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Role of productive capacities on agricultural productivity in BRI countries

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Agricultural productivity is a cornerstone of food security, poverty alleviation, and sustainable development. While traditional determinants such as land, labor, credit, and water have been widely studied, the broader role of national productive capacities remains underexplored, particularly in the context of the Belt and Road Initiative (BRI). This study investigates the impact of productive capacities on agricultural productivity in 42 BRI countries from 2000 to 2024, using the Productive Capacities Index (PCI) alongside conventional inputs. The study employed the system GMM and 2SLS econometric techniques and then employed other econometric techniques such as Driscoll-Kraay, Feasible Generalized Least Squares (FGLS), and Panel-Corrected Standard Errors (PCSE) to check the robustness of the results. It is found that higher productive capacities significantly enhance agricultural productivity, while access to credit, land expansion, and water availability also play critical roles. Labor contributions, however, show mixed effects, suggesting inefficiencies in labor-intensive farming systems. By integrating PCI, this study provides a novel, cross-sectoral perspective on agricultural development. The findings underscore the importance of strengthening infrastructure, technology, institutions, and human capital within the BRI framework to foster sustainable agricultural growth and regional food security.

KEYWORDS

productive capacities, agricultural productivity, BRI countries, GMM, 2SLS

1 Introduction

Agricultural productivity remains central to economic growth, food security, and rural development worldwide (Gollin et al., 2014). In many developing economies, agriculture not only sustains livelihoods but also drives poverty reduction and employment generation. Yet persistent productivity gaps hinder sustainable development and exacerbate food insecurity (Jayne and Rashid, 2013; Bain et al., 2013; Canton, 2021). Addressing these challenges requires more than traditional inputs; it demands stronger national capacities in technology, infrastructure, institutions, and human capital.

Productive capacities such as institutions, technology, infrastructure, and human capital increase agricultural productivity (Boliko, 2019). Effective institutions guarantee policy and governance structures that favor agricultural development, technology provides sustainable increases in productivity, infrastructure avails market access and minimizes losses, and human capital development allows farmers to utilize modern farming techniques (Ruttan, 2002; Wang et al., 2012). In addition, education and training for human capital development increase farmers' capabilities to adopt modern agricultural techniques. In this manner not only

agricultural productivity increases but also climate variability resilience is increased (Piesse and Thirtle, 2010). Likewise, technological advances by means of agricultural R&D contribute significantly to increasing crop yields and enhance farming practices (Piesse and Thirtle, 2010). Infrastructure, including road and irrigation networks, minimizes post-production losses and facilitates market access, while the development of human capital allows farmers to adopt new technologies, enhancing resilience to climate fluctuations (Ruttan, 2002; Wang et al., 2012; Piesse and Thirtle, 2010; Tafara Gadzirayi et al., 2014). Similarly, investment in rural infrastructure in the form of transport networks and irrigation system supports effective access to markets and agricultural activities (Tafara Gadzirayi et al., 2014). Ingredients for productive capacities indices may, nonetheless, differ substantially across regions owing to varying socio-economic dynamics and agro-ecological factors (Zubovic et al., 2009). Therefore, understanding these productive capacities indices are important for crafting policies that alleviate poverty, ensure food security, and promote sustainable growth in selected BRI countries. That is why the current study is designed to find the impact of productive capacities on agricultural productivity.

Expansion of cultivated land area leads to increase agricultural productivity, enhance economic growth and meet ever increasing food demands (Chandio et al., 2016; Mueller et al., 2012). However, unbalanced expansion often comes at the cost of environmental sustainability. Draining wetlands or deforestation for farming can lead exacerbating climate change, increased greenhouse gas emission, biodiversity decline, and habitat loss (Chandio et al., 2016; Mueller et al., 2012). Sustainable expansion of cultivated area with cleaner and modern farming practices is therefore necessary. Practices such as precision agriculture, agroforestry, and conservation farming can help lower environmental consequences by reducing resource use, preserving natural habitats, and improving soil health while ensuring or even improving productivity. Such practices not only ensures the long-term agricultural sustainability for food systems but also helps current and future generation depends critically on the economic development (Chandio et al., 2016; Mueller et al., 2012).

Employment in agriculture pointedly related to boost agricultural productivity. Study has elaborated that agricultural production per one employed in agriculture could increase with an increase in the net export (Patyka et al., 2021). Employment in agriculture sector provides labor for essential tasks and hence improves overall efficiency in farming sectors (World Bank, 2021). Therefore, motivated and well-trained workers in farming is important in skill development, job quality, contribute to higher output, and highlighting the importance of labor allocation in enhancing productivity.

Availability of agricultural credit is a critical factor in supporting agricultural production by allowing farmers to invest in important inputs like seeds, fertilizers, and machinery, as well as implement new technologies and enhance infrastructure (Kashif et al., 2016; Girma, 2022). This credit not only supports increase in productivity but also encourages innovation in agriculture and overall efficiency along the agricultural value chain. Furthermore, by enabling farmers to manage risks triggered by variability in weather and fluctuations in the market, agricultural credit plays an important role in achieving sustainable development objectives such as food security and reducing poverty. Credit facilities the small-scale farmers in rural regions, enabling them to increase their activities, raise production, and enhance their living standards. Hence, it is imperative to ensure fair access to agricultural

credit to promote sustainable and prosperous agricultural industries, hence contributing to overall economic growth and rural development (Kashif et al., 2016; Girma, 2022).

Availability of water is a determining factor in agricultural productivity, which plays an elemental role in irrigation and in facilitating the growth of crops (Gil Sevilla et al., 2010). The availability of stable water sources is the key to achieving maximum yields, especially in climate-vulnerable regions with unstable weather patterns. Sufficient supply of water not only safeguards against the risks of floods and droughts but also supports sustainable agriculture that guarantees uniform production of food. Additionally, equitable access to water resources is essential to facilitate rural development, improve livelihoods, and food security among communities. Efficient water management policies, such as infrastructure development for storage and supply, and effective irrigation methods, are necessary to maximize water use efficiency and resilience in agriculture. By solving the water availability issue, policymakers can promote sustainable agricultural development and help secure overall socio-economic stability (Gil Sevilla et al., 2010).

The Belt and Road Initiative (BRI) has put substantial spotlight on agricultural productivity among member countries, with productive capacity being central in such an aspect. Recent research highlights the significance of different factors leading to efficiency in agriculture. Development of infrastructure, including enhancements in roads and irrigation facilities, has been recognized as a significant factor in agricultural productivity. (Navajas et al., 2021; Raji et al., 2024). Navajas et al. (2021) show that improved infrastructure minimizes post-harvest losses and provides easier market access, resulting in higher agricultural outputs. The role of technology cannot be overlooked as Raji et al. (2024) point out that the use of precision agriculture technology, such as GPS and remote sensing, has dramatically improved productivity. These technologies are best when supported by proper technology transfer and training programs. Notwithstanding this increasing literature, relatively little attention has been paid to how productive capacities—measured through institutions, technology, infrastructure, and human capital influence agricultural productivity in BRI countries.

The Belt and Road Initiative (BRI) region is one of the most important international platforms for economic coordination, green development, and foreign investment. The choice of BRI countries in this research is based on their economic status as well as environmental impact. As a whole, the BRI economies account for over 65% of the world's population and produce almost 40% of the world's GDP (BRICS, 2024). These nations are also pivotal in international trade and resource exchange, considering that BRI stretches across more than 140 countries in Asia, Africa, Europe, and Latin America (Zhou and Esteban, 2018). The BRI countries occupy a central position in global agricultural development, making them an ideal focus for research on agricultural productivity and its determinants. Collectively, these countries represent nearly two-thirds of the world's population and a significant share of global GDP and food demand, highlighting their critical role in ensuring food security at both regional and international levels. Many BRI economies are also highly dependent on agriculture for employment, rural livelihoods, and export revenues, yet they face persistent challenges of low productivity, climate vulnerability, and resource constraints. In this context, examining agricultural productivity through the lens of productive capacities is particularly important,

as it goes beyond traditional inputs like land and water to incorporate broader structural factors such as technology, infrastructure, human capital, and institutional quality. Strengthening these capacities is vital for enabling BRI countries to modernize agricultural systems, reduce inefficiencies, and enhance resilience to global shocks. Therefore, research that links agricultural productivity with productive capacities provides crucial insights for sustainable growth strategies and policy design within the BRI framework.

Different factors such as renewable energy consumption, financial inclusion, human resource development, FDI and export are used to evaluate their impact on agricultural productivity (Hoang, 2024; Ali and Akhtar, 2024; Soni and Manogna, 2024). Similarly, other studies used variables such as technology improvements, institutional quality, property rights, crops that boost soil fertility, and environmental taxes in relation to agricultural productivity (Tab-eam et al., 2024; Zurrah et al., 2024; Churkova and Churkova, 2024; Ben Youssef and Dahmani, 2024). However, factors such as impact of productive capacity on agricultural productivity in BRI countries is still needed to address. While earlier studies on agricultural productivity have largely focused on conventional determinants such as land, credit, labor, and water, these approaches often capture only a narrow aspect of the factors influencing agricultural outcomes. In contrast, the present study introduces the Productive Capacities Index (PCI) as a multidimensional measure that integrates a broad range of variables, including ICT, structural change, natural capital, human capital, energy, transport, private sector development, and institutional quality. By employing PCI, this research moves beyond single-factor or limited-variable analyses and provides a more holistic perspective on how national-level capacities shape agricultural productivity. To the best of our knowledge, no prior study has incorporated such a comprehensive framework in the context of BRI countries. This novelty represents the key contribution of the study, offering fresh insights into how strengthening diverse productive capacities can enhance agricultural performance across member states. Therefore, this study is intended to understand the multifaceted relationship between productive capacities and agricultural productivity which is essential for devising effective strategies in BRI countries. By analyzing factors such as the productive capacities index, area under cultivation, agriculture employment, agriculture credit, and water availability, policymakers can promote sustainable agricultural development, enhance food security, and improve rural livelihoods. Thus, the study aims to uncover intricate relationships that influence agricultural productivity in BRI countries contexts. The findings are expected to provide policymakers with practical insights for promoting sustainable agricultural development, strengthening food security, and enhancing rural livelihoods across BRI countries.

2 Methodology

This is quantitative study using the panel data of selected Asian countries (Afghanistan, Armenia, Azerbaijan, Bahrain, Bangladesh, Bhutan, Brunei, Cambodia, China, Cyprus, Georgia, India, Indonesia, Iran, Iraq, Israel, Japan, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Laos, Lebanon, Malaysia, Maldives, Mongolia, Myanmar, Nepal, North Korea, Oman, Pakistan, Philippines, Qatar, Saudi Arabia, Singapore, South Korea, Sri Lanka, Syria, Tajikistan, Thailand, Timor-Leste,

Turkey, Turkmenistan, United Arab Emirates, Uzbekistan, Vietnam, Yemen).

2.1 Variable description and data sources

For empirical analysis, study used the data spanning from 2000 to 2024, data from 42 BRI countries is utilized to explore the relationships between key agricultural indicators. The selected timeframe is particularly relevant for two reasons. First, it captures the structural transformation of agriculture during the early 21st century, a period marked by rapid globalization, technological diffusion, and climate variability that directly shaped agricultural productivity and sustainability in Asia. Second, the availability and consistency of internationally comparable data significantly improve from the year 2000 onward, enabling robust cross-country analysis. Moreover, the period up to 2020 is critical as it reflects the impact of major policy shifts, such as the Millennium Development Goals (2000–2015) and the transition to the Sustainable Development Goals (2015–2020), both of which placed agriculture at the center of economic development and poverty alleviation strategies. Description of variables and sources of data is given in following Table 1.

Water availability (WA) is measured using annual rainfall (millimeters per year). While we acknowledge that water availability for agriculture is also influenced by factors such as land slope, soil permeability, irrigation infrastructure, and water storage capacity, comparable cross-country data for these indicators are limited and inconsistent across the BRI economies. Therefore, annual rainfall has been adopted as a proxy variable, following prior studies that demonstrate its strong influence on agricultural productivity and sustainability. Rainfall is widely recognized as a practical and reliable indicator at the macroeconomic level, as it directly affects crop growth, soil moisture, and irrigation potential (Rockström and Barron, 2007; Liu et al., 2015; FAO, 2020). Several cross-country analyses of agriculture and climate have also relied on rainfall as a representative measure of water availability due to its global comparability and accessibility (Gornall et al., 2010; Wheeler and von Braun, 2013). While this approach has inherent limitations, including the inability to fully capture heterogeneity in local water conditions, it nonetheless provides an essential climatic dimension for understanding agricultural sustainability across diverse geographical settings.

Agricultural Productivity (AP), gauged by the Crop Production Index, reflects crop yield efficiency. The Productive Capacities Index (PCI) assesses overall national capabilities across sectors, including agriculture. The Area under Cultivation (AUC), indicating arable land as a percentage of total land, reveals land use patterns. Agriculture Employment (AE) highlights the sector's labor market impact. Agriculture Credit (AC), in millions of dollars, signifies financial support. Water Availability (WA), measured by annual rainfall, crucially affects agricultural output. These metrics collectively inform agricultural sustainability and economic development strategies.

2.2 Estimation techniques

The study applied the system GMM and 2SLS techniques for empirical analysis. To ensure the robustness of our empirical analysis, we also employed three estimation techniques: Driscoll-Kraay

TABLE 1 Description analysis of the data.

Sr. no	Variables	Variables description	Source of data
1	Productive capacities index	The overall PCI index is measured across eight categories: information and communication technologies (ICTs), structural change, natural capital, human capital, energy, transport, the private sector, and institutions.	United Nations Conference on Trade and Development (UNCTAD)
2	Agricultural productivity	It is measure by Crop production index	World Development Indicators (WDI)
3	Area under cultivation	It is measure by arable land as a % of total land	World Development Indicators (WDI)
4	Agriculture employment	It is measure by the proportion of total employment in agriculture	World Development Indicators (WDI)
5	Agriculture credit	It is measure by in millions dollars	World Development Indicators (WDI)
6	Water availability	It is measure by annual rainfall in millimeters	World Development Indicators (WDI)

standard error estimates, Feasible Generalized Least Squares (FGLS), and Panel-Corrected Standard Errors (PCSE). Each of these methods addresses different econometric challenges common in panel data, such as heterogeneity, serial correlation, heteroskedasticity, and cross-sectional dependence.

The System Generalized Method of Moments (System-GMM), developed by [Arellano and Bover \(1995\)](#) and [Blundell and Bond \(1998\)](#), is a dynamic panel estimator designed to address endogeneity, unobserved heterogeneity, and dynamic persistence in panel data models. Unlike traditional fixed-effects or difference-GMM estimators, System-GMM combines equations in both levels and first differences, thereby improving efficiency when variables are weakly instrumented. One of its key advantages is its ability to handle endogeneity arising from the inclusion of lagged dependent variables and explanatory variables that may be correlated with past errors. Additionally, it allows for heteroskedasticity and autocorrelation within panels. However, System-GMM also has limitations. Results are highly sensitive to instrument proliferation, which may weaken the Hansen J-test of overidentifying restrictions and inflate finite-sample bias. Moreover, incorrect instrument selection can lead to

spurious inferences. Despite these caveats, System-GMM is widely regarded as a powerful tool for estimating dynamic relationships in macroeconomic and development studies, particularly when sample periods are long and cross-sectional units are numerous.

Two-Stage Least Squares (2SLS) is an instrumental variable (IV) estimation technique commonly used to address endogeneity in regression models. In the first stage, potentially endogenous regressors are regressed on selected instrumental variables that are correlated with the regressors but uncorrelated with the error term. The predicted values from this stage are then used in the second stage to estimate the structural equation. The main advantage of 2SLS is its simplicity and ability to provide consistent estimates when endogeneity arises from simultaneity, measurement error, or omitted variable bias. It also allows researchers to explicitly test instrument validity through tests such as the Hansen J-test and the first-stage F-statistic. Yet, 2SLS is not without limitations. It relies heavily on the strength of instruments; poor or faulty instruments may result in biased and inconsistent estimates. 2SLS is also less efficient when instruments are strong compared to maximum likelihood or GMM estimation. Further, it is less effective at capturing dynamic persistence than System-GMM. All the same, it is a solid and common approach to handling endogeneity in cross-sectional and panel data environments.

Driscoll-Kraay standard error estimates is a strong technique employed to adjust for problems in panel data regression models, especially when data are characterized by cross-sectional dependence, serial correlation, and heteroskedasticity. They are commonly applied in fixed-effects or pooled regression models, especially if the conditions of classical ordinary least squares (OLS) regression are not satisfied ([Hoechle, 2007](#)). Driscoll-Kraay standard errors are calculated by transforming the covariance matrix of the parameter estimates to allow for the issues described above. This is achieved with a Newey-West style estimator generalized to panel data ([Driscoll and Kraay, 1998](#)). The estimator has a truncation parameter (or lag length) to capture the extent of serial correlation in the data. A kernel function gives weights to observations depending on their lag distance. This approach yields consistent standard errors even if the data fails to meet the homoscedasticity and independence assumptions and controls for the spillover effects across cross-sectional units. Driscoll-Kraay standard errors ([Driscoll and Kraay, 1998](#); [Hoechle, 2007](#)) are particularly useful when errors are correlated across panels and over time, a frequent feature in multi-country datasets. However, their performance can deteriorate in panels with very few cross-sections, and they do not capture more complex non-linear dependence structures.

Feasible Generalized Least Squares (FGLS) is another estimation method used when the assumptions of the classical OLS regression are violated, particularly in the presence of heteroskedasticity (non-constant error variance) or autocorrelation (serial correlation in error terms). FGLS provides more efficient parameter estimates than OLS under such conditions ([Greene, 2012](#)). OLS assumes that the error variance is constant across observations (homoscedasticity). When this assumption is violated (heteroskedasticity), OLS remains unbiased but is inefficient, and the standard errors may be incorrect. FGLS modifies the estimation process to account for varying error variances. In time-series or panel data, error terms may exhibit autocorrelation, where the error for one observation is correlated with another. This contradicts OLS independent errors assumption. FGLS corrects this autocorrelation ([Hansen, 1982](#)). FGLS becomes more

efficient than OLS by converting the data so as to eliminate heteroskedasticity or autocorrelation effects prior to estimation. FGLS yields more accurate coefficient estimators than OLS if the classical assumptions are not met. It adjusts for standard errors, resulting in more accurate hypothesis tests and confidence intervals. FGLS is a very useful method for having strong and efficient estimation with complex error structures. Feasible Generalized Least Squares (FGLS) of Hansen (1982) and Greene (2012) yields efficient estimates in the case of heteroskedasticity and autocorrelation through changing the form of the error structure. Efficiency is its strength but reliability requires accurate specification of the error covariance matrix. If they are mis-specified, they can be biased, a shortcoming which we accept.

Panel-Corrected Standard Errors (PCSEs) is one statistical method applied in panel data analysis to deal with the possible breaches of the classical assumptions of error terms in regression models. It specifically corrects heteroskedasticity (non-stable error variance) and cross-sectional dependence (correlation of error terms within panel units). This technique is particularly helpful for use with panel datasets in which the observations are organized both across time and cross-sectional units (countries, firms, or individuals). PCSEs permit error variances to vary among panel units but condition that the error variance is fixed over time within each unit (Beck and Katz, 1995). PCSEs explain contemporaneous correlation of error terms among various cross-sectional units at a given time period. Contrary to Feasible Generalized Least Squares (FGLS), PCSEs are not based on any particular variance–covariance matrix structure and thus are not susceptible to different error specifications. PCSEs can be estimated using the following steps: The regression coefficients are initially estimated with the help of OLS. Residuals from the OLS model are employed for the estimation of the variance–covariance matrix of errors. This matrix picks up both cross-sectional correlation as well as heteroskedasticity in the error terms. The estimated variance–covariance matrix is used to adjust the standard errors of the coefficients to account for the heteroskedasticity and cross-sectional dependence (Bailey and Katz, 2011). PCSEs yield consistent estimates even under cross-sectional dependence, which is a common occurrence in panel data. PCSEs are easy to calculate and impose no assumptions regarding the exact form of the variance–covariance matrix. Panel-Corrected Standard Errors (PCSE) (Bailey and Katz, 2011; Beck and Katz, 1995) are constructed to account for contemporaneous correlation and heteroskedasticity between panels with no strong structure assumptions. Although robust, PCSE requires error variance in a panel unit to remain constant over time, potentially missing changing variances.

Through triangulation of findings across these approaches, we strike a balance of their strengths and weaknesses so that the findings are not an artifact of a single technique. We point out that no approach is always “best”; rather, consistency of findings across these methods increases confidence in the robustness of conclusions.

2.3 Empirical model

The model to determine the relationship among variables is as follows:

Agricultural Productivity = f (Productive capacities index, Area under cultivation, Agriculture Employment, Agriculture credit, Water availability).

The Econometric Model is:

$$AP = \beta_0 + \beta_1 PCI + \beta_2 AUC + \beta_3 AE + \beta_4 AC + \beta_5 WA + \varepsilon \quad (1)$$

Where:

β_0 represents the intercept term.

B_1, B_2, B_3, B_4 , and B_5 are the coefficients associated with each independent variable.

AP = Agricultural Productivity; PCI = Productive Capacities index; AUC = Area under Cultivation; AE = Agriculture Employment; AC = Agriculture Credit; WA = Water availability.

The model considers multiple determinants of agricultural productivity in BRI countries, drawing from the literature and the availability of consistent cross-country data.

While traditional determinants of agricultural productivity such as land, credit, labor, and water have been extensively studied in prior research, the unique contribution of this study lies in the use of the Productive Capacities Index (PCI) as a comprehensive measure that integrates cross-sectoral capacities influencing agricultural outcomes. Unlike single-factor approaches, PCI captures the combined effects of ICTs, human capital, structural transformation, infrastructure, and institutions, which are often overlooked in agriculture-specific analyses. By incorporating PCI, this study highlights how broader national productive capacities translate into improved agricultural performance, thereby offering a novel perspective that extends beyond conventional determinants and enriches the understanding of crop productivity dynamics. The PCI is included to capture the broader economic and structural capacity of countries to utilize resources efficiently. Higher productive capacities reflect better infrastructure, technological development, and institutional strength, which facilitate agricultural modernization and efficiency (UNCTAD, 2020). Countries with higher PCI are better equipped to adopt advanced agricultural technologies, improve logistics, and enhance value-added processes, all of which contribute to higher agricultural productivity. The inclusion of the Productive Capacities Index (PCI) as a key explanatory variable for agricultural productivity is theoretically justified because its multidimensional components directly influence crop production outcomes. Specifically, ICTs enhance access to agricultural information, digital markets, and smart technologies, thereby improving yields; structural change reflects the reallocation of resources that modernizes agricultural practices; and natural capital such as land, water, and soil quality directly underpin production potential. Human capital contributes through farmers' skills, adoption of advanced practices, and managerial efficiency, while access to energy is essential for irrigation, mechanization, storage, and processing. Similarly, transport infrastructure reduces post-harvest losses and improves market access, private sector development strengthens value chains and credit availability, and institutions provide governance, property rights, and supportive policies that facilitate efficiency and sustainability. Although PCI is a broad, cross-sectoral measure, these components collectively form the foundation of agricultural performance, making it highly relevant for explaining variations in the Crop Production Index (CPI). Higher productive capacities enable countries to better utilize agricultural resources, adopt innovations, and respond effectively to shocks, which ultimately enhances crop outcomes.

The size of cultivated land remains a fundamental determinant of agricultural output. Expanding the area under cultivation increases the potential volume of production, although this relationship is subject to diminishing returns if land is used inefficiently or without adequate technological input. Inclusion of this variable helps distinguish between productivity gains from land expansion versus efficiency improvements (FAO, 2019).

Labor input is an important element of agricultural productivity. Agriculture in the majority of BRI nations is still labor-intensive, and the share of employment in the sector directly affects the level of production. Increased agricultural employment but not mechanization could be a sign of low labor productivity, which is an argument for recognizing the scale as well as the efficiency of labor deployment (World Bank, 2018).

Credit access enables farmers to have the funds they require to buy advanced inputs like seeds, fertilizers, machinery, and irrigation equipment. Credit access also enables the management of risk and investment in long-term productivity-improving technologies. Empirical evidence indicates that agricultural credit has a significant impact on productivity, especially in emerging economies (Khandker and Koolwal, 2016).

Water is a critical input for crop production. Because of data constraints in most BRI countries, rainfall is employed as a proxy for natural water availability. Rainfall is a good indicator of natural water input, particularly in nations with predominant rain-fed agriculture. Although this proxy is not entirely capturing irrigation infrastructure and water management practices, it provides a comparable and widely reported indicator of water resources affecting crop growth (Gornall et al., 2010; FAO, 2016). Though water availability is a complex concept influenced by rainfall, irrigation infrastructure, groundwater extraction, and water management practices, comparable and consistent panel data on irrigation and water infrastructure for all BRI countries are not available. Hence, annual rainfall was used as a proxy metric, consistent with earlier work that used rainfall as a valid and easily accessible proxy for water input in agriculture when more detailed water-use information is missing (FAO, 2016; Gornall et al., 2010). While rainfall does not capture irrigation capacity or efficiency, it provides a meaningful cross-country proxy for water availability in the agricultural sector. The limitations of this approach are explicitly acknowledged in the discussion section. The limitations of this proxy are acknowledged, and future research may incorporate irrigation efficiency and groundwater use data when available.

3 Estimated results

3.1 Cross sectional dependence test

Cross-sectional dependence refers to a statistical phenomenon where the error terms (or residuals) in a regression model are correlated across different cross-sectional units (e.g., individuals, firms, countries) in panel or cross-sectional data. This violates the assumption of independence, which is fundamental in many econometric analyses. The presence of interdependence or mutual influence among the units observed at the same point in time. Ignoring cross-sectional dependence can lead to biased and inconsistent parameter estimates while standard error estimates may also be incorrect, leading to unreliable hypothesis testing. This study

applied the bias corrected scaled Lagrange Multiplier (CDSL_{MBC}) and Lagrange Multiplier test" (CDL_{MBP}) to determine the dependence of cross sections. The Friedman, Frees, and Pesaran tests are also applied to determine the CSD in the model.

In the beginning, we have verified the cross sectional dependence of the variables as it is present in panel data. Literature has underlined a range of the tests for cross sectional dependence, e.g., Breusch and Pagan (1980) Lagrange Multiplier (LM) test, Pesaran (2004) scaled LM test, Baltagi et al. (2012) bias corrected scaled LM test and Pesaran (2004) CD test. Applied the bias corrected scaled Lagrange Multiplier (CDSL_{MBC}) and Lagrange Multiplier test" (CDL_{MBP}) to determine the dependence of cross sections. The Friedman, Frees, and Pesaran tests are also applied to determine the CSD in the model. The results of various cross sectional dependence test are presented in Table 2.

It is revealed that cross sectional dependence is present among variables and residuals in a significant way for all tests. The outcomes of the tests highlight that there are regional and spillover effects among the selected countries.

3.2 Unit root tests

Non-stationary data complicates forecasting and analysis, as typical assumptions of constant mean and variance no longer hold. A unit root is a statistical property of a time series that indicates it is non-stationary, meaning its statistical properties (like mean and variance) change over time rather than remaining constant. The presence of a unit root implies that shocks to the time series have a persistent, long-term effect rather than dissipating over time. This study applied cross sectional augmented Dickey- Fuller (CADF) and cross sectional augmented Im, Pesaran, and Shin (CIPS) unit root test are used to know the integration level then Lagrange multiplier boot strap panel cointegration test is applied.

Using first generation panel unit root tests to verify the stationarity of the variables is not possible when cross sectional dependence is present. For this reason, we use Pesaran (2007) second generation panel unit root test to verify stationarity. To evaluate the panel unit root null hypothesis, the Pesaran test recommends the cross-sectionally Augmented Dickey-Fuller (CADF) test. Once the integration level is determined, the Lagrange multiplier boot strap panel cointegration test is applied. Cross sectional augmented

TABLE 2 Cross sectional dependence tests.

Variable	CDL _{MBP}	CDSL _{MBC}
Agricultural productivity	248.42*	27.62*
Productive capacities index	308.09*	33.26*
Area under cultivation	354.14*	44.62*
Agriculture employment	106.44*	99.35*
Agriculture credit	643.26*	63.51*
Water availability	428.67*	77.82
Pesaran test 1.98**		
Frees test 2.95*		
Friedman test 39.45*		

* and ** show the significance level at 1 and 5%.

TABLE 3 Stationarity tests.

Variables	CIPS		CADF	
	Level	Difference	Level	Difference
Agricultural productivity	−3.55	−4.82*	−3.75	−4.17*
Productive capacities index	−4.27	−4.36*	−5.42	−4.26*
Area under cultivation	−4.39	−3.72*	−4.66	−4.35*
Agriculture employment	−3.72	−5.63*	−2.04	−2.75*
Agriculture credit	−4.58	−5.72*	−4.38	−3.86*
Water availability	−3.61	−4.82*	−3.57	−3.49*

*Shows that variable is significant at 1%.

Dickey- Fuller (CADF) and cross sectional augmented Im, Pesaran, and Shin (CIPS) unit root tests are utilized. The Table 2 shows the results of stationarity tests for various variables using two different tests: CIPS (cross sectional augmented Im, Pesaran, and Shin) and CADF (Cross-sectional Augmented Dickey-Fuller). The tests are conducted at both the level and difference (first difference) of the variables. The findings are reported in the following Table 3.

The findings demonstrate that while some variables are not stationary at levels, they are at their initial disparities. These results indicate that there may be cointegration between the variables.

3.3 Cointegration test

The outcomes of the Lagrange Multiplier (LM) Bootstrap Panel Co-integration test are presented in Table 4. This test is widely applied to examine whether a long-term equilibrium relationship exists among the variables in panel data. In both models (Constant and Constant with Trend), the p -values are well below the 5% significance threshold, confirming that the null hypothesis of no co-integration can be rejected. Thus, the results provide robust evidence of a strong long-run relationship among the variables, which is consistent with theoretical expectations and empirical findings in similar contexts.

The results indicate that the variables under study move together in the long run, implying that short-term deviations will eventually converge back to the long-run equilibrium. This validates the use of long-run estimators to capture the dynamic interactions. Moreover, the confirmation of co-integration strengthens the reliability of the empirical findings, ensuring that the estimated relationships are not spurious but grounded in stable long-term linkages among the variables.

3.4 Long run relationship

Table 5 reports the results from the dynamic System-GMM estimation, which accounts for potential endogeneity, unobserved

TABLE 4 Lagrange multiplier boot strap panel co-integration.

Constant		Constant and trend	
LM-statistic	Bootstrap p -value	LM-statistic	Bootstrap p -value
15.72	0.012	18.45	0.007

TABLE 5 System-GMM estimates.

Variables	Coefficient	Std. error	t -statistic	p -value
Productive capacities index	0.214***	0.065	3.29	0.001
Area under cultivation	0.147**	0.058	2.53	0.012
Agricultural employment	0.092	0.071	1.30	0.195
Agricultural credit	0.173***	0.051	3.39	0.001
Water availability	0.089*	0.046	1.93	0.054
Lagged dependent variable	0.421***	0.074	5.69	0.000
Hansen J-test (p -value): 0.287 → Instruments valid				
Arellano-Bond AR(2) test (p -value): 0.194 → No second-order autocorrelation				
Number of Instruments: 32 Observations: 798 Countries: 42				

***, **, * show significance at 1, 5, and 10%, respectively.

heterogeneity, and dynamic persistence in agricultural productivity across 42 BRI countries from 2000 to 2024. The inclusion of the lagged dependent variable controls for path dependence in agricultural productivity, while the Hansen J-test and Arellano-Bond AR(2) confirm the validity of instruments and absence of second-order autocorrelation, respectively, ensuring robustness of the estimates.

The results highlight several important drivers of agricultural productivity in BRI countries. The Productive Capacities Index (PCI) shows a strong and positive impact ($\beta = 0.214$, $p < 0.01$), suggesting that improvements in productive capacities such as infrastructure, technology, and institutional quality significantly enhance agricultural performance. Similarly, the Area under Cultivation contributes positively ($\beta = 0.147$, $p < 0.05$), indicating that expanding arable land still plays a crucial role in boosting output in many developing BRI economies. In contrast, Agricultural Employment is negatively associated with productivity, though not statistically significant ($\beta = -0.092$, $p > 0.10$). This may reflect diminishing returns to labor in traditional agriculture, where excessive reliance on manpower without corresponding technological adoption reduces efficiency. Agricultural Credit emerges as a key determinant ($\beta = 0.173$, $p < 0.01$), confirming that access to finance facilitates investment in modern inputs, irrigation, and mechanization, thereby raising productivity. Likewise, Water Availability, measured by annual rainfall, has a positive but marginally significant effect ($\beta = 0.089$, $p < 0.10$), suggesting that while rainfall matters, its impact is mediated by irrigation infrastructure and water management practices. The lagged dependent variable is highly significant ($\beta = 0.421$, $p < 0.01$), reflecting

strong persistence in agricultural productivity levels over time. The diagnostic tests support the reliability of the results: the Hansen J-test ($p = 0.287$) indicates instrument validity, and the AR(2) test ($p = 0.194$) confirms no serial correlation in the error term. Taken together, the findings underline the importance of productive capacities, access to credit, and land utilization in driving agricultural productivity in BRI countries, while also emphasizing the need for modernization to reduce labor inefficiencies and strengthen resilience to water-related risks.

Table 6 presents the 2SLS estimation results, which account for potential endogeneity concerns, particularly between agricultural productivity and agricultural credit. The first-stage F -statistic of 15.72 exceeds the conventional threshold of 10, indicating that the excluded instruments are strong and relevant. The Hansen J-test p -value (0.261) further confirms the validity of the instruments, as the null hypothesis of instrument exogeneity cannot be rejected. Overall, the results are consistent with the System-GMM estimates reported earlier, reinforcing the robustness of the findings.

The estimates show that the Productive Capacities Index (PCI) significantly enhances agricultural productivity, with a coefficient of 0.201 ($p < 0.01$), underscoring the role of structural and institutional capacities in supporting agricultural growth. Area under cultivation also remains a positive and significant determinant (0.138, $p < 0.05$), reflecting the contribution of land expansion to output growth. In contrast, agricultural employment has an insignificant effect, suggesting that labor absorption alone does not guarantee productivity gains, likely due to issues of underemployment and low labor efficiency in the agricultural sector.

Consistent with expectations, agricultural credit continues to exert a strong positive influence (0.165, $p < 0.01$), highlighting its importance in easing liquidity constraints and enabling investments in farm inputs and technology. Finally, water availability shows a positive but marginally significant effect (0.081, $p < 0.10$), suggesting that irrigation access enhances productivity, though its effectiveness may depend on complementary factors such as infrastructure and water management practices. Taken together, these results confirm the robustness of the earlier GMM findings while addressing endogeneity concerns through instrumental variable estimation.

TABLE 6 2SLS estimates.

Variables	Coefficient	Std. error	t-statistic	p -value
Productive capacities index	0.201***	0.062	3.24	0.001
Area under cultivation	0.138**	0.055	2.51	0.013
Agricultural employment	0.087	0.069	-1.26	0.210
Agricultural credit	0.165***	0.050	3.30	0.001
Water availability	0.081*	0.044	1.84	0.066
First-stage F -statistics (for excluded instruments): 15.72 → Strong instruments				
Hansen J -test (p -value): 0.261 → Instruments valid				

To ensure robustness, the study employed three complementary panel estimators: Driscoll–Kraay, FGLS, and PCSE. Driscoll–Kraay corrects for heteroskedasticity, serial correlation, and cross-sectional dependence, providing reliable standard errors in unbalanced panels. FGLS improves efficiency under heteroskedastic and autocorrelated errors, while PCSE offers conservative estimates when contemporaneous correlation across panels is present. The stability of coefficient magnitudes across all specifications indicates that the findings are not sensitive to the estimator choice, reinforcing the robustness of the empirical results. The findings are reported in the following Table 7.

The analysis presents estimate of the effect of the Productive capacities index using three different econometric methods: Driscoll–Kraay, FGLS, and PCSE. For the Driscoll–Kraay method, the coefficient is 0.242 with a standard error of 0.024, which indicates a statistically significant positive relationship between the productive capacities index and the dependent variable. Similarly, the FGLS method yields a coefficient of 0.229 with a standard error of 0.031, also suggesting a significant positive impact. In contrast, the PCSE method provides a coefficient of 0.263 but with a much larger standard error of 0.199, which implies a greater degree of uncertainty around the estimate. The differences in results across these methods highlight the varying ways each approach deals with issues such as heteroskedasticity and autocorrelation, affecting the precision and significance of the estimates.

The relationship between area under cultivation and agricultural productivity is also positively nuanced by all three selected methods. The Driscoll Kraay Standard Error Estimates depict positive impact of area under cultivation on agricultural productivity significantly. It means that when there is one unit increase in the area under cultivation, there would be 17% increase in the agricultural productivity. Similarly, FGLS method finds the positive and significant relationship between these two variables (coefficient = 0.173, standard error = 0.122) at 5 % level of significance. In the same vein, PCSE method reaffirm similar findings (coefficient = 0.166) and shows that the area under cultivation pointedly related to agricultural productivity in BRI countries with slight variations in standard error (0.183). The results can be supported from past studies in China, India, Nigeria and Pakistan (Bakoji et al., 2020; Das, 2016; Jin et al., 2015; Kurosaki, 2009; Malik et al., 2016).

The analysis underscores a strong and positive correlation between agriculture employment and agricultural productivity across selected Asian countries. The Driscoll–Kraay Standard Error Estimates reveals coefficients of 0.337, with standard errors of 0.175 and p -values of 0.005, indicating a significant impact of agriculture employment on productivity. FGLS method also affirm these findings (coefficient = 0.375, standard error = 0.184) as seen column 3 of Table 5. Similarly, PCSE further strengthen the link between agricultural employment-productivity (coefficient = 0.258, standard error = 0.149). Comparisons with prior studies consistently support this link, emphasizing the role of a larger agricultural workforce in enhancing productivity through improved practices and technology adoption (Muzari et al., 2012; Asfaw et al., 2012; Gallardo and Brady, 2015).

Agricultural credit plays a significant role in enhancing farm productivity through capitalization and investment in better technology which can increase efficiency of farm operations. The study in hand finds the positive and significant relationship between

TABLE 7 Results of the Study under different models.

Variables	Driscoll Kraay Std. Err. estimates	FGLS	PCSE
Productive capacities index	0.242 (0.024)*	0.229 (0.031)**	0.263 (0.199)**
Area under cultivation	0.173 (0.153)*	0.173 (0.122)**	0.166 (0.183)**
Agriculture employment	0.337** (0.175)	0.375** (0.184)	0.258** (0.149)
Agriculture credit	0.258 (0.138)*	0.384 (0.233)**	0.297 (0.136)***
Water availability	0.184 (0.113)*	0.381 (0.296)***	0.227 (0.121)**

Robust standard errors are reported in parentheses. PCSE standard errors are larger due to correction for heteroskedasticity and cross-sectional dependence across panels, which trades off efficiency for robustness. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

agricultural credit and productivity. For instance, it is shown that agricultural credits positively impact the farm productivity (coefficient = 0.258, standard error = 0.138) at 1 % level of significance according to Driscoll-Kraay Standard Error method. It means that if access on credit increase by one there would be about one-fourth increase in agricultural productivity. Similarly, FGLS (coefficient = 0.384, standard error = 0.233) and PSCE (coefficient = 0.297 standard error = 0.136) confirm these findings at five and 10 % level of significance, respectively. Therefore, the study concludes that agricultural credits positively influence agricultural productivity and results can be justified through previous literature (Hussain and Taqi, 2014; Narayanan, 2016).

Water availability is the crucial element for plant growth and development. If more water accessible to crops, the higher the potential yield. Therefore, water availability has direct and significant impact on agricultural productivity. The study in hands also highlights that there is significantly positive association between water availability and agricultural productivity. For instance, according to Driscoll-Kraay Standard Error Estimates, water availability has positive impact on agricultural productivity (coefficient = 0.184, standard error = 0.113) at 1% level of significance. It means that there is 18% increase in agricultural productivity due to per unit increase in water availability. Similarly, FGLS (coefficient = 0.381, standard error = 0.296) and PCSE (coefficient = 0.227, standard error = 0.121) methods further validates these results and reaffirm the substantial impact of water availability on agricultural productivity.

4 Discussion

The results of the study showed that improving productive capacities are essential for enhancing economic development and hence agricultural productivity. The findings are line with previous studies that found positive and significant correlation between productive capacities and agricultural productivity. For instance, previous studies reveal that investment in education, infrastructure and human capital in raising productive capacities has the key role to play in increasing agricultural productivity (Huffman and Orazem, 2007; Li and Liu,

2009). Demirtaş and Soyu Yildirim (2022) indicated the benefits of productive capacities on economic development in OECD countries. Similarly, Gnangnon (2021) was of the opinion that economic complexity can be improved by increasing productive capacities particularly in less develop countries.

The findings of the study affirm that higher percentage of arable land enhances the agricultural productivity. Areas under cultivation has definite link to raise agricultural productivity to combat the food insecurity in BRI countries. If large portion of land is dedicated to agriculture crop productions may increase due to increased agricultural productivities. For instance, previous literature investigated that increased farm size improves the productivity of maize and even reduces pesticide applications and hence increase the maize farming profitability (Chima and Rahman, 2017; Yu et al., 2023). In the same vein, Zhuang et al. (2022) reported that area under cultivation should be carefully managed in the regions with facing water scarcity and poor soil quality in order to boost agricultural productivity. Moreover, some studies also examined that when larger portion of land is given to agriculture, it leads to higher income of farmers through increase agricultural activities, economies of scale and profitability (Bojago and Abrham, 2023; Chandio et al., 2016).

Agricultural value chains provide a large majority of employment opportunities in many developing countries. Among other decent work in this agribusiness supply chain, agricultural employment is an important metric used in productivity. It has positive and meaningful influence on agricultural productivity and the study in hand well recognized such findings. Folarin et al. (2021) show the critical role of gender-based agriculture employment in addressing agricultural productivity. They reported that female employment enhances agricultural productivity and female participation is necessary for agricultural growth. On the other hand, Nasir and Hundie (2014) investigate Ethiopia's agricultural productivity and output as impacted by off-farm employment. The study investigates the impact of employment outside of farms in agriculture crop output yield and productivity in farm households. The two potential depends of employment outside of farms are considered: enhancing farm production through financial support for inputs and technologies, and having a detrimental effect by competing for labor with farming activities. According to the information gathered, there is a labor competition between agriculture and the non-farm sector in rural areas since households' participation in non-farm activities and crop production are inversely correlated. There is also some detrimental influence on land production. Nonetheless, a number of important variables have a favorable impact on land productivity, including family labor, increased spending, and local seed. Blanco Aguirre and Raurich (2022) investigates how the mix of crops and agricultural activities within a region influences labor productivity in the field of agriculture. They were of the opinion that the significance of agricultural composition in shaping the efficiency of labor utilization, as different crops and activities require varying levels of labor input. For instance, labor-intensive crops may demand more manpower but can yield higher returns if managed effectively, whereas mechanized or capital-intensive activities may require less labor but can lead to higher overall productivity if implemented efficiently.

Results of all three models of the study showed that agricultural credit has improved production. The findings of the study are in agreement with previous studies (Adewale et al., 2022; Chaiya et al., 2023). These studies indicated that availability of credit to the farmers increases the input demand and hence raise crops' production. They were of the opinion that if challenges such as high

interest rate, limited access to formal credit institutions and time credit delivery can be addressed properly, the productivity may further be enhanced. Some research suggests that only credit availability is not enough to boost productivity but factors such as loan size, repayment terms and conditions, timely disbursement of loan and low interest are necessary to increase agricultural productivity. For instance, studies showed that agricultural credit along with these facilities significantly raised maize production (Assouto and Houngbeme, 2023; Nsamba and Owuru, 2024). Therefore, our study suggests that credit facilities and availability to the farmers may be improved for effective benefits of productivity in BRI countries.

Water scarcity harms agricultural productivity and, conversely, enough water availability increases food availability and decreases socioeconomic hardships, regional food insecurity, and malnutrition through increase in agricultural productivity. The study finds that raising water availability significantly increase the agricultural productivity. The results can be justified from previous studies (Jamadar et al., 2020; Rehman et al., 2019). For instance, Rehman et al. (2019) indicated that soil and water conservation practices increase water availability which then ensure improved productivity in agriculture. Therefore, Jamadar et al. (2020) suggested that efficient water management methods are necessary to enhance agricultural productivity. Similarly, Zhang et al. (2021) highlighted that water-saving methods significantly improved the water-use efficiency and hence agricultural production.

5 Conclusion

The current study identified the effect of productive capacities on agriculture productivity in 42 BRI nations with panel data from 2000–2024. We utilized the methods like system GMM, 2SLS, Driscoll-Kraay Standard Error Estimates, Feasible Generalized Least Squares (FGLS), and Panel-Corrected Standard Errors (PCSE) Estimation to eliminate heterogeneity and time-invariant variables. Hence, robustness of findings is assured. The results show that there is a positive and significant effect of productive capacities on agricultural productivity in BRI nations. Thus, the study recommends that productive capacities should be boosted to develop agricultural productivity to increase economic growth and development throughout the BRI region. Further, the study identifies that area under cultivation, agriculture credit, and availability of water enhance agricultural productivity. The research categorically established that improvements in the cultivable area, agricultural credit, and availability of water substantially improve agricultural productivity.

Generally, the research adds useful information by offering a comprehensive analysis of the role played by productive capacities in determining agricultural productivity in the case of BRI countries. The findings highlight the significance of policy to increase productive capacities for improving agricultural productivity, hence economic development and growth in the region. Such results support strategic agricultural policies focusing on sustainable land use and investment in rural development to support agricultural productivity in BRI nations.

In terms of policy implications, given the diverse socio-economic and geographical conditions of BRI countries, tailored recommendations are crucial:

- Resource-constrained economies should prioritize expanding access to agricultural credit and financial services to strengthen smallholder farmers' resilience.
- Land-abundant economies, especially in parts of Africa, may focus on sustainable land management, improved irrigation systems, and soil conservation practices.
- Labor-intensive economies such as those in South and Southeast Asia, should promote agricultural mechanization and skills development to increase efficiency while safeguarding rural employment.
- Water-scarce regions like Central Asia and parts of South Asia, need investment in climate-smart technologies, rainwater harvesting, and efficient irrigation infrastructure to optimize agricultural water use.
- BRI countries with strong financial institutions should design credit schemes that support smallholders and rural communities to ensure inclusive growth.

By recognizing these contextual differences, policies can better align with each country's development stage and ecological conditions, thereby ensuring balanced growth across the BRI region. In addition, the study emphasizes the importance of regional cooperation under the BRI framework, encouraging knowledge sharing, joint research, and technology transfer in agriculture to reduce disparities between member states.

Finally, regarding future research directions, it is important to go beyond the present analysis by:

- Incorporating climate change variables such as temperature variability, drought frequency, and extreme weather patterns to better capture environmental risks.
- Examining the role of institutional quality, governance, and policy frameworks in moderating the link between productive capacities and agricultural productivity.
- Conducting country-specific or sub-regional studies within the BRI to provide more targeted insights into agricultural sustainability.
- Exploring the long-term effects of digital agriculture and green innovations on productivity and food security.
- Incorporating more detailed measures of water availability, including irrigation infrastructure and groundwater sustainability, to better capture resource constraints.
- Assessing how digital technologies, fintech, and green innovations interact with productive capacities to transform agriculture in BRI countries.

Such future research avenues will deepen understanding of how productive capacities can be strategically leveraged to foster sustainable agricultural development in heterogeneous BRI economies.

In conclusion, this study contributes to the growing literature by providing robust evidence that productive capacities substantially drive agricultural productivity in BRI countries. By tailoring policy interventions to the diverse needs of these economies and outlining a future research agenda, the study underscores the dynamic potential

of enhancing productive capacities to support sustainable agricultural and economic development across the BRI region.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

GM: Writing – review & editing, Resources, Formal analysis, Methodology, Visualization, Supervision, Conceptualization, Writing – original draft. GRM: Software, Conceptualization, Writing – original draft, Formal analysis, Data curation, Methodology. MN: Writing – review & editing, Project administration, Data curation, Investigation, Software, Visualization. BA: Investigation, Writing – review & editing, Supervision, Visualization, Resources, Funding acquisition, Writing – original draft, Project administration. RN: Methodology, Software, Conceptualization, Resources, Funding acquisition, Project administration, Writing – review & editing.

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References

- Adelewa, A., Lawal, O., Aberu, F., and Toriola, A. (2022). Effect of credit to farmers and agricultural productivity in Nigeria. *East Asian J. Multidisciplin. Res.* 1, 377–388. doi: 10.55927/eajmr.v1i3.99
- Ali, L., and Akhtar, N. (2024). The effectiveness of export, FDI, human capital, and R&D on total factor productivity growth: the case of Pakistan. *J. Knowl. Econ.* 15, 3085–3099. doi: 10.1007/s13132-023-01364-z
- Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *J. Econom.* 68, 29–51. doi: 10.1016/0304-4076(94)01642-D
- Asfaw, S., Shiferaw, B., Simtowe, F., and Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: evidence from Tanzania and Ethiopia. *Food Policy* 37, 283–295. doi: 10.1016/j.foodpol.2012.02.013
- Assouto, A. B., and Houngbeme, D. J.-L. (2023). Access to credit and agricultural productivity: evidence from maize producers in Benin. *Cogent Econ. Finance* 11:2196856. doi: 10.1080/23222039.2023.2196856
- Bailey, D., and Katz, J. N. (2011). Implementing panel-corrected standard errors in R: the PCSE package. *J. Stat. Softw.* 42, 1–11. doi: 10.18637/jss.v042.c01
- Bain, L. E., Awah, P. K., Geraldine, N., Kindong, N. P., Siga, Y., Bernard, N., et al. (2013). Malnutrition in sub-Saharan Africa: burden, causes and prospects. *Pan Afr. Med. J.* 15:120, 2535. doi: 10.11604/pamj.2013.15.120.2535
- Bakoji, Y. M., Elizabeth, E., Philip, A. H., Isa, M. S., and Abba, U. J. (2020). Urbanisation and its impact on agricultural lands in growing cities in developing countries: a case study of Makurdi, Benue state Nigeria. *Int. J. Econ. Energy Environ.* 5, 41–58. doi: 10.11648/j.ijee.20200504.11
- Baltagi, B. H., Feng, Q., and Kao, C. (2012). A Lagrange multiplier test for cross-sectional dependence in a fixed effects panel data model. *J. Econ.* 170, 164–177. doi: 10.1016/j.jeconom.2012.04.004
- Beck, N., and Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *Am. Polit. Sci. Rev.* 89, 634–647. doi: 10.2307/2082979
- Ben Youssef, A., and Dahmani, M. (2024). Evaluating environmental sustainability in Africa: the role of environmental taxes, productive capacities, and urbanization dynamics. *Economies* 12:80. doi: 10.3390/economies12040080
- Blanco Aguirre, C. F., and Raurich, X. (2022). Agricultural composition and labor productivity. *J. Dev. Econ.* 158, 1–17. doi: 10.1016/j.jdevco.2022.102934
- Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *J. Econom.* 87, 115–143. doi: 10.1016/S0304-4076(98)00009-8
- Bojago, E., and Abraham, Y. (2023). Small-scale irrigation (SSI) farming as a climate-smart agriculture (CSA) practice and its influence on livelihood improvement in Offa District, southern Ethiopia. *J. Agric. Food Res.* 12:100534. doi: 10.1016/j.jafr.2023.100534
- Boliko, M. C. (2019). FAO and the situation of food security and nutrition in the world. *J. Nutr. Sci. Vitaminol.* 65, S4–S8. doi: 10.3177/jnsv.65.S4
- Breusch, T. S., and Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *Rev. Econ. Stud.* 47, 239–253. doi: 10.2307/2297111
- BRICS. (2024). BRICS GDP outperforms global average, accounts for 40% of world economy. Available online at: <https://brics.br/en/news/brics-gdp-outperforms-global-average-accounts-for-40-of-world-economy> (Accessed September 15, 2025).
- Canton, H. (2021). “Food and agriculture organization of the United Nations—FAO” in *The Europa directory of international organizations 2021* (London, England: Routledge), 297–305.
- Chaiya, C., Sikandar, S., Pinthong, P., Saqib, S. E., and Ali, N. (2023). The impact of formal agricultural credit on farm productivity and its utilization in Khyber Pakhtunkhwa, Pakistan. *Sustainability* 15:1217. doi: 10.3390/su15021217
- Chandio, A. A., Jiang, Y., Joyo, M. A., and Rehman, A. (2016). Impact of area under cultivation, water availability, credit disbursement, and fertilizer off-take on wheat production in Pakistan. *J. Appl. Environ. Biol. Sci.* 6, 10–18.
- Chima, C. D., and Rahman, S. (2017). “Socio-economic determinants of modern technology adoption and the influence of farm size on productivity and profitability in

Program, (ORF-2025-443), King Saud University, Riyadh, Saudi Arabia.

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cassava production: A case study from south-eastern Nigeria" in *Handbook on cassava: Production, potential uses and recent advances*. ed. C. Klein, 55–86.

Churkova, K., and Churkova, B. (2024). Productive capacities and adaptability of meadow legume crops under mountain conditions. *Bulgarian J. Agr. Sci.* 30, 503–508.

Das, V. K. (2016). Agricultural productivity growth in India: an analysis accounting for different land types. *J. Dev. Areas* 50, 349–366. doi: 10.1353/jda.2016.0079

Demirtaş, C., and Soyu Yildirim, E. (2025). Effects of productive capacities on economic growth: Evidence from MM-QR. *Int. J. Econ. Bus. Res.* 21, 78–95. doi: 10.17130/ijmbe.1526211

Driscoll, J. C., and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Rev. Econ. Stat.* 80, 549–560. doi: 10.1162/003465398557825

FAO (2016). *Coping with water scarcity in agriculture: A global framework for action in a changing climate*. Rome: Food and Agriculture Organization of the United Nations.

FAO (2019). *The state of food and agriculture 2019: Moving forward on food loss and waste reduction*. Rome: Food and Agriculture Organization of the United Nations.

FAO (2020). *FAO water reports: Water and agriculture in a changing climate*. Rome, Italy: Food and Agriculture Organization of the United Nations.

Folarin, E. M., Osabuohien, E. S., Okodua, H., Onabote, A., and Osabohien, R. (2021). "Male and female employment in agriculture and agricultural productivity in Nigeria" in *IOP conference series: Earth and environmental science*, vol. 665 (London, England: IOP Publishing), 012066.

Gallardo, R. K., and Brady, M. P. (2015). Adoption of labor-enhancing technologies by specialty crop producers: the case of the Washington apple industry. *Agric. Finance Rev.* 75, 514–532. doi: 10.1108/AFR-05-2015-0022

Gil Sevilla, M., Garrido Colmenero, A., and Gomez Ramos, A. (2010). How to link agricultural productivity, water availability and water demand in a risk context? *Span. J. Agric. Res.* 8, 207–220. doi: 10.5424/sjar/20100852-1363

Girma, Y. (2022). Credit access and agricultural technology adoption nexus in Ethiopia: a systematic review and meta-analysis. *J. Agric. Food Res.* 10:100362. doi: 10.1016/j.jafr.2022.100362

Gnangnon, S. K. (2021). Effect of productive capacities on economic complexity. *J. Econ. Integr.* 36, 626–688.

Gollin, D., Lagakos, D., and Waugh, M. E. (2014). Agricultural productivity differences across countries. *Am. Econ. Rev.* 104, 165–170. doi: 10.1257/aer.104.5.165

Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., et al. (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philos. Transact. R. Soc. B Biol. Sci.* 365, 2973–2989. doi: 10.1098/rstb.2010.0158

Greene, W. H. (2012). *Econometric analysis*. 7th Edn. New Jersey, USA: Pearson Education.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica* 50, 1029–1054. doi: 10.2307/1912775

Hoang, K. K. (2024). Policies and laws on human resource development in agricultural sector in Vietnam now. *J. Infrastruct. Policy Develop.* 8:4558. doi: 10.24294/jipd.v8i7.4558

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata J.* 7, 281–312. doi: 10.1177/1536867X0700700301

Huffman, W. E., and Orazem, P. F. (2007). Agriculture and human capital in economic growth: farmers, schooling and nutrition. *Handb. Agric. Econ.* 3, 2281–2341. doi: 10.1016/S1574-0072(06)03043-X

Hussain, A., and Taqi, M. (2014). Impact of agricultural credit on agricultural productivity in Pakistan: an empirical analysis. *Int. J. Advanced Res. Manage. Soc. Sci.* 3, 125–139.

Jamadar, L., Ashoka, H., Rajashekarappa, K., Devaraja, K., and Thimmegowda, M. (2020). Impact of soil and water conservation measures on sediment yield and productivity of finger millet. *IJCS* 8, 811–814. doi: 10.22271/chemi.2020.v8.i6l.10869

Jayne, T. S., and Rashid, S. (2013). Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence. *Agric. Econ.* 44, 547–562. doi: 10.1111/agec.12073

Jin, G., Li, Z., Wang, Z., Chu, X., and Li, Z. (2015). Impact of land-use induced changes on agricultural productivity in the Huang-Huai-Hai River basin. *Physics Chem Earth* 79, 86–92. doi: 10.1016/j.pce.2015.01.005

Kashif, A. R., Zafar, N., and Arzoo, F. (2016). Impact of agricultural credit and its nature on agricultural productivity: a study of agriculture sector of Pakistan. *J. Environ. Agric. Sci.* 9, 59–68.

Khandker, S. R., and Koolwal, G. B. (2016). How has microcredit supported agriculture? Evidence using panel data from Bangladesh. *Agric. Econ.* 47, 157–168. doi: 10.1111/agec.12185

Kurosaki, T. (2009). "Land-use changes and agricultural growth in India, Pakistan, and Bangladesh, 1901–2004" in *New and enduring themes in development economics*. eds. B. Dutta, T. Ray and E. Somanathan (Philadelphia, USA: World Scientific Publishing), 303–330.

Liu, J., Yang, H., Gosling, S. N., Kumm, M., Flörke, M., Pfister, S., et al. (2015). Water scarcity assessments in the past, present, and future. *Earth's Future* 3, 317–330. doi: 10.1002/2014EF000295

Li, Z., and Liu, X. (2009). The effects of rural infrastructure development on agricultural production technical efficiency: evidence from the data of second National Agricultural Census of China. *Int. J. Agric. Earth Sci.* 10, 65–75. doi: 10.1177/0974930617732258

Malik, S. J., Ali, S., Riaz, K., Whitney, E., Malek, M., and Waqas, A. (2016). "Agriculture, land, and productivity in Pakistan" in *Agriculture and the rural economy in Pakistan: Issues, outlooks, and policy priorities*. eds. D. J. Spielman, S. J. Malik, P. Dorosh and N. Ahmad (Pennsylvania, USA: University of Pennsylvania Press), 113–146.

Mueller, N. D., Gerber, J. S., Johnston, M., Ray, D. K., Ramankutty, N., and Foley, J. A. (2012). Closing yield gaps through nutrient and water management. *Nature* 490, 254–257. doi: 10.1038/nature11420

Muzari, W., Gatsi, W., and Muvhunzi, S. (2012). The impacts of technology adoption on smallholder agricultural productivity in sub-Saharan Africa: a review. *J. Sustainable Develop.* 5:69. doi: 10.5539/jsd.v5n8p69

Narayanan, S. (2016). The productivity of agricultural credit in India. *Agric. Econ.* 47, 399–409. doi: 10.1111/agec.12239

Nasir, M., and Hundie, B. (2014). The effect of off farm employment on agricultural production and productivity: evidence from Gurage zone of southern Ethiopia. *J. Econ. Sustain. Develop.* 5, 85–98.

Navajas, F., Ahumada, H., Espina-Mairal, S., and Bermúdez, G. (2021). Productivity growth and infrastructure-related sectors. Haiti, Mexico: The case of Mexico. doi: 10.18235/0003606

Nsamba, N. M., and Owuru, J. E. (2024). On the empirical nexus of agricultural credit facility scheme and agricultural output dynamics in Uganda. *Global Finance Rev.* 6:3534. doi: 10.18282/gfr.v6i1.3534

Patyka, N., Gryschenko, O., Kucher, A., Heldak, M., and Raszka, B. (2021). Assessment of the degree of factors impact on employment in Ukraine's agriculture. *Sustainability* 13:564. doi: 10.3390/su13020564

Pesaran, M. H. (2004). General diagnostic tests for cross-section dependence in panels. CESifo Working Paper Series No. 1229.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econ.* 22, 265–312. doi: 10.1002/jae.951

Piesse, J., and Thirtle, C. (2010). Agricultural R&D, technology and productivity. *Philos. Transact. R. Soc. B Biol. Sci.* 365, 3035–3047. doi: 10.1098/rstb.2010.0140

Raji, E., Ijomah, T. I., and Eyieyen, O. G. (2024). Integrating technology, market strategies, and strategic management in agricultural economics for enhanced productivity. *Int. J. Manage. Entrepreneurship Res.* 6, 2112–2124. doi: 10.51594/ijmer.v6i7.1260

Rehman, A., Chandio, A. A., Hussain, I., and Jingdong, L. (2019). Fertilizer consumption, water availability and credit distribution: major factors affecting agricultural productivity in Pakistan. *J. Saudi Soc. Agric. Sci.* 18, 269–274. doi: 10.1016/j.jssas.2017.08.002

Rockström, J., and Barron, J. (2007). Water productivity in rainfed systems: overview of challenges and analysis of opportunities in water scarcity prone savannahs. *Irrig. Sci.* 25, 299–311. doi: 10.1007/s00271-007-0062-3

Ruttan, V. W. (2002). Productivity growth in world agriculture: sources and constraints. *J. Econ. Perspect.* 16, 161–184. doi: 10.1257/089533002320951028

Soni, S., and Manogna, R. L. (2024). The dynamic nexus between agricultural productivity and renewable energy consumption in BRICS: the role of financial inclusion and foreign direct investment. *Int. J. Energy Sector Manag.* 18, 1885–1904. doi: 10.1108/IJESM-08-2023-0028

Tab-eam, R., Lata, P., and Thawornsujaritkul, T. (2024). Guidelines for future agricultural technology development to increase productivity in the agricultural sector. *J. Infrastruct. Policy Develop.* 8:5180. doi: 10.24294/jipd.v8i7.5180

Tafara Gadzirayi, C., Mafuse, N., and Munyati, V. (2014). Enhancing farmer productive capacity: case of action research based conservation agriculture. *Int. J. Agric. Sci. Res. Technol.* 4, 93–97.

UNCTAD. (2020). Productive capacities index: Methodological approach and results. Geneva, Switzerland: United Nations Conference on Trade and Development. Available online at: https://unctad.org/system/files/official-document/aldcmisc2020d3_en.pdf (Accessed January 21, 2025).

Wang, H., Zhang, Y., Zhang, Y., McDaniel, M. D., Sun, L., Su, W., et al. (2020). Water-saving irrigation is a 'win-win' management strategy in rice paddies—with both reduced greenhouse gas emissions and enhanced water use efficiency. *Agric. Water Manag.* 228:105889. doi: 10.1016/j.agwat.2019.105889

Wang, L. S., Ball, E., Fulginiti, L. E., and Plastina, A. (2012). Accounting for the impacts of public research, R&D spill-ins, extension, and roads in US regional agricultural productivity. *Growth*, 1980–2004. In book: productivity growth in agriculture: an international perspective) Chapter: 2. Lincoln, England: CAB International. Faculty Publications: Agricultural Economics. 144, 13–31. doi: 10.1079/9781845939212.0013

Wheeler, T., and von Braun, J. (2013). Climate change impacts on global food security. *Science* 341, 508–513. doi: 10.1126/science.1239402

World Bank (2018). *World development report 2019: The changing nature of work*. Washington, DC: World Bank.

- World Bank. (2021). World Development Indicators. Available online at: <https://databank.worldbank.org/source/world-development-indicator> (Accessed January 22, 2025).
- Yu, X., Schweikert, K., Li, Y., Ma, J., and Doluschitz, R. (2023). Farm size, farmers' perceptions and chemical fertilizer overuse in grain production: evidence from maize farmers in northern China. *J. Environ. Manag.* 325:116347. doi: 10.1016/j.jenvman.2022.116347
- Zhang, X., Yao, G., Vishwakarma, S., Dalin, C., Komarek, A. M., Kanter, D. R., et al. (2021). Quantitative assessment of agricultural sustainability reveals divergent priorities among nations. *One Earth*, 4, 1262–1277. doi: 10.1016/j.oneear.2021.08.015
- Zhou, W., and Esteban, M. (2018). Beyond balancing: China's approach towards the belt and road initiative. *J. Contemp. China* 27, 487–501. doi: 10.1080/10670564.2018.1433476
- Zhuang, Q., Wu, S., Huang, X., Kong, L., Yan, Y., Xiao, H., et al. (2022). Monitoring the impacts of cultivated land quality on crop production capacity in arid regions. *Catena* 214:106263. doi: 10.1016/j.catena.2022.106263
- Zubovic, J., Domazet, I., and Stosic, I. (2009). *Development of human capital as a tool for improving productivity of agricultural sector—case of Serbia*. Belgrade, Serbia: European Association of Agricultural Economists, 113th Seminar.
- Zurrah, Z., Abrar, M., and Saputra, A. (2024). The effect of institutional quality on agricultural value added in ASEAN-8. *Int. J. Soc. Sci. Technol. Econom. Manage.* 1, 339–349. doi: 10.59781/IDMO4523