestivum* L.), the third most significant crop globally after maize and rice, is a vital carbohydrate supply for millions of people. Wheat is considered one of the largest and most important cereal grains. Wheat possesses a high nutritional value. The composition of the substance consists of 14.7 % protein, 2.1 % fat, 2.1 % mineral content, and 78.11 % starch [11]. The North China Plain (NCP) is a significant region in China known for its substantial contribution to grain production. It is responsible for around 75 % and 35 % of China's wheat and maize yields [12].

It is worth noting that public investment has been found to have a considerable influence on the enhancement of agricultural output [13]. According to Oriakhi and Arodoye [14], the agricultural sector is primarily driven by their contributions, which are significant in long-term economic and capital growth. It creates employment and investment opportunities in rural areas and helps urban areas [15]. In the case of China, Fig. S2 illustrates the trend of public investment in agriculture, indicating a rise from 960 million Yuan in 1995 to



a *Global export of wheat in Billion USD. Source: OEC Data (2022)* ***b*** *Global import of wheat in Billion USD. Source: OEC Data (2022)*

Fig. 1. a: *Global export of wheat in Billion USD. Source: OEC Data (2022)* Fig. 1b: *Global import of wheat in Billion USD. Source: OEC Data (2022).*



a Import of wheat by China in Billion USD. *Source: OEC Data (2022)* **b** Historical wheat import by China (Russia & Ukraine on Secondary Axis)

Fig. 2. a Import of wheat by China in Billion USD. *Source: OEC Data (2022)* Fig. 2b: Historical wheat import by China (Russia & Ukraine on Secondary Axis).

133,936 million Yuan in 2020. This data portrays the country's pro-agricultural policies and devotion to the agricultural sector [10]. Yang et al. [16] suggested that the rapid rise in public investment, mainly in the agricultural sector for modernization, increased grain production in China; however, the climatic conditions hampered the growth [17].

The existing literature on the collective influence of public spending and farm management practices in the field of agriculture is limited. For instance, Zhu [13], Xu et al. [10], and Gao et al. [18] studied the impact of public spending in China, Matthew and Mordecai [19] and Ewubare and Ologhadien [20] checked the same effect in Africa, Salim and Islam [21] in Australia, De [15] in India, and Ahmed et al. [22] and Usman et al. (2021) in Pakistan. However, these studies have separately considered the effect of public spending on either grain production or carbon emissions. In a similar vein, Zhai et al. [17], Zhang et al. [12], Qiu and Luo [23], and Yu et al. [24] investigated the impact of farm management practices in the agricultural sector in China, Burchfield et al. [25] checked the same effect in America, and Belton et al. [26] in Myanmar. Similar to the studies on public spending, these researchers have also checked the impact on grains, agricultural farms, and land transfer. Only the Chandio et al. [27] study collectively investigated the impact of public spending and grains in China. Nevertheless, this study also used R&D investment as a proxy for public spending and checked the impact on overall China, which posits a gap in the literature as well as for the policymakers.

In light of this objective, it has become essential to investigate the enduring effects of public investment in agriculture and farm management strategies, such as pesticide application levels, fertilizer consumption, overall power utilization for agricultural machines, and the rural labour force, on wheat production. The research gathers data from a specific set of nine regions in China spanning the period from 1995 to 2020. The study employs AMG and CCEMG methods, as well as robust cointegration tests, to validate the existence of a long-term connection amid the variables under investigation. Compared to the aforementioned research, our analysis diverges in three key dimensions. Firstly, it considers agriculture-specific public expenditure and employs pesticide application quantity, fertiliser usage, total power for agricultural machines, and rural labour force as indicators for farm management practices. This approach offers empirical support from several viewpoints and mitigates the occurrence of omitted variable bias. Secondly, this study focuses exclusively on nine provinces in China that are known for their high wheat yields. The existing studies that have examined the comprehensive data for China have yielded generalised findings, which are inadequate for generating specific policy implications for the nine high-yielding wheat provinces in concern. Finally, the research employs sophisticated econometric methodologies to examine the panel dataset comprising nine provinces in China. Therefore, the results hold significant value for scholars and practitioners in shaping policies and promoting wheat (grains) production in China. This will help sustain the competitiveness of the nine provinces involved and contribute to China's self-sufficiency in grain production. Additionally, this study will generate a discourse surrounding China's grain imports from other global regions. Furthermore, the following research questions are addressed in the current study.

RQ1. Does public investment improve wheat production in grain-producing regions of China?

RQ2. Do farm management practices increase wheat production in grain-producing regions of China?

The remainder of the paper is as follows: the next section reviews the available literature on the investigated variables, followed by the data and methodology section. The subsequent section presents the results and discussion, and the final section concludes the paper with policy implications and directions for future research.

2. Literature review, research gap and hypotheses formulation

The presenet study investigates the enduring influence of agricultural public investment and farm management practices on wheat production. The study employs a panel dataset of nine high-yielding provinces of China from 1995 to 2020. While there is a body of literature on the phenomena being examined, the subsequent part provides an overview of the current literature on crop output, public expenditure in the agricultural sector, and agricultural management strategies. In pursuit of this objective, the subsequent portion comprises two primary subsections. The initial segment of this study investigates the existing body of literature pertaining to public agricultural investment and its influence on crop production, irrespective of the specific type of crops, such as cereals or oil seed crops.

The subsequent section delves into the realm of farm management practices and the existing body of literature on crop production. Fig. 3 illustrates the relationship among the variables under investigation.

2.1. Nexus between agriculture public investment and wheat production

In the past, governments have resorted to public expenditures in the agricultural sector as a means to stimulate food production systems and augment farm income [10]. In terms of financial spending, Guo, Guo, Tang, Su and Li [28] studied the impact of financial assistance on agriculture, the use of chemical fertilizers, and carbon emissions. The study used panel data from 30 Chinese provinces from 2000 to 2019. The findings revealed that financial assistance had a statistically significant and negative impact on carbon dioxide emissions, whereas chemical fertilizers had a positive impact. Further investigation into the causality revealed the presence of an uni-dimensional causality running from agricultural financial assistance to carbon dioxide emissions in China. In contrast, there is bidirectional causality between agricultural financial support and chemical fertilizer use, as well as chemical fertilizer use and CO_2 emissions.

In a similar vein, Salim and Islam [21] analyzed the influence of climatic changes and research and development (R&D) expenditures on the agricultural productivity of Western Australia. Based on the 1977–2005 annual time series data, the results indicated that R&D expenditures and climatic changes are crucial for the agricultural sector's growth. Specifically, the long-run elasticity of total factor productivity remained at 0.497 for R&D spending and 0.506 for climatic changes. The results of the causality test suggested the existence of a unidirectional causal relationship between R&D spending and agricultural growth. Another study by Chandio et al.(27) [] examined the dynamic effect of R&D investment and credit to the agricultural sector, fertilizer consumption, machinery use, and carbon emission on China's grain crop yield using annual time series data from 1990 to 2017. The results suggested the existence of a long-term correlation between the study variables. The findings of the study revealed a noteworthy and statistically significant correlation between the allocation of resources towards research and development (R&D) and loan provision to the agricultural sector, the extent of land utilized for cultivation, and the utilization of fertilizers, with respect to the production of grain crops in China. Simultaneously, carbon emissions exerted an adverse influence.

Xu et al. [10] examined the effect of various types of public spending on China's food-based economy, utilizing a dynamic computable general equilibrium model. The study examined the effects on food crops. The results indicated that public spending impacted crop production, prices, and trade significantly. Specifically, the increase in public spending on agricultural, irrigation, and subsidy research and development moderately impacted GDP growth, i.e., the industry and services sector. In the case of the Meghalaya state of India, Dkhar and Kumar [29] analyzed the relationship between public spending on agriculture and related activities and economic growth, using data from 1984 to 2014. The study found that public spending had a statistically significant impact on agriculture but a negative impact on irrigation, dairy, and forestry. The findings highlighted the importance of connections between agriculture and its other sectors, such as irrigation, dairy, and forestry.

In their study, Matthew and Mordecai [30] examined the impact of public expenditure in the agricultural domain on crop output within the context of Nigeria. The study utilized annual time series data spanning from 1981 to 2014. The findings derived from the econometric analyses indicate a favourable relationship between commercial bank loans allocated to the agricultural sector and agricultural output. On the contrary, government expenditure on agriculture yields adverse consequences.

An additional investigation [13] examined the correlation between government expenditures on agricultural research and irrigation and Chinese cereal crop production. A statistically significant positive correlation was found between agricultural expenditures

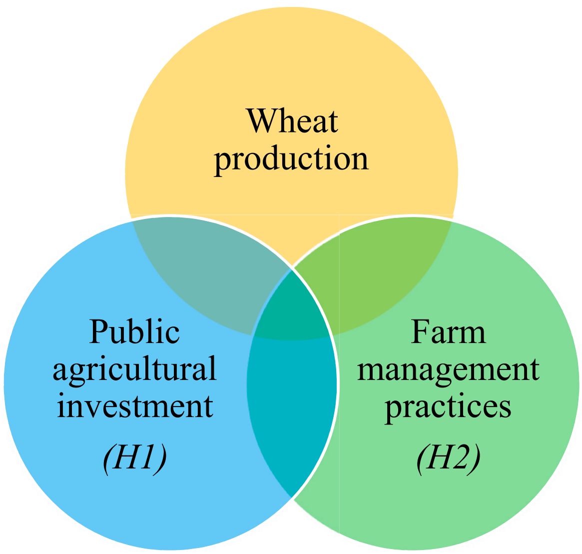


Fig. 3. Connection between the studied variables.

and output, suggesting that allocating more resources towards agricultural research will result in a more cost-effective increase in output.

Specific to Pakistan, Usman, Hameed, Saboor, Almas and Hanif [31] examined the impact of R&D innovation and climatic changes on Pakistan's total factor productivity. Based on a time series of annual data from 1972 to 2020, the authors concluded that agricultural R&D innovation adoption had a significant positive effect on the total factor productivity of Pakistani farmers. Specifically, precipitation, fertilizers, innovative seeds, and tractors significantly positively affect total factor productivity, while moderate climate conditions favour productivity. Likewise, Ahmed, Khan and Naeem [22] examined the effect of government spending on expanding the agricultural industry, using the data from 1972 to 2014. The findings indicated a mixed growth pattern in the agricultural sector and a stable long-term correlation. Specifically, public spending on roads, health, and education significantly affects agricultural productivity.

Ewubare [32] conducted a study in Africa to examine the effects of government expenditure, gross capital formation, deposit money, and bank loans on the agricultural sector on Nigeria's agricultural sector. The outcomes indicated that the coefficient of the error correction method was negative and statistically significant for the model that was implemented. More specifically, gross capital formation and government expenditure continued to have a negative impact; on the other hand, deposit money to banks had a negative impact. Following this, Gao, Ji, Chandio, Gul, Ankrah Twumasi and Ahmad [33] examined the impact of public investment on irrigation and agricultural R&D, as well as the controlled effects of capital, fertilizer usage, carbon emissions, and mechanization level. From 1986 to 2017, annual time series data were analyzed in the study. The findings revealed that public expenditures on fertiliser use, capital, irrigation agricultural research and development, and capital had a statistically significant positive impact on crop productivity. Nevertheless, productivity was negatively impacted by carbon emissions.

H1. Public agricultural investment is a key factor in promoting wheat production in China.

2.2. Nexus between farm management practices and wheat production

Along with agricultural spending, another critical factor is mechanization, which includes using a tractor and other farm machinery to increase agricultural productivity [34]. The last decade saw an increase in the intensive mechanization of agricultural development [35], particularly in China since 2004 [36]. A study by Qiu and Luo [23] suggested that agricultural mechanization is paramount in pushing farmers (particularly small landholders) to engage in modern-day agricultural practices. Their study investigated the preference of 3440 wheat farmers for adopting agricultural technology by small landholders in the Henan province of China. The results suggest the inverted U-shaped adoption behavior by the small landholder, implying that as the farm size increases, the mechanization adoption increases. However, after reaching its maximum, the mechanization adoption declines. The results also pointed out that the large landholders usually invest in buying the machinery, whereas the small landholders incorporate family labor.

Xu et al. [34] investigated the relationship between farm equipment and land transfer. The research utilized information from 810 rice farmers in the Chinese province of Sichuan. Using the IV Probit and Tobit models, the results indicated that incidence and land transfer-in of rice farmers have a significantly positive impact. Specifically, a one per cent increase in farm equipment increases the likelihood of rice farmers transferring their land by 2.4 %. Another study by Belton, Win, Zhang and Filipski [35] conducted a descriptive survey of farmers and retailers of farm machinery in two intensive agricultural zones in Myanmar. Based on the surveys of 2016 and 2017, the results revealed a swift surge during 2011–20. In particular, the utilization of agricultural machinery for land preparation, harvesting, and threshing remained scale-neutral. Such utilization resulted in convenience, saved labour, reduced labour work, increased time-saving and speed, lesser grain loss, and reduced climatic impacts.

Similarly, Zhai et al. [17] investigated how technological advancements in agriculture and climatic changes affect global cereals (wheat) production. The study collected annual time series data for the Henan province of China from 1970 to 2014. The findings indicated the co-motion of the investigated constructs. Specifically, the impact of machinery and fertilizer remained positively significant on the per unit area wheat productivity, indicating that a one per cent increase in machinery and fertilizer use will increase the per unit area wheat productivity by 0.21 and 0.19%, respectively. Similarly, the study of Chandio, Jiang, Akram, Ozturk, Rauf, Mirani and Zhang [27] also analyzed the dynamic impact of farm machinery on China's grain crop yield from 1990 to 2017. Despite the significant effects of other factors, the results suggested that agricultural machinery has negative short-term effects and positive long-term effects on grain production.

Burchfield et al. [25] studied the impact of changes in technologies and climate on crop yields in the central part of the USA. The authors developed yield scenarios using the data of the lowest, average, and highest technology-driven crop yield surge for 1980–2017. The results suggested that keeping technological innovation constant, by the end of the century, there will be a decrease of 22.4%, 27.9%, and 20% for maize, soybeans, and wheat. However, keeping the rate of technological changes lowest, there will be an increase of 25% and 30.2% for maize and soybean, respectively. Hence, technological changes can reduce the impact of climatic changes.

There is also growing literature on the impact of pesticide usage on crop yield; however, the results are uncertain about whether a decrease in pesticide usage will increase production. To this end, Hossard et al. [37] examined the impact of pesticide usage on wheat yield loss in France. The results reckoned that a 50% reduction in pesticide application could decrease the wheat yield by 5–13%. Moreover, if these results are extrapolated to France, the country would see a decrease of 2–3 million tons of wheat, decreasing the wheat exports in France by 15%.

H2. Farm management practices enhance wheat production in China.

2.3. Research gap

Based on the literature, the authors of this study have identified two primary areas of research that require attention to address existing gaps in knowledge: (i) limited research has been conducted to investigate the effects of public agricultural investment on wheat production within the major grain-producing regions of China, and (ii) there is a lack of evidence in the current body of research on the utilization of panel datasets combined with advanced estimate methodologies. Several studies have employed the DOLS, FMOLS, and ARDL methodologies to examine the effects of public investment on agricultural output across various global regions. Nevertheless, the present study employs more rigorous estimation techniques for panel datasets, including cross-sectional dependency (CSD) tests, cross-section Augmented Dickey-Fuller (CADF) test, Westerlund panel cointegration, Augmented Mean Group (AMG), and Common Correlated Effect Mean Group (CCEMG) methods, and Dumitrescu and Hurlin (D-H) causality tests. These techniques have been overlooked in previous studies.

3. Data, economic modeling, and methodological strategy

3.1. Data

This research investigates the enduring impacts of public investment in agriculture and farm management strategies on wheat output in nine Chinese provinces, namely Hebei, Shanxi, Henan, Shandong, Anhui, Hubei, Jiangsu, Sichuan, and Shaanxi, spanning the period from 1995 to 2020. The availability of data determines the selected timeframe. In the regression analysis, the explained series wheat production and the regressors are a public agricultural investment, wheat sowing area, fertilizer consumption, agricultural machinery power consumption, pesticide use, and agricultural labour force. The selected acronyms, units, measurements, and data sources are available in Table 1. Tables 2 and 3 show the descriptive statistics and bivariate correlation analysis.

3.2. Economic specification

In the current investigation, the authors explore the long–run influences of agricultural public investment on wheat productivity, at the same time as controlling wheat sown area, power consumption of agricultural machinery, fertilizer consumption, pesticide use, and agricultural labour force as other imperative drivers of wheat production, the model specification in Eq. (1) as:

$$WP = f(GINV, WSA, PC, FER, PES, AL) \tag{1}$$

All the selected series are transformed into the natural logarithmic algorithms (*ln*) to evade the problem of autocorrelation, scale equivalence, data sharpness, and heteroscedasticity.

The modified version of Eq. (1) can be specified in the form of Eq. (2) as follows:

$$Ln(WP_{it}) = \beta_0 + \beta_1\ Ln(GINV_{it}) + \beta_2 Ln(WSA_{it}) + \beta_3 Ln(PC_{it}) + \beta_4 Ln(FER_{it}) + \beta_5 Ln(PES_{it}) + \beta_6 Ln(AL_{it}) + \varepsilon_{it} \tag{2}$$

where ***LnWP***, ***LnGINV***, ***LnWSA***, ***LnPC***, ***LnFER***, ***LnPES***, and ***LnAL*** are the natural logarithm of wheat productivity, public agricultural investment, wheat sown area, power consumption of agricultural machinery, fertilizer consumption, pesticide use, and agricultural labour force. Further, β_0 denotes the intercept and $\beta_1 \rightarrow \beta_6$ denotes the slope parameters of selected variables. The term ε_{it} indicates the random error term, and i and t represent the province and time.

3.3. Econometric modeling

3.3.1. AMG and CCEMG estimators

In this study, we applied two robust tests believed to change the final analysis schema. To this end, the AMG and CCEMG methods are applied as robustness checks. Both AMG and CCEMG tests provide the remarkable ability to tackle the issue of CSD and slope heterogeneity. These can continue an exclusive path because of how typically influenced effects are tackled. For the AMG test, such results show a single unremitting transformation that can be reimbursed by subtracting it from the explained feature. The heterogeneous panel AMG method developed by Eberhardt and Bond [38] and Eberhardt and Teal [39] was used in this work following the

Table 1
Variables, acronyms and description.

Variables	Code	Description
Wheat production	WP	Wheat production (10,000 tons)
Agricultural public investment	GINV	Agricultural public investment (100 million Yuan)
Wheat sown area	WSA	Wheat sown area (1000 ha)
Power consumption of agricultural machinery	PC	Power consumption of agricultural machinery (10,000 kW)
Fertilizer consumption	FER	Fertilizer consumption (10,000 tons)
Pesticide use	PES	Pesticide use (10,000 tons)
Agricultural labor force	AL	Agricultural labour force (10,000 people)

Source: The data points on all of the mentioned variables were taken from the website of CSY.

Table 2
Descriptive information.

	LnWP	LnGINV	LnWSA	LnPC	LnFER	LnPES	LnAL
Mean	6.648355	4.920943	7.511353	8.250769	5.597092	1.844811	7.880774
Median	6.652542	5.025228	7.640291	8.286123	5.678345	2.123458	7.924883
Maximum	8.230337	7.199947	8.655188	9.499498	6.573806	2.989533	8.593206
Minimum	5.018405	2.261409	6.283948	6.659935	4.345103	−0.030459	6.853299
Std. Dev.	0.856206	1.514041	0.654406	0.707772	0.498446	0.812786	0.457622
Skewness	0.052732	−0.124670	−0.058076	−0.085822	−0.575555	−1.086787	−0.580775
Kurtosis	1.765905	1.520009	1.998141	1.995563	3.119246	2.972266	2.369961
Jarque-Bera	14.95760	21.96229	9.917815	10.12397	13.05792	46.07065	17.02495
Probability	0.000565	0.000017	0.007021	0.006333	0.001461	0.000000	0.000201
Sum	1555.715	1151.501	1757.657	1930.680	1309.720	431.6858	1844.101
Sum Sq. Dev.	170.8099	534.1104	99.78154	116.7194	57.88850	153.9249	48.79444
Observations	234	234	234	234	234	234	234

Table 3
Bivariate correlation analysis.

Variables	LnWP	LnGINV	LnWSA	LnPC	LnFER	LnPES	LnAL
LnWP	1.000000						
LnGINV	0.163216	1.000000					
Statistic	2.519828	–					
P-value	0.0124	–					
LnWSA	0.979090	0.009771	1.000000				
Statistic	73.30928	0.148834	–				
P-value	0.0000	0.8818	–				
LnPC	0.783391	0.503062	0.659635	1.000000			
Statistic	19.19822	8.865973	14.50543	–			
P-value	0.0000	0.0000	0.0000	–			
LnFER	0.805046	0.319821	0.672247	0.632814	1.000000		
Statistic	20.67066	5.141398	14.12589	12.96865	–		
P-value	0.0000	0.0000	0.0000	0.0000	–		
LnPES	0.602191	0.165021	0.581518	0.669566	0.616541	1.000000	
Statistic	11.48904	2.548462	10.88760	13.73070	11.54416	–	
P-value	0.0000	0.0115	0.0000	0.0000	0.0000	–	
LnAL	0.739173	0.287260	0.527750	0.692787	0.650381	0.532517	1.000000
Statistic	16.71638	4.567933	10.16223	14.04714	12.61691	10.38985	–
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	–

appearance below:

AMG (First stage):

$$\Delta Z_{it} = \Psi_i + \beta_i \Delta Y_{it} + \eta_i k_t + \sum_{t=2}^{T} \xi_i \Delta D_t + \varepsilon_{it} \tag{3}$$

AMG (Second stage):

$$\widehat{\beta}_{AMG} = N^{-1} \sum_{i=1}^{N} \widehat{\beta}_i \tag{4}$$

where Ψ_i shows the intercept, Y_{it} and Z_{it} illustrate selected variables, k_t denotes the observed familiar dynamic with individual heterogeneous segments, $\widehat{\beta}_{AMG}$ explores the mean group (MG) of the AMG method and ε_{it} shows the random error term. Considering CSD and heterogeneity issues, Pesaran [40] proposed the CCEMG test that generates robust and reliable results. The CCEMG approach permits each China province's slope heterogeneous parameter crossways by the origination of the average individual province elasticity. The estimation process of the CCEMG estimator is as follows:

$$X_{it} = \theta_{1i} + \pi_i Y_{it} + \lambda_i \xi_{it} + \mu_{it} \tag{5}$$

The augmented description with averages of all individuals (i) of all series abovementioned (explained and regressors) is presented in Eq. (6) as follows:

$$X_{it} = \theta_{1i} + \pi_i Y_{it} + \Psi_i \overline{y}_{it} + \delta_i \overline{z}_{it} + + \eta_i \xi_{it} + \varepsilon_{it} \tag{6}$$

3.3.2. Dumitrescu and Hurlin (D-H) causality test

In the last stage, this study applied Dumitrescu and Hurlin's [41] (D-H) causality approach to expose causal interconnections between selected variables of attention that were not revealed in the long-term estimation analysis. The paths of relationships among the inspected series and the long-term projections findings offer the government and policymakers of China the information they require to institute efficient and appropriate wheat production policies. Further, this approach is suitable even in the presence of CSD. In addition, it is used in both conditions when the periods (t) exceed the cross-sections (i) and vice versa [42]. The following equation recognizes the causal interlinkages between selected variables:

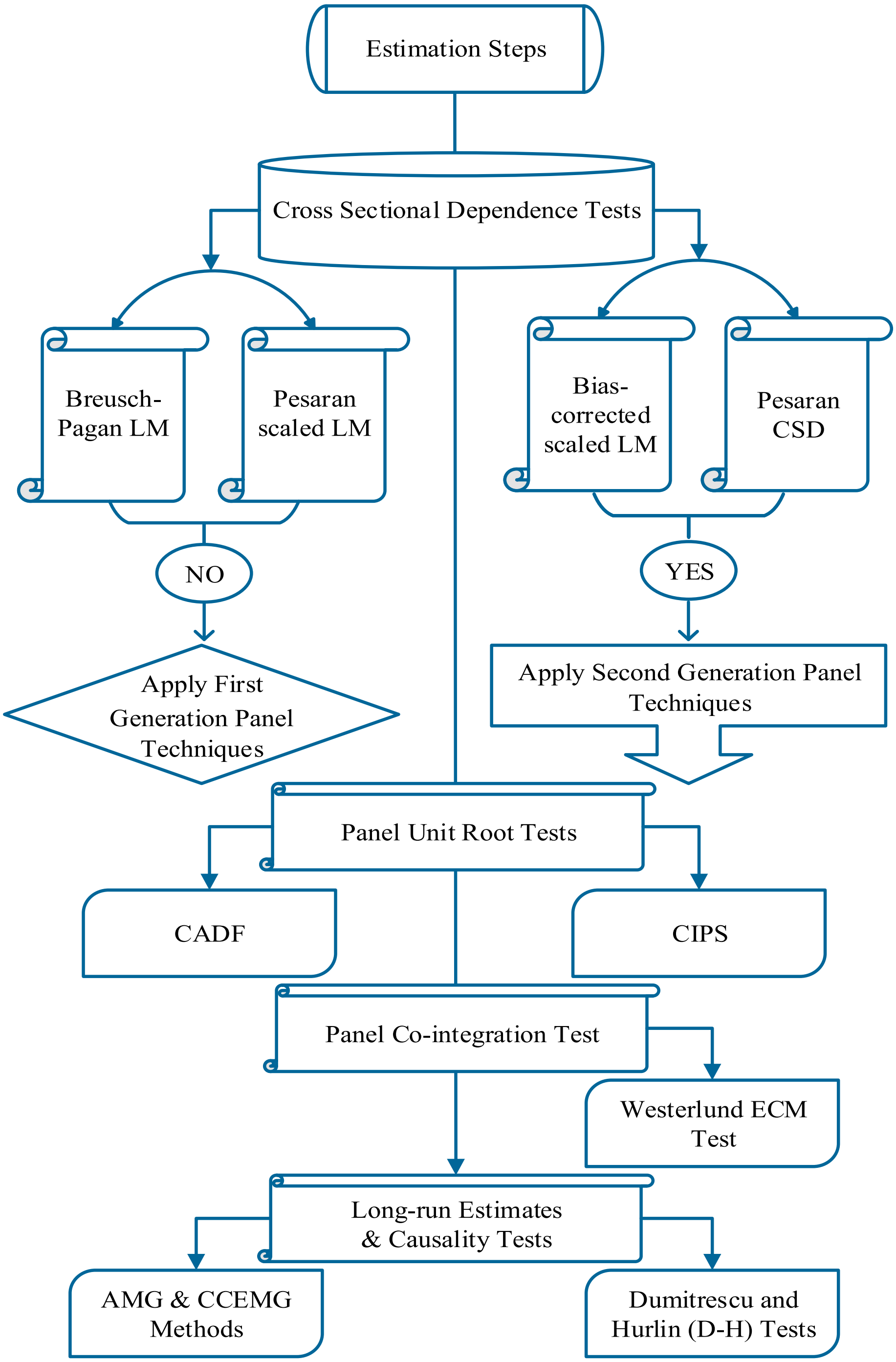


Fig. 4. The procedural steps involved in the estimating process of the study.

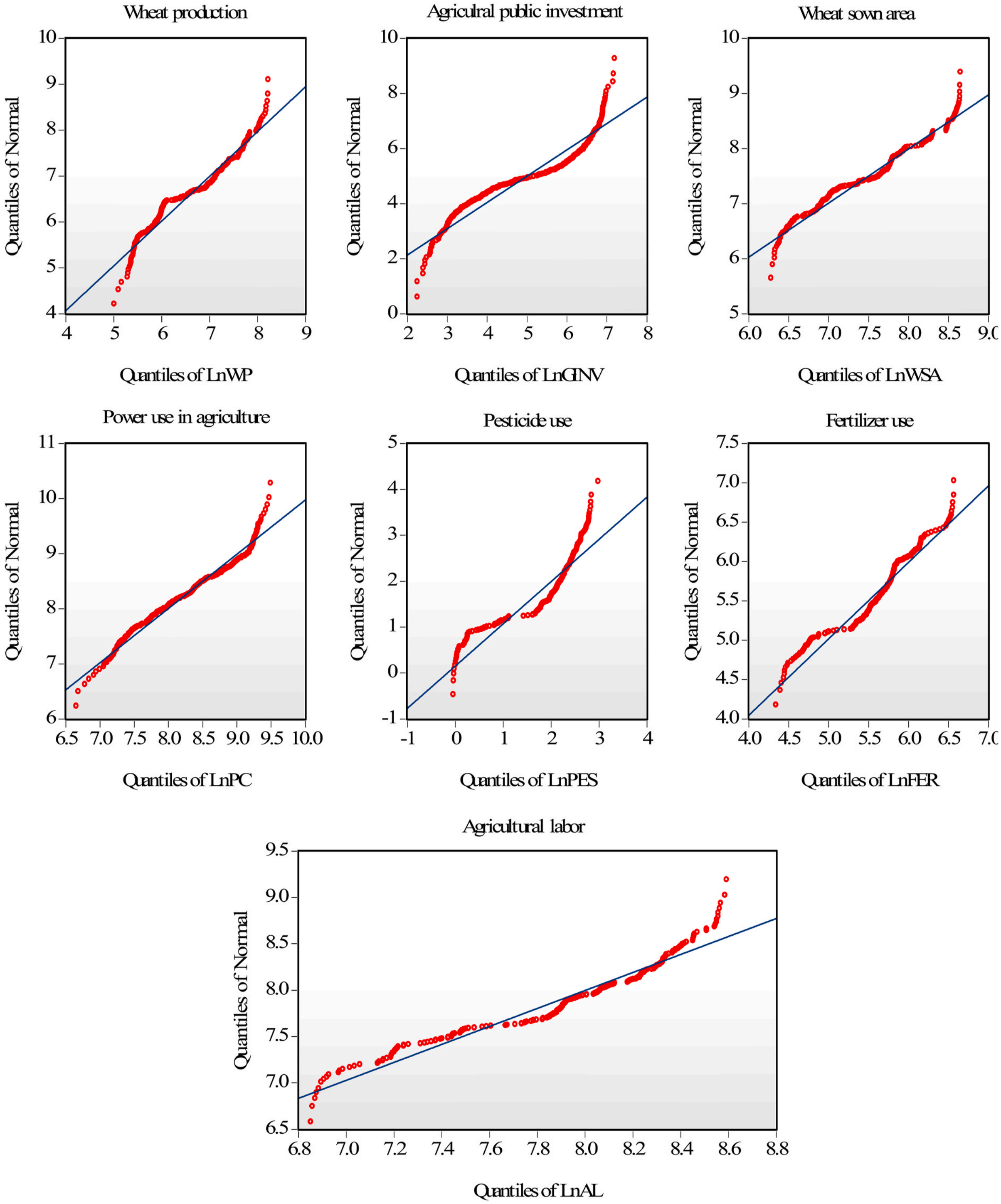


Fig. 5. Plots of Quantiles of studied variables.

$$X_{it} = \psi_i + \sum_{j-1}^{J} \lambda_i^j X_{i(t-j)} + \sum_{j-1}^{J} \Upsilon_i^j Z_{i(t-j)} + \varepsilon_{it} \tag{7}$$

where X and Z explore for observables; λ_i^j and Υ_i^j show the autoregressive coefficient and estimated regression parameters, which are assumed to differ across provinces. Fig. 4 illustrates the stages of estimation employed in the research.

4. Results and discussion

This paper explores the descriptive statistical analysis of the underlying variables for selected nine provinces of China. Table 2 shows the descriptive data in brief. The mean values of LnWP, LnGINV, LnWSA, LnPC, LnFER, LnPES, and LnAL are 6.648, 4.920, 7.511, 8.250, 5.597, 1.844, and 7.880, respectively. Whereas the standard deviations of the LnWP, LnGINV, LnWSA, LnPC, LnFER, LnPES, and LnAL are 0.856, 1.514, 0.654, 0.707, 0.498, 0.812, and 0.457, respectively. Furthermore, Fig. 5 reveals that all underlying variables follow the normal distribution. The summary of all variables: LnWP, LnGINV, LnWSA, LnPC, LnFER, LnPES, and LnAL from 1995 to 2020 is revealed using box plots (see Fig. S3). The correlation matrix investigation between our concerned variables is available in Table 3. It is observed that all variables, such as public agricultural investment, wheat sown area, power consumption, fertilizer consumption, pesticide use, and agricultural labour force, are positively and highly significantly linked with wheat productivity in selected nine provinces.

Before performing the long-run investigation, checking for CSD is a precondition. Therefore, we applied the Breusch-Pagan_LM, Pesaran scaled_LM, Bias-corrected scaled_LM, and Pesaran_CSD methods, and the results are available in Table 4. In all CSD tests, the p-value of *Ln_Wheat yield*, *Ln_Investment*, *Ln_Sown-area*, *Ln_Power*, *Ln_Fertilizer*, *Ln_Pesticide*, and *Ln_Labor* is highly significant at the 1 % level, thereby indicating that all our concerned variables are moving equally and the variation among the data is relatively comparable. This outcome may be due to similar policies. The next step of the analysis is to check the stationarity property of the concerned variables by using CADF and CIPS tests, and the outcomes are available in Table 4.

Table 5 indicates that *Ln_Wheat yield*, *Ln_Investment*, *Ln_Sown-area*, *Ln_Power*, *Ln_Fertilizer*, *Ln_Pesticide*, and *Ln_Labor* are integrated at first difference. It shows the long-run relationship among the variables under consideration. After exploring the stationarity property of the concerned variables, the next step of the study is to discover the cointegration among the studied variables using the Westerlund panel cointegration method. This method provides robust and reliable outcomes by considering the CSD in the panel data.

The Westerlund panel cointegration results are available in Table 6. It is observed that the Westerlund G_τ, G_a, P_τ, and P_a statistics are highly significant at the 1 % level when using the intercept. It implies rejecting the null hypothesis of "no cointegration" and confirming that the underlying variables are cointegrated in the long run. Therefore, we affirmed the long-run interlinks between wheat productivity, agricultural public investment, wheat sown area, power consumption, fertilizer consumption, pesticide use, and agricultural labour force in selected 9-provinces.

Once the cointegration between variables has been identified, the subsequent phase in the analysis involves determining the long-run elasticity. The present study employed the AMG and CCEMG methodologies to ascertain the long-term elasticities. The outcomes of both approaches may be found in Table 7. Additionally, Fig. 6 displays the baseline long-term results. The findings indicate that a marginal increase of one per cent in public investment in the agricultural sector leads to a corresponding long-term rise of 0.3061 % in wheat production. Similar results are reported by Salim and Islam [21] for Australia, Tijani et al. [43] for Nigeria, Dkhar and De [15] for Meghalaya, and Adetutu and Ajayi [44] for sub-Saharan Africa. In the context of Pakistan, the study conducted by Usman et al. [45] focused on analysing the effects of R&D innovation and climatic variations on the overall factor productivity. The authors concluded that the adoption of agricultural R&D innovation has a notable and favourable impact on the agricultural productivity. The historical data on grain output in China indicates a consistent upward route, mostly attributed to the implementation of successful regulations and advancements in agricultural technologies, such as improvements in cultivar genetics and farming management practises. Wheat holds significant importance in China's food security and sustainability within the realm of cereal crops. The largest grain production regions in China include Hebei, Shanxi, Henan, Shandong, Anhui, Hubei, Jiangsu, Sichuan, and Shaanxi. These regions collectively contribute to nearly 75 % of China's wheat output [12].

The positive coefficient of power consumption of agricultural machinery is also significant. This result implies that a one per cent increase in power consumption of agricultural machinery augments 0.1026 % of wheat production in the long run. Similar results were

Table 4
CSD tests outcomes.

Series	Breusch-Pagan_LM		Pesaran scaled_LM		Bias-corrected scaled_LM		Pesaran_CSD	
	Statistics	Prob.	Statistics	Prob.	Statistics	Prob.	Statistics	Prob.
Ln_Wheat yield	394.4396[a]	0.0000	41.18185[a]	0.0000	41.00185[a]	0.0000	6.976375[a]	0.0000
Ln_Investment	928.2957[a]	0.0000	104.0974[a]	0.0000	103.9174[a]	0.0000	30.46787[a]	0.0000
Ln_Sown-area	399.0528[a]	0.0000	41.72553[a]	0.0000	41.54553[a]	0.0000	4.699644[a]	0.0000
Ln_Power	671.2755[a]	0.0000	73.80728[a]	0.0000	73.62728[a]	0.0000	25.27422[a]	0.0000
Ln_Fertilizer	472.1272[a]	0.0000	50.33742[a]	0.0000	50.15742[a]	0.0000	18.93276[a]	0.0000
Ln_Pesticide	293.6238[a]	0.0000	29.30059[a]	0.0000	29.12059[a]	0.0000	12.13227[a]	0.0000
Ln_Labor	480.7657[a]	0.0000	51.35548[a]	0.0000	51.17548[a]	0.0000	15.84454[a]	0.0000

[a] Significant at 1 %.

Table 5
Outcomes of panel unit root methods.

Series	Level		First Difference	
	Î	Î & T	Î	Î & T
CADF_Test				
Ln_Wheat yield	−1.636	−1.274[a]	−4.855[a]	−5.092[a]
Ln_Investment	−2.625[a]	−3.291[a]	−3.715[a]	−3.694[a]
Ln_Sown-area	−1.655	−1.641	−3.102[a]	−3.158[a]
Ln_Power	−1.137	−1.526	−3.328[a]	−3.426[a]
Ln_Fertilizer	−1.780	−2.592	−3.526[a]	−3.950[a]
Ln_Pesticide	−2.212***	−2.923**	−3.496[a]	−3.588[a]
Ln_Labor	−2.842[a]	−2.744***	−3.666[a]	−3.868[a]
CIPS_Test				
Ln_Wheat yield	−2.079	−2.741	−5.310[a]	−5.502[a]
Ln_Investment	−2.952[a]	−3.522[a]	−5.389[a]	−5.567[a]
Ln_Sown-area	−1.084	−2.368	−5.086[a]	−5.181[a]
Ln_Power	−1.208	−2.845**	−4.029[a]	−4.440[a]
Ln_Fertilizer	−1.998	−2.324	−4.271[a]	−4.651[a]
Ln_Pesticide	−2.122***	−2.285	−4.739[a]	−5.000[a]
Ln_Labor	−2.008	−2.087	−4.584[a]	−4.863[a]

[a] Significant at 1 %. **Significant at 5 %. *** Significant at 10 %. Î stands for Intercept, while Î & T shows the Intercept and trend.

Table 6
Outcomes of Westerlund panel cointegration tests.

Statistics	Value	Z-values	P-value	Robust P-value
Intercept				
G_τ	−3.892[a]	−3.298	0.001	0.000
G_a	−9.858**	2.432	0.993	0.030
P_τ	11.312[a]	−3.328	0.000	0.007
P_a	−9.864**	1.151	0.875	0.037
Intercept and Trend				
G_τ	−4.045[a]	−2.828	0.002	0.000
G_a	−7.538	4.242	0.999	0.260
P_τ	−9.466***	−0.608	0.272	0.080
P_a	−7.322	3.244	0.999	0.280

[a] Significant at 1 %. **Significant at 5 %. *** Significant at 10 %.

Table 7
Outcomes of long-run elasticity estimates.

Variables	AMG		CCEMG	
	Coefficient	*P*-value	Coefficient	*P*-value
Ln_Investment	0.306156**	0.000	0.3682563**	0.039
Ln_Sown-area	0.872593**	0.000	0.5656124**	0.023
Ln_Power	0.102624*	0.004	0.1747348*	0.001
Ln_Fertilizer	0.143292	0.064	−0.0054360	0.125
Ln_Pesticide	0.22303***	0.027	0.3731342***	0.067
Ln_Labor	−0.23039**	0.001	−0.0166377**	0.044
Constant	−0.717096	0.993	−0.8383541	0.537
RMSE	0.0242		0.0320	

*Significant at 1 %. **Significant at 5 %. *** Significant at 10 %.
RMSE represents the Root Mean Squared Error (sigma) value.

stated by Zhai et al. [17] for Henan Province-China, Ozdemir [46] for Asian economies, and Zhang et al. [12] for North China. Enhancing agricultural productivity is of paramount importance in enhancing the welfare of small-scale farmers residing in rural regions of China. Over the past few years, there has been a significant increase in the population of China, resulting in a scarcity of arable land due to the processes of urbanisation and industrialisation. In the given context, it is evident that the implementation of contemporary technology interventions within the agricultural industry emerges as the sole viable option for China to effectively address the challenges of sustaining its rapidly growing population and generating more employment opportunities [47,48].

Regarding coefficients of agrochemical inputs (i.e., fertilizer and pesticide) are positive and significant. This means that a one per cent increase in agrochemical inputs enhances 0.1432 % and 0.2230 % wheat production in the long run. He et al. (2022) revealed that advanced agricultural technologies, such as chemical fertilizers and enhanced agronomic methods, significantly contributed towards sustainable food production in the case of Sichuan Province-China. Likewise, Zhang et al. [12] testified that agrochemical inputs such

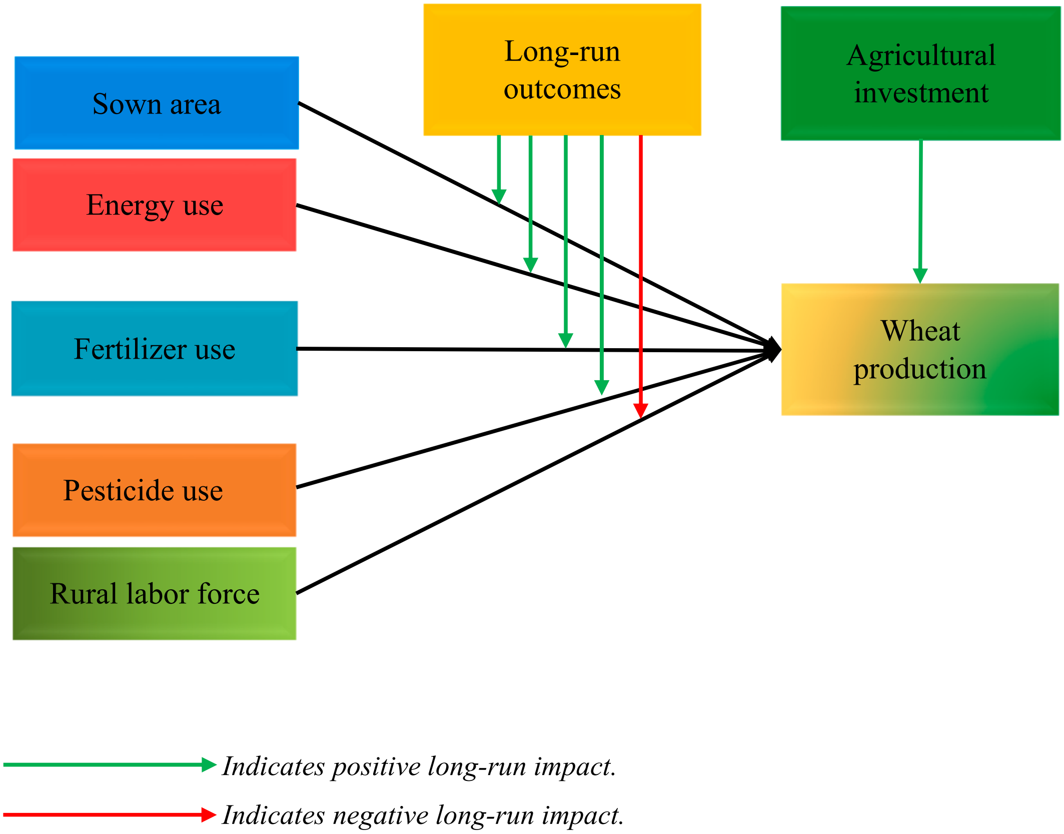


Fig. 6. Summary of long-run results.

Table 8
Outcomes of the D-H panel causality tests.

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
LnGINV ⇒ LnWP	3.96826	2.06654	0.0388
LnWP ⇒ LnGINV	6.04049	4.53766	0.0000
LnWSA ⇒ LnWP	5.88936	4.35745	0.0000
LnWP ⇒ LnWSA	6.04101	4.53829	0.0000
LnPC ⇒ LnWP	3.92609	2.01626	0.0438
LnWP ⇒ LnPC	3.24168	1.20010	0.2301
LnFER ⇒ LnWP	6.87041	5.52734	0.0000
LnWP ⇒ LnFER	6.20182	4.73005	0.0000
LnPES ⇒ LnWP	3.17424	1.11968	0.2628
LnWP ⇒ LnPES	6.23940	4.77486	0.0000
LnAL ⇒ LnWP	4.37910	2.55647	0.0106
LnWP ⇒ LnAL	9.84786	9.07792	0.0000

as fertilizer are essential for achieving high and rapid rates of agricultural return. On the other hand, pesticide usage negatively influenced soybean yields in China [47]. Our findings are comparable with the outcomes of Rehman et al. [49], Gul et al. [50], Abbas [51], and Ozdemir [46].

The last step of the analysis is to find the panel causality to determine the direction of long-run associations. We applied the Dumitrescu and Hurlina (2012) panel causality method to attain the study's objective. The findings of the causality method are available in Table 8. This study finds that agricultural public investment, sown area, fertilizer usage, and labour are bi-directionally associated with wheat production. In contrast, power consumption of agricultural machinery and wheat production have a unidirectional relationship by applying the DH causality test. These outcomes imply that agricultural public investment and input factors significantly enhance wheat production and ensure China's food security.

5. Conclusion and policy recommendations

The allocation of public funds towards agricultural activities plays a crucial role in driving advancements in agricultural output, enhancing production efficiency, and safeguarding food security. This study investigated the long-term effects of agricultural public investment and input parameters on wheat output in the central wheat-producing provinces of China throughout the period from 1995 to 2020. The analysis of the panel data involved the application of many econometric methods, including the CCE method, second-generation panel unit root tests such as the CADF and CIPS tests, panel cointegration techniques, the AMG estimator, and the Dumitrescu and Hurlin causality test for panel data. The findings of the panel cointegration test conducted by Westerlund provided evidence supporting the existence of long-term cointegration relationships among the variables under investigation. The findings from the AMG and CCEMG estimators indicate that agricultural public investment exerts a statistically significant and beneficial influence on wheat production in the long term.

Moreover, the findings from the long-term analysis indicate that many production factors, including sown area, fertilizer application, and pesticide usage, had a substantial positive impact on the overall wheat yield. Besides, the panel Dumitrescu and Hurlin causality test revealed a two-way causality between agricultural public investment, sown area, fertilizer usage, and labour and wheat production. In contrast, a one-way causality exists between power consumption and wheat production.

This study proposes that the allocation of sufficient funds by central and regional governments to agriculture in China's selected wheat production provinces is crucial in promoting sustainable agricultural production. This investment is seen as instrumental in enhancing grain food production, improving the overall well-being of rural areas, and ensuring food security. Therefore, it is recommended that public investment in agriculture be increased to achieve higher grain yields and effectively meet the domestic food demand. Furthermore, the Chinese government places a significant emphasis on the allocation of financial resources towards information and communication technology (ICT) infrastructure in rural regions. This strategic approach enables farmers to access current and relevant information pertaining to weather conditions, input markets, and the sale of their agricultural goods. Consequently, this initiative aims to enhance farmers' income levels and foster advancements in farm management techniques. In conclusion, it is recommended that regional governments take the initiative to coordinate agricultural skills training programmes in rural regions. These programmes would serve the purpose of enhancing farmers' comprehension of the inputs employed in grain production processing, as well as fostering environmental preservation efforts.

This simplified visual representation shows how public investment influences farm management practices, leading to improved wheat production and broader economic, social, and environmental outcomes. It also underscores the policy implications that can be drawn from these relationships. The actual circular flow chart can be further detailed and customised with specific data and findings to visualise the impact more comprehensively.

The top section represents different categories of agricultural public investment, including infrastructure development, research and development, extension services, and policy and regulation. The arrows indicate the flow of resources, knowledge, and support from public investment to farm management practices and strategies. The bottom section represents the combined impact of public investment and farm management practices on wheat production, economic and social outcomes, environmental sustainability, and policy implications.

Funding

The authors of this study extend their appreciation to Researchers Supporting Project number (RSPD2023R932), King Saud University, Riyadh, Saudi Arabia.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Abbas Ali Chandio: Writing – original draft, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohamad Alnafissa:** Validation, Funding acquisition. **Waqar Akram:** Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis. **Muhammad Usman:** Writing – review & editing, Methodology, Investigation, Formal analysis. **Mumtaz Ali Joyo:** Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors of this study extend their appreciation to Researchers Supporting Project number (RSPD2023R932), King Saud University, Riyadh, Saudi Arabia.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e22982.

References

[1] UN, United Nations – UN, Goal 2: zero hunger, Retrieved from, https://www.un.org/sustainabledevelopment/hunger/, 2022, 2022.
[2] R. Qin, F. Zhang, C. Yu, Q. Zhang, J. Qi, F.-m. Li, Contributions made by rain-fed potato with mulching to food security in China, Eur. J. Agron. 133 (2022), 126435.
[3] AAH, Action Against Hunger – AAH, World Hunger Facts, 2022. Retrieved from, https://www.actionagainsthunger.org/the-hunger-crisis/world-hunger-facts/, 2022.
[4] WFP, World Food Programme – WFP, A global food crisis: 2022: a year of unprecedented hunger, Retrieved from, https://www.wfp.org/global-hunger-crisis#:~:text=2022%3A%20a%20year%20of%20unprecedented%20hunger&text=As%20many%20as%20828%20million,on%20the%20edge%20of%20famine, 2022, 2022.
[5] R. Osman, S.T. Ata-Ul-Karim, M.N. Tahir, W. Ishaque, M. Xu, Multi-model ensembles for assessing the impact of future climate change on rainfed wheat productivity under various cultivars and nitrogen levels, Eur. J. Agron. 139 (2022), 126554.
[6] UNDP, United Nations Development Programme China – UNDP, The Living Standards Dimension of the Human Development Index: Measuring Poverty with Big Data in China, Retrieved from extension:, 2022, 2022.
[7] O. Lazard, Russia's Ukraine Invasion and Climate Change Go Hand in Hand. Carnegie Europe, 2022. Retrieved from, https://carnegieeurope.eu/2022/03/04/russia-s-ukraine-invasion-and-climate-change-go-hand-in-hand-pub-86574.
[8] OEC, Observatory of Economic Complexity Data Base, 2022. https://oec.world.
[9] P. Hellegers, Food security vulnerability due to trade dependencies on Russia and Ukraine, Food Secur. 14 (6) (2022) 1503–1510.
[10] S. Xu, Y. Zhang, X. Diao, K.Z. Chen, Impacts of Agricultural Public Spending on Chinese Food Economy: A General Equilibrium Approach, China Agricultural Economic Review, 2011.
[11] M. Bhardwaj, P. Kumar, S. Kumar, V. Dagar, A. Kumar, A district-level analysis for measuring the effects of climate change on production of agricultural crops, ie, wheat and paddy: evidence from India, Environ. Sci. Pollut. Control Ser. (2022) 1–25.
[12] H. Zhang, Y. Tang, A.A. Chandio, G.R. Sargani, M. Ankrah Twumasi, Measuring the effects of climate change on wheat production: evidence from northern China, Int. J. Environ. Res. Publ. Health 19 (19) (2022), 12341.
[13] J. Zhu, Public investment and China's long-term food security under WTO, Food Pol. 29 (1) (2004) 99–111.
[14] D.E. Oriakhi, L.N. Arodoye, The government size-economic growth relationship: Nigerian econometric evidence using a vector autoregression model, Int. J. Bus. Manag. 8 (10) (2013) 126.
[15] U. De, Public expenditure on agriculture and economic growth: a case study of Meghalaya, Agric. Econ. Res. Rev. 31 (2) (2018) 271–279.
[16] J. Yang, Z. Huang, X. Zhang, T. Reardon, The rapid rise of cross-regional agricultural mechanization services in China, Am. J. Agric. Econ. 95 (5) (2013) 1245–1251.
[17] S. Zhai, G. Song, Y. Qin, X. Ye, J. Lee, Modeling the impacts of climate change and technical progress on the wheat yield in inland China: an autoregressive distributed lag approach, PLoS One 12 (9) (2017), e0184474.
[18] X. Gao, L. Ji, A.A. Chandio, A. Gul, M. Ankrah Twumasi, F. Ahmad, Towards sustainable agriculture in China: assessing the robust role of green public investment, Sustainability 14 (6) (2022) 3613.
[19] A. Matthew, B.D. Mordecai, The impact of public agricultural expenditure on agricultural output in Nigeria (1981-2014), Asian Journal of Agricultural Extension, Economics & Sociology 11 (2) (2016) 1–10.
[20] D.B. Ewubare, S.T. Ologhadien, Impact of agricultural financing on cassava production in Nigeria, Int. J. Econ. Finance Manag. 4 (2019) 50–57.
[21] R.A. Salim, N. Islam, Exploring the impact of R&D and climate change on agricultural productivity growth: the case of Western Australia, Aust. J. Agric. Resour. Econ. 54 (4) (2010) 561–582.
[22] T. Ahmed, K.S. Khan, M. Naeem, The effect of public spending on agricultural growth: evidence from 1972 to 2014 in Pakistan, Sarhad J. Agric. 35 (2) (2019).
[23] T. Qiu, B. Luo, Do small farms prefer agricultural mechanization services? Evidence from wheat production in China, Appl. Econ. 53 (26) (2021) 2962–2973.
[24] X. Yu, X. Yin, Y. Liu, D. Li, Do agricultural machinery services facilitate land transfer? Evidence from rice farmers in sichuan province, China, Land 10 (5) (2021) 466.
[25] E. Burchfield, N. Matthews-Pennanen, J. Schoof, C. Lant, Changing yields in the Central United States under climate and technological change, Climatic Change 159 (3) (2020) 329–346.
[26] B. Belton, M.T. Win, X. Zhang, M. Filipski, The rapid rise of agricultural mechanization in Myanmar, Food Pol. 101 (2021), 102095.
[27] A.A. Chandio, Y. Jiang, W. Akram, I. Ozturk, A. Rauf, A.A. Mirani, H. Zhang, The impact of R&D investment on grain crops production in China: analysing the role of agricultural credit and CO2 emissions, Int. J. Finance Econ. 28 (4) (2022) 4120–4138.
[28] L. Guo, S. Guo, M. Tang, M. Su, H. Li, Financial support for agriculture, chemical fertilizer use, and carbon emissions from agricultural production in China, Int J Environ Res Public Health 19 (12) (2022).
[29] D.S. Dkhar, D.U. Kumar, Public expenditure on agriculture and economic growth: a case study of Meghalaya, Agric. Econ. Res. Rev. 31 (2) (2018).
[30] A. Matthew, B. Mordecai, The impact of public agricultural expenditure on agricultural output in Nigeria (1981-2014), Asian Journal of Agricultural Extension, Economics & Sociology 11 (2) (2016) 1–10.
[31] M. Usman, G. Hameed, A. Saboor, L.K. Almas, M. Hanif, R&D innovation adoption, climatic sensitivity, and absorptive ability contribution for agriculture TFP growth in Pakistan, Agriculture 11 (12) (2021).
[32] D.B. Ewubare, J.A. Eyitope, The effects of public expenditure on agricultural production output in Nigeria, Journal of Research in Humanities and Social Science 3 (11) (2015) 7–23.
[33] X. Gao, L. Ji, A.A. Chandio, A. Gul, M. Ankrah Twumasi, F. Ahmad, Towards sustainable agriculture in China: assessing the robust role of green public investment, Sustainability 14 (6) (2022).
[34] X. Yu, X. Yin, Y. Liu, D. Li, Do agricultural machinery services facilitate land transfer? Evidence from rice farmers in sichuan province, China, Land 10 (5) (2021).
[35] B. Belton, M.T. Win, X. Zhang, M. Filipski, The rapid rise of agricultural mechanization in Myanmar, Food Pol. 101 (2021).
[36] J. Yang, Z. Huang, X. Zhang, T. Reardon, The rapid rise of cross-regional agricultural mechanization services in China, Am. J. Agric. Econ. 95 (5) (2013) 1245–1251.
[37] L. Hossard, A. Philibert, M. Bertrand, C. Colnenne-David, P. Debaeke, N. Munier-Jolain, M.-H. Jeuffroy, G. Richard, D. Makowski, Effects of halving pesticide use on wheat production, Sci. Rep. 4 (1) (2014) 1–7.
[38] M. Eberhardt, S. Bond, Cross-section Dependence in Nonstationary Panel Models: a Novel Estimator, 2009.
[39] M. Eberhardt, F. Teal, Aggregation versus Heterogeneity in Cross-Country Growth Empirics, 2010.
[40] M.H. Pesaran, Estimation and inference in large heterogeneous panels with a multifactor error structure, Econometrica 74 (4) (2006) 967–1012.
[41] E.-I. Dumitrescu, C. Hurlin, Testing for Granger non-causality in heterogeneous panels, Econ. Modell. 29 (4) (2012) 1450–1460.

[42] Y. Huang, M. Haseeb, M. Usman, I. Ozturk, Dynamic association between ICT, renewable energy, economic complexity and ecological footprint: is there any difference between E-7 (developing) and G-7 (developed) countries? Technol. Soc. 68 (2022), 101853.
[43] A.A. Tijani, O. Oluwasola, O.I. Baruwa, Public sector expenditure in agriculture and economic growth in Nigeria: an empirical investigation, Agrekon 54 (2) (2015) 76–92.
[44] M.O. Adetutu, V. Ajayi, The impact of domestic and foreign R&D on agricultural productivity in sub-Saharan Africa, World Dev. 125 (2020), 104690.
[45] M. Usman, G. Hameed, A. Saboor, L.K. Almas, M. Hanif, R&D innovation adoption, climatic sensitivity, and absorptive ability contribution for agriculture TFP growth in Pakistan, Agriculture 11 (12) (2021) 1206.
[46] D. Ozdemir, The impact of climate change on agricultural productivity in Asian countries: a heterogeneous panel data approach, Environ. Sci. Pollut. Control Ser. 29 (6) (2022) 8205–8217.
[47] H. Zhang, A.A. Chandio, F. Yang, Y. Tang, M. Ankrah Twumasi, G.R. Sargani, Modeling the impact of climatological factors and technological revolution on soybean yield: evidence from 13-major provinces of China, Int. J. Environ. Res. Publ. Health 19 (9) (2022) 5708.
[48] W. He, W. Chen, A.A. Chandio, B. Zhang, Y. Jiang, Does agricultural credit mitigate the effect of climate change on cereal production? Evidence from sichuan province, China, Atmosphere 13 (2) (2022) 336.
[49] A. Rehman, A.A. Chandio, I. Hussain, L. Jingdong, Fertilizer consumption, water availability and credit distribution: major factors affecting agricultural productivity in Pakistan, Journal of the Saudi Society of Agricultural Sciences 18 (3) (2019) 269–274.
[50] A. Gul, A.A. Chandio, S.A. Siyal, A. Rehman, W. Xiumin, How climate change is impacting the major yield crops of Pakistan? an exploration from long-and short-run estimation, Environ. Sci. Pollut. Control Ser. 29 (18) (2022) 26660–26674.
[51] S. Abbas, Climate change and major crop production: evidence from Pakistan, Environ. Sci. Pollut. Control Ser. 29 (4) (2022) 5406–5414.