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Unleashing the power of innovation and sustainability: Transforming cereal production in the BRICS countries☆

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A B S T R A C T

Amidst escalating food insecurity and climate change threats, which exacerbate food shortages and increase agricultural emissions, this paper explores transformative strategies in cereal production within the BRICS countries from 1990 to 2021. The uncontrolled growth of intensive agriculture, aimed at satisfying the growing global demand for food in a context already threatened by climate change, has led to a uniformity of crops with devastating impacts on biodiversity and ecosystem functioning, resulting in a transformation of soil and its capacity to implement ecosystem services, such as food, fiber, and raw material production, nutrient recycling, carbon sequestration, clean water availability, and the regulation of water regimes and local temperatures. These changes have had negative consequences on agricultural production. Thus, sustainable agriculture faces three closely related challenges: reducing environmental impact, in-creasing productivity, and adapting to and mitigating climate change. This analysis utilizes advanced econometric tools such as panel second-generation unit root tests, Westerlund's cointegration test, second-generation long-run estimators, and the Dumitrescu-Hurlin causality test, together with several machine learning algorithms, to investigate the influence of technological innovations and improved land management on cereal yields. The findings demonstrate a positive correlation between technological advancements, enhanced land management for cereal cultivation, and the food production index with increased cereal output. At the same time, emissions from agriculture significantly reduce yields over time. Furthermore, an interaction analysis reveals that the comprehensive integration of these factors significantly boosts cereal productivity. The study also identifies directional causal relationships between technological and emission factors and cereal production, suggesting a complex interplay with land use. Sustainable land use is one of the key conditions for ensuring the ecological resilience of agricultural practices in terms of providing ecosystem services. Implementing these strategies calls for a collaborative approach among governments, policymakers, farmers, researchers, and other stakeholders, considering each BRICS nation's unique environmental, socio-economic, and local contexts, and fostering regional cooperation to promote sustainable agricultural practices.

1. Introduction

Food security and scarcity have become increasingly critical and formidable challenges, exacerbated by a rapidly growing population, diminishing cropland, escalating food demands, and decreased soil fertility and productivity (Beddington et al., 2012; Chandio et al.,

Abbreviations: AMG, Augmented Mean Group; BRICS, Brazil, Russia, India, China, and South Africa; CADF, Cross-sectionally Augmented Dickey-Fuller; CCEMG, Common Correlated Effects Mean Group; CH_4, Methane; CIPS, Cross-sectionally augmented Im-Pesaran-Shin; CSD, Cross-Sectional Dependency; GLM, Generalized Linear Model; IPCC, Intergovernmental Panel on Climate Change; KNN, K-Nearest Neighbor; MAE, Mean Absolute Error; ML, Machine Learning; MSE, Mean Squared Error; NO_2, Nitrogen Oxide; RF, Random Forest; RMSE, Root Mean Squared Error; SDGs, Sustainable Development Goals; SVM, Support Vector Machines.

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2023b). Soil, the top layer of the earth, comprises mineral components, organic matter, water, air, and living organisms, representing the interface between land, air, and water while hosting a significant portion of the biosphere. Its functions are manifold: it provides food, biomass, and raw materials, serves as the platform for human activities, acts as a central element of the landscape and cultural heritage, and plays a fundamental role as a habitat and gene pool. Healthy soils offer essential 'regulating' services by providing nutrients, remediating and storing contaminants, mitigating floods, storing carbon, recycling waste, and regulating pests and diseases (Evangelista et al., 2023). These characteristics, combined with their ability to absorb water and reduce the risk of floods and droughts, make soils indispensable allies in climate change mitigation strategies (Adhikari and Hartemink, 2016).

Global environmental changes, habitat loss or fragmentation, climate change, and practices associated with intensive agriculture have had significant and negative impacts on natural capital and biodiversity (Foley et al., 2005). Oversimplification of landscapes and increasingly unsustainable land use have led to habitat changes primarily caused by land use changes, which have strained biodiversity conservation on a planetary scale (Billeter et al., 2008; Karp et al., 2012; Dainese et al., 2019).

The global population is expected to surge from 6 to 9 billion people between 2000 and 2050 (Smith and Olesen, 2010). Despite this, per capita cereal production has slightly increased over time, mainly due to technological advancements, particularly in high-yield wheat and rice varieties developed during the Green and Clean Revolutions. These innovations have played a key role in meeting the food demands of the growing population (Pingali, 2012). Dietary patterns have evolved in response to rapid population growth, leading to the overexploitation of available resources to meet increased food production demands. Retrospectively, the population growth rate peaked at 1.66 percent over the last three decades before declining to below 0.5 percent by 2009 (Koondhar et al., 2021).

Previous research on food supply forecasts and demand patterns of Brazil, Russia, India, China, and South Africa (commonly referred to as the BRICS countries) has offered limited insight into the potential food security and scarcity challenges these nations may face. The BRICS region has significant potential for enhancing cereal grain productivity and food consumption. However, the integration of environmental considerations into technological adoptions is crucial, especially in countries that have also experienced rapid and strong economic growth driven by fossil fuel use, with serious environmental repercussions. The BRICS countries' significant contribution to the world's energy consumption underscores the urgent need for ecological and environmental attention in these nations, particularly regarding renewable energy consumption, human capital development, and natural resource sustainability (Yang et al., 2023). Incorporating technology into agricultural practices aims to reduce chemical inputs on farms, enhancing production through smart agriculture and precision farming. Minimizing chemical methods on farms can preserve soil faunal diversity, which is at risk due to excessive use of insecticides, pesticides, and herbicides (Pandey and Pandey, 2023). This study emphasizes that achieving Sustainable Development Goals (SDGs) is possible through agronomy, which directly and indirectly affects all other SDGs.

This study contributes to the existing literature in several ways. Firstly, it examines the complex interplay among technological innovations (TEC), land use for cereal productivity (LU), the Food Production Index (FPI), and emissions from the agricultural sector (e.g., agricultural methane and nitrous oxide emissions: PAG) on cereal food productivity for BRICS nations, aiming to reduce food insecurities and promote food sustainability. It distinguishes itself from previous studies by focusing on Cereal Food Productivity (CFP), considering the BRICS economies' continued concern with self-sufficiency in cereals as a solution to regional food insecurity, where capital accumulation, social reproduction, and politics remain key problems of the 'agrifood question' (Escher, 2021). Secondly, it introduces food technological innovations, land harvested for cereal production, an index for food production, and pollution from the agriculture sector as variables in the cereal food productivity model, which have yet to be explored in earlier literature, especially for the BRICS economies. Thirdly, this paper addresses the research gap by employing recent panel data techniques: the Cross-sectionally Augmented Dickey-Fuller (CADF) test, Cross-sectionally augmented Im-Pesaran-Shin (CIPS) test, Westerlund's cointegration tests, Augmented Mean Group (AMG) estimator, Common Correlated Effects Mean Group (CCEMG) long-run elasticity estimator, and the Dumitrescu and Hurlin (2012) causality approach to address various data issues such as outliers, serial correlation, cross-country dependency, and slope heterogeneity. Lastly, ensemble Machine Learning (ML) models are used to test the econometric estimates' robustness.

The empirical findings of this research can guide policymakers in formulating and implementing new strategies to enhance cereal food productivity, optimize resource utilization, and reduce emissions from the agricultural sector. Incorporating these insights into the existing body of knowledge may facilitate the development of a comprehensive policy framework applicable worldwide.

The remainder of the study is organized as follows: Section 2 discusses the current literature, and Section 3 outlines the conceptual framework and hypothesis development for the modeling process. Section 4 introduces the data, while Section 5 presents the empirical strategy. Section 6 gives the results. Section 7 reports a discussion derived from the study's findings, and Section 8 is devoted to illustrating the robustness checks, ensuring the reliability and validity of previous findings. Finally, the last section concludes the study, offering conclusions and policy recommendations based on the empirical findings obtained.

2. Literature review

Food security and scarcity intersect with several SDGs, including SDG-1 (No Poverty), SDG-2 (Zero Hunger), SDG-3 (Good Health and Well-being), SDG-13 (Climate Action), and SDG-15 (Life on Land). Effectively addressing these issues requires a synergy between technology and agriculture through the adoption of bioeconomy, sustainable agronomy, precision farming, and innovative technologies such as machinery, geospatial technology, and Artificial Intelligence. Recent trends in global food security have seen the adoption of technological advancements (Shah et al., 2024).

The relationship between land use management for cereal productivity and cereal food production is critically linked, involving the interplay among land distribution, allocations, agricultural practices, and conservation measures and their impact on cereal crop yields. For example, the reduction of green cover and expanding built-up areas have accelerated the increase in drought severity (Taiwo et al., 2023). Land use management decisions, such as the distribution of farming and arable lands and the adoption of sustainable practices like crop diversity and rotation, directly influence the quality and quantity of cereal food production. Conversely, cereal food production practices can significantly affect land use, as unsustainable agricultural methods and land degradation may reduce soil fertility and overall productivity. Thus, advanced techniques for land monitoring are essential (Zhang et al., 2023). Balancing sustainable land use management with cereal food production is imperative to ensure long-run environmental sustainability, food security, and resilient agricultural systems.

It has also been highlighted that there is no significant increase in land use for cereal food production. In light of this, Koondhar et al. (2021) showed that the area sown and FPI contribute to increased cereal food production. The benefits of an increase in FPI on cereal food production are evident in both short- and long-run effects. The FPI includes all edible crops from nutritious agricultural operations, while cereal food production specifically pertains to crops harvested for their dry grains. Consequently, this study incorporates these indicators into the empirical analysis, positing that an increase in the FPI will likely enhance cereal production.

The agricultural sector has been identified as a clear booster for economic growth and social advancement within the BRICS nations. However, the relentless pressure exerted on existing resources by expanding populations and extensive cultivation has altered landscapes, escalated methane (CH_4) and nitrogen oxide (NO_2) emissions, and adversely affected the BRICS environment. Intensive agricultural practices, which push for nutrient efficiency, prolonged resistance to pests, and drought tolerance, have yielded returns in terms of productivity but have also incurred high environmental costs, threatening biodiversity and the sustainability of food production (Bommarco et al., 2018; Caira and Ferranti, 2023). Traditional practices supporting ecosystem services have been abandoned (Tilman et al., 2001).

The intensification of agricultural activities has been one of the most decisive factors in the loss of biodiversity in terrestrial ecosystems (Kehoe et al., 2017). The uncontrolled growth of intensive agriculture, aimed at satisfying the growing global demand for food (Foley et al., 2005) in a context already threatened by climate change (Omerkhil et al., 2020), has led to agricultural management models that increase yields through the use of herbicides, pesticides, fertilizers, high-impact mechanical systems, and intensive irrigation methods (Zhang et al., 2013). These practices have had dramatic consequences, particularly the loss of crop diversification, leading to more homogeneous agricultural landscapes (Leblois et al., 2017). This uniformity of crops has had devastating impacts on biodiversity and ecosystem functioning (Foley et al., 2005; Laterra et al., 2012), resulting in a transformation of soil and its capacity to implement ecosystem services, such as food, fiber, and raw material production (Daily et al., 1997), nutrient recycling (Safaei et al., 2019), carbon sequestration (Adhikari and Hartemink, 2016), clean water availability (Pouyat et al., 2002), biodiversity conservation (Giraldo-Perez et al., 2021), and the regulation of water regimes and local temperatures (Dominati et al., 2010). These changes have had negative consequences on agricultural production.

Among the most significant impacts of intensive agriculture are its effects on biogeochemical and hydrological cycles, exacerbating climate change and ecosystem degradation, with consequent impacts on human health (Bouwman et al., 2013), such as reduced availability of drinking water. Improving food production towards sustainable models is imperative, with over 200 million people suffering from extreme food insecurity (FSIN & GNAFC, 2023). Sustainable agriculture faces three closely related challenges: reducing environmental impact, increasing productivity, and adapting to and mitigating climate change (Wei et al., 2023). Pakrooh et al. (2024) used a C-Vine Copula model to measure the correlations together with the Granger causality test to analyze the causality direction and correlation structure among selected horticulture, farming crops, livestock, and poultry products and carbon dioxide (CO_2), nitrogen dioxide (N_2O), and methane emissions (CH_4) in the Iranian agriculture sector over the period 1961–2019.

The agricultural industry within the BRICS faces the daunting challenge of safeguarding against climate change and global warming (Usman and Makhdum, 2021; Ojekemi et al., 2023). In the next decades, the agricultural sector in the BRICS may struggle to produce enough food to sustain the global population, given the significant impact of pollution from agricultural activities. Introducing carbon-free and energy-efficient technology in agriculture is crucial for enhancing agricultural productivity in the face of climate change and air pollution (Shah et al., 2023). Emissions from the agricultural sector pose significant challenges, affecting nearly all aspects of society and the food supply, including cereal production. Long-run agricultural-induced carbon emissions lead to climatic changes that adversely affect agricultural productivity in various ways, such as changing rainfall patterns, rising temperatures, and prolonged environmental emissions impacting water availability for irrigation, crop maturation cycles, and pest outbreaks. The BRICS economies are particularly vulnerable to environmental pollution due to their diverse geographical features, vast territories, and significant exposure to global warming and environmental changes (Yang et al., 2023; Shu et al., 2024).

Given the preceding discussion, various hypotheses exist regarding the impact of technological innovations, land use for cereal productivity, the food production index, and emissions from the agricultural sector on cereal yields. These hypotheses employ different models for diverse datasets to explore relationships among these variables across different economies, assessing both long- and short-term effects. Consequently, the relationship among technological innovations, land use for cereal productivity, the food production index, emissions from the agricultural sector, and cereal productivity remains ambiguous, particularly in the BRICS context. This study aims to illuminate how the cereal cultivation system for this group of countries can be made more robust while considering the constraints posed by these factors.

3. Theoretical framework and research hypotheses

Technological innovations are depicted as a spectrum of advancements that enhance agricultural management practices, and, subsequently, cereal food production, specifically public investment, plays a statistically significant influence on wheat production (Chandio et al., 2023a). Land use management strategies, including crop rotation and conservation agriculture, are identified as pivotal factors that significantly affect both production levels and environmental sustainability.

FPI serves as a crucial gauge for tracking fluctuations in food productivity over time. Furthermore, emissions emanating from agricultural activities, such as the use of fertilizers and livestock management practices, are acknowledged contributors to global warming and climate change. Examining these intertwined factors, the framework facilitates governmental and policy-making entities in formulating strategies that promote sustainable cereal food production systems. These systems aim to elevate production efficiency while mitigating adverse environmental impacts. This investigation's theoretical and conceptual foundations are visually summarized in Fig. 1, providing a comprehensive overview of the study's underpinning logic and contribution to the scholarly discourse on sustainable agriculture and food production.

The diminution of arable land due to urban expansion and the rapid increase in population heightens reliance on fertilizers in traditional farming practices, as Hussain et al. (2018) noted, leading to elevated emissions from the agricultural sector. Concurrently, Ramankutty et al. (2018) highlighted how such agricultural emissions contribute to global warming and climate change, adversely affecting agricultural food productivity. Agriculture is, in fact, a case in point, as it has a dual role: on the one hand, it has always been a major sector for greenhouse gas emissions, thus becoming a major driver of climate change; on the other

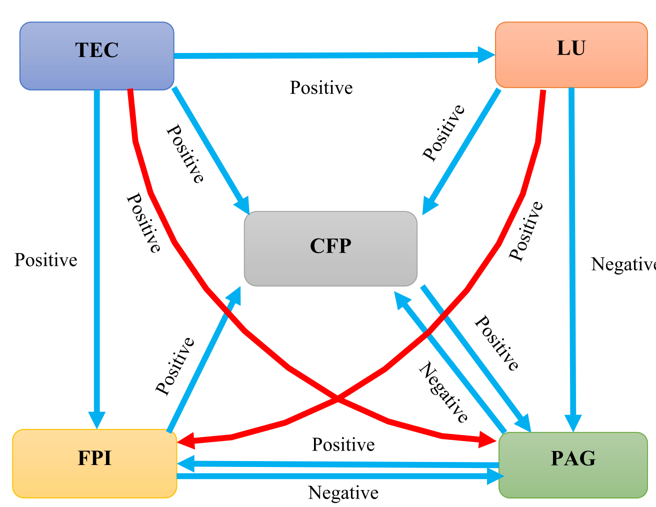

Fig. 1. Theoretical Framework.

hand, it is also deeply affected by climate change. In fact, the 2023 Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) estimated that the emissions from agriculture, forestry, and other land uses in 2019 were responsible for 22 % of global greenhouse gas emissions (IPCC, 2023).

Considering that cereal food productivity constitutes a significant portion of the overall agricultural yield, Koondhar et al. (2021) posited that enhancing crop productivity could bolster cereal production. Gani (2022) observed that, following improvements in food productivity, cereal yields also play a role in the levels of emissions. Pakrooh et al. (2024) analyzed the causality flow among selected horticulture, farming crops, livestock, and poultry products and CO_2, nitrogen dioxide, and methane emissions for Iran in the 1961–2019 years. Magazzino et al. (2024) showed that domestic credit, renewable consumption, exports, and urbanization reduce CH_4 emissions.

The synthesis of conceptual frameworks and hypotheses from prior research underscores the multifaceted impacts on cereal food production, such as the beneficial effects of technological innovations, land use management, and the food production index, alongside the detrimental relationship between cereal food production and environmental pollution. Conversely, improved land management practices exert less pressure on agricultural land and negatively impact environmental pollution from the agricultural sector within an efficient production system. Moreover, previous investigations identified a bidirectional relationship between environmental pollution and factors such as technological innovations, cereal food productivity, and the food production index. In light of the contributions and identified research gaps from preceding studies, this study posits the following hypotheses to be empirically tested within the context of the BRICS nations, drawing upon the available dataset:

- H1: Technological innovation plays a crucial role in enhancing cereal food productivity in the BRICS countries.
- H2: The food production index exerts a positive impact on cereal food productivity in the BRICS countries.
- H3: Land use management specifically for cereal production positively affects cereal food productivity in the BRICS countries.
- H4: Emissions of agricultural CH_4 and NO_2 have a direct impact on cereal food productivity in the BRICS countries.
- H5: The synergistic effect of technological innovation, food production index, and emissions of CH_4 and NO_2, in conjunction with land use management for cereal production, positively affects cereal food productivity in the BRICS countries.

4. Data

The major objective of the current study is to analyze the various factors contributing to the extent of cereal production in the BRICS region. To do this, a panel dataset has been constructed from 1990 to 2021. The intended form of cereal food production function is presented in Eq. (1) as follows:

$$\mathrm{CFP}_{it} = f(\mathrm{TEC}_{it}, \mathrm{LU}_{it}, \mathrm{FPI}_{it}, \mathrm{PAG}_{it}) \tag{1}$$

where CFP represents the concept of cereal food production, TEC is technological innovations (trademark applications in the form of nonresident and resident by count), LU stands for land use under cereal productivity (or simple harvested land for cereal production), FPI denotes food production index (2014–2016 = 100), and PAG shows methane and nitrous oxide emissions from the agriculture sector. By presuming an asymmetric relationship occurs in Eq. (1), it can be converted to Eq. (2) as follows:

$$\mathrm{CFP}_{it} = \beta_1\mathrm{TEC}_{it} + \beta_2\mathrm{LU}_{it} + \beta_3\mathrm{FPI}_{it} + \beta_4\mathrm{PAG}_{it} + \mu_{it} \tag{2}$$

This model is transformed into a natural logarithm format to smoothen the long-run test process presented in Eq. (3) as:

$$\textbf{Model1}: \ln(\mathrm{CFP}_{it}) = \alpha_0 + \alpha_1\ln(\mathrm{TEC}_{it}) + \alpha_2\ln(\mathrm{LU}_{it}) + \alpha_3\ln(\mathrm{FPI}_{it}) + \alpha_4\ln(\mathrm{PAG}_{it}) + \mu_{it} \tag{3}$$

In addition to examining the direct impacts of the selected model (Model 1), this study establishes three further distinct functions to investigate their moderating effects. These models, referred to as Model 2, Model 3, and Model 4 throughout the empirical analysis in Eqs. (4)–(6), respectively, are outlined as follows:

$$\textbf{Model2}: \ln(\mathrm{CFP}_{it}) = \beta_0 + \beta_1\ln(\mathrm{TEC}_{it}) + \beta_2\ln(\mathrm{FPI}_{it}) + \beta_3\ln(\mathrm{PAG}_{it}) + \beta_4\ln(\mathrm{LU}^*\mathrm{TEC}_{it}) + \mu_{it} \tag{4}$$

$$\textbf{Model3}: \ln(\mathrm{CFP}_{it}) = \gamma_0 + \gamma_1\ln(\mathrm{TEC}_{it}) + \gamma_2\ln(\mathrm{FPI}_{it}) + \gamma_3\ln(\mathrm{PAG}_{it}) + \gamma_4\ln(\mathrm{LU}^*\mathrm{FPI}_{it}) + \mu_{it} \tag{5}$$

$$\textbf{Model4}: \ln(\mathrm{CFP}_{it}) = \delta_0 + \delta_1\ln(\mathrm{TEC}_{it}) + \delta_2\ln(\mathrm{FPI}_{it}) + \delta_3\ln(\mathrm{PAG}_{it}) + \delta_4\ln(\mathrm{LU}^*\mathrm{LAG}_{it}) + \mu_{it} \tag{6}$$

where *i* denotes the cross-sections (countries), and *t* represents the time span from 1990 to 2021. The intercept term of all four functions can be reported as $\alpha_0, \beta_0, \gamma_0, \delta_0$, the long-run coefficients are $\alpha_1 - \alpha_4$, $\beta_1 - \beta_4$, $\gamma_1 - \gamma_4$, $\delta_1 - \delta_4$, while the error term is presented by μ. Table 1 reports the description of the variables, measurement units, and data sources.

Fig. 2 presents a box plot summarizing the distributions of various variables. CFP shows a high median and range with a skewness of 1 and kurtosis of −0.15, indicating a right-skewed, flatter distribution. FPI's box indicates lower variability, with skewness close to zero (−0.05) and slightly platykurtic (kurtosis of −0.98). LU exhibits a lower range and

Table 1
Data overview.

Acronym	Variable's description	Measurement units	Data sources
CFP	Cereal food production	Metric tons	(WDI, 2022)
TEC	Patent applications	Residents and non-residents	(WDI, 2022)
LU	Land use under cereal production	Total hectares	(WDI, 2022)
FPI	Food production index	(2014–2016 = 100) index	(WDI, 2022)
PAG	Agricultural CH_4 and NO_2	Thousand metric tons of CO_2 equivalent	(WDI, 2022)

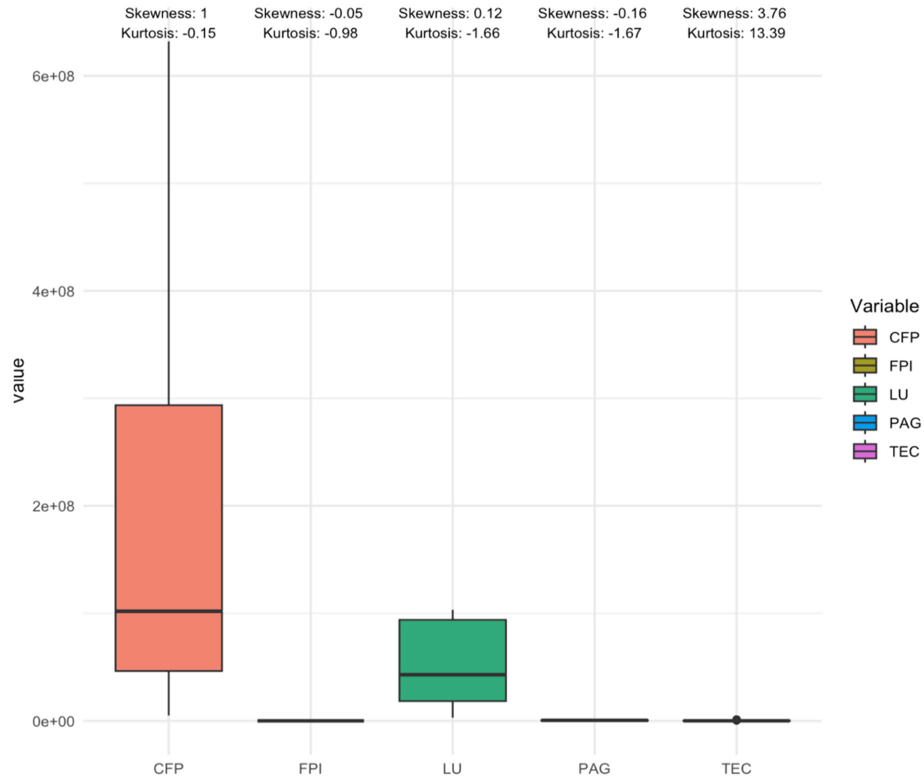

Fig. 2. Box plots of the variables.

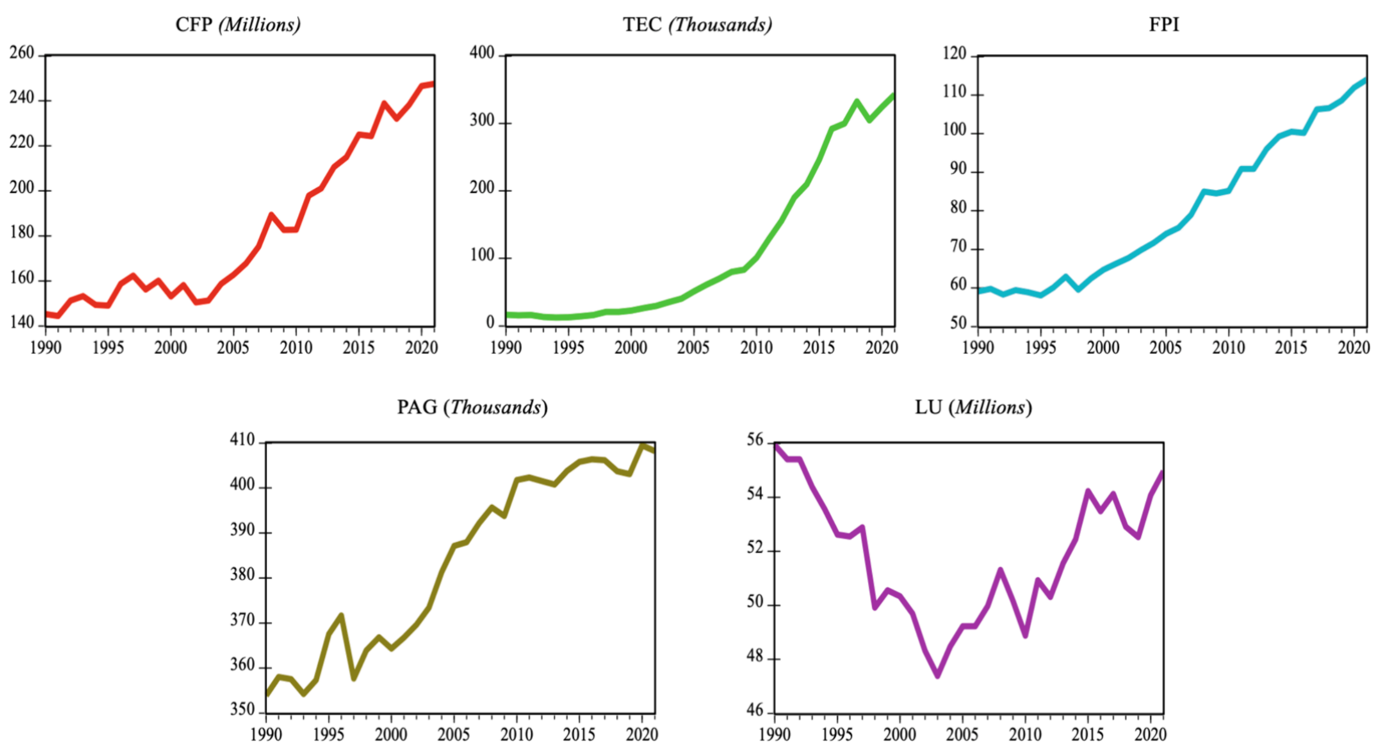

Fig. 3. Evolution of the series.

slight positive skewness (0.12) with a platykurtic distribution (kurtosis of −1.66). PAG has minimal skewness (−0.16) and is platykurtic (kurtosis of −1.67), suggesting a flat distribution. TEC, with a skewness of 3.76 and kurtosis of 13.39, is highly right-skewed and peaked, with most values clustering near the median.

Fig. 3 displays time series data for CFP, TEC, FPI, PAG, and LU from 1990 to 2020. CFP and FPI trends show consistent increases, indicative of rising food production levels. TEC also demonstrates notable growth,

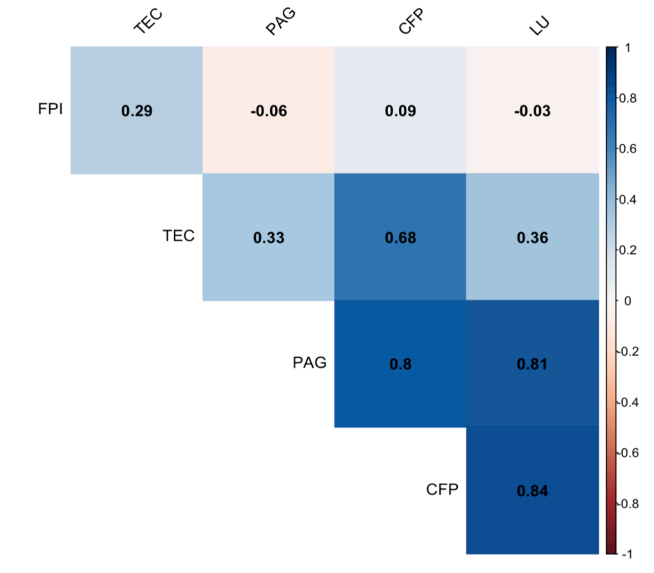

Fig. 4. Correlation matrix.

implying a positive relationship with productivity advancements. Conversely, PAG trends upwards, highlighting potential environmental concerns related to increased production. LU exhibits minor fluctuations with a general increase, pointing to evolving land management strategies.

The correlation matrix for all considered variables is reported in Fig. 4.

Examining the matrix reveals that TEC and CFP have a positive correlation of 0.68, implying that technological advances are strongly associated with increases in cereal food production. A similarly strong positive correlation is observed between PAG and CFP (0.81), suggesting that agricultural pollution levels are closely linked with cereal production outputs, which may reflect the input-intensive nature of cereal production. This is corroborated by the significant positive correlation of 0.84 between CFP and LU, indicating that land use dedicated to cereal production is strongly associated with the volume of cereal production.

Conversely, the correlation between PAG and FPI is slightly negative at −0.06, indicating a very weak inverse relationship, potentially suggesting that as the food productivity index increases, there is a negligible decrease in pollution from agriculture. This could imply that increased efficiency in food production does not necessarily translate into proportional increases in pollution levels, perhaps due to improved practices or technologies that enhance productivity without proportionately increasing pollution. Furthermore, the correlations involving FPI with TEC and LU are positive but modest (0.29 and 0.09, respectively), implying a mild positive association between these variables. Notably, the correlation between LU and FPI is particularly weak, which could suggest that land use changes have a relatively small direct impact on the food production index. Lastly, the negative correlation of −0.03 between FPI and LU is negligible, almost suggesting no relationship, which is intriguing as it may imply that land use patterns do not significantly influence the food production index or that the relationship is overshadowed by other factors not captured by this study.

5. Empirical strategy

In its empirical testing, this research explores the complex aspects of panel data analysis, methodically addressing essential issues such as Cross-Sectional Dependency (CSD), slope heterogeneity, unit root characteristics, and long-run relationships. This comprehensive approach leads to the precise estimation of long-run elasticities and the delineation of causal relationships. Furthermore, to ensure the reliability of our findings, the study incorporates ensemble ML techniques for robustness validation.

The estimation of panel data is frequently accompanied by challenges, among which CSD is a critical consideration that requires resolution before advancing further analytical processes. Ignoring CSD can result in biased coefficients and estimators, leading to erroneous conclusions. In the context of the BRICS nations, CSD is an anticipated phenomenon due to the intricate interconnections fostered by globalization and collaboration, often resulting in homogenous economic and financial traits among these countries. To address CSD, this research adopts four CSD tests, namely: CSD due to Pesaran (2015, 2021), CSD_W following the method of Juodis and Reese (2022), CSD_{W+} as introduced by Fan et al. (2015), and CSD* as conceptualized by Pesaran and Xie (2021). The CSD test developed by Pesaran (2015, 2021) is implemented due to its operational applicability, with its mathematical expression delineated in Eqs. (7)–(8):

$$\mathrm{CSD} = \sqrt{\frac{2(\mathrm{T})}{\mathrm{N}(\mathrm{N}-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\delta}_{ij}\right)\ \mathrm{N}(0,1)\ \mathrm{i},\mathrm{j} \tag{7}$$

$$\mathrm{M} = \sqrt{\frac{2(\mathrm{T})}{\mathrm{N}(\mathrm{N}-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\delta}_{ij}\right)\left[\frac{(\mathrm{T}-\mathrm{K})\widehat{\delta}_{ij}^{2}-(\mathrm{T}-\mathrm{K})\widehat{\delta}_{ij}^{2}}{\mathrm{Var}(\mathrm{T}-\mathrm{K})\widehat{\delta}_{ij}^{2}}\right] \tag{8}$$

The term $\widehat{\delta}_{ij}^{2}$ denotes the bivariate pairwise cross-correlation of sample estimates, which is estimated through the simple regression method. The expression for CSD_W is defined as:

$$\mathrm{CSD_W} = \sqrt{\frac{2}{\mathrm{Tn}(\mathrm{n}-1)}}\sum_{t=1}^{T}\sum_{i=2}^{N}\sum_{j=1}^{i-1}\omega_i e_{it}\omega_j e_{jt} \tag{9}$$

As identified by Juodis and Reese (2022), this expression addresses the issue of power loss in the test. To ameliorate this limitation, Juodis and Reese (2022) devised an augmented power test statistic, building upon the work of Fan et al. (2015). This revised method incorporates a component screening element, denoted as Δ_{nT}, to CSD_W, to derive the CSD_{W+} statistic, which is defined in the ensuing mathematical articulation:

$$\mathrm{CSD_{W+}} = \mathrm{CSD_W} + \Delta_{nT} \tag{10}$$

$$\Delta_{nT} = \sum_{i=2}^{N}\sum_{j=1}^{i-1}\left|\widehat{\rho}_{ij,T}\right| > 2\sqrt{\frac{\ln(n)}{\mathrm{T}}} \tag{11}$$

Finally, for the CSDW+ method, it is important that Δ_{nT} diverges sufficiently swiftly with respect to both T (time dimension) and n (cross-section dimension) under the alternative hypothesis, which typically encompasses network or spatial dependencies. Pesaran and Xie (2021) further contributed to the literature on CSD tests by introducing an alternative CSD test that integrates the $\widehat{\theta}_{nT}$ term within the panel data framework. The operational structure of this method is mathematically formulated as follows:

$$\mathrm{CSD}^{*}\left(\widehat{\theta}_{nT}\right) = \mathrm{CSD}^{*} = \frac{CSD + \sqrt{\frac{T}{2}}\widehat{\theta}_{nT}}{1-\widehat{\theta}_{nT}} \tag{12}$$

Here, $\mathrm{CSD}^{*}(\widehat{\theta}_{nT})$ denoting CSD^{*}, is the bias-adjusted CSD test statistic, and this refined test is denoted as the CSD^{*} approach, founded on the aforementioned principle.

Within panel data analytics, slope heterogeneity refers to the dissimilarities in the relationship between the dependent and the independent variables across distinct entities or individuals. This phenomenon emerges when the impact of the independent variables on the dependent variable is not uniform across the entities or individuals within the panel data (Pesaran and Yamagata, 2008). The analysis of slope heterogeneity is instrumental in identifying whether interactions among variables manifest differently under varying conditions. Recognizing the presence of slope heterogeneity is crucial, necessitating the consideration of entity-specific or individual-specific heterogeneity when estimating relationships among variables and deducing conclusions from the empirical data (Blomquist and Westerlund, 2013). Therefore, conducting this test is also beneficial in informing the selection of an appropriate model for the data at hand.

Acknowledging the significance of CDS within the dataset, it is imperative to select stationary tests for the variables that can concurrently facilitate a long-run cointegration analysis to manage CSD concerns effectively. Consequently, this study employs the CADF and CIPS tests as proposed by Pesaran (2007) to assess the stationarity of the targeted variables. These methodologies are recognized for their consistency and appropriateness in detecting variations across the specified panels. Additionally, they are instrumental in identifying characteristics essential for analyzing second-order dynamics in unique longitudinal datasets.

After identifying CDS characteristics among variables and implementing a unit root test tailored to the specific panel characteristics, selecting an appropriate long-run cointegration test becomes relevant. This test must adequately address the CSD issue within the context of the model under investigation. Consequently, employing traditional first-generation panel cointegration tests in this scenario may yield ambiguous and unreliable outcomes when scrutinizing for rejecting the null hypothesis (H_0), which postulates the absence of cointegration. The second-generation cointegration testing methodology, as introduced by Westerlund (2007), is adopted in response to this challenge. This advanced approach is designed to effectively manage the CSD problem, thereby enhancing the accuracy and reliability of conclusions drawn regarding the H_0, ensuring the precision and validity of the inferential outcomes regarding the long-run relationship.

Upon establishing a long-run relationship between the variables of interest, the subsequent phase in the econometric analysis entails estimating the long-run elasticities. This is accomplished by AMG and CCEMG methods. The AMG method, introduced by Eberhardt and Bond (2009), stands out for its suitability and consistency over traditional models, particularly due to its allowance for heterogeneous slope parameters across individual cross-sections. Both AMG and CCEMG methodologies are adept at addressing critical issues prevalent in panel data analysis, such as CSD, slope heterogeneity, and endogeneity.

The AMG estimator's operational mechanism unfolds in two stages. The first stage is articulated as follows:

$$\Omega Y_{it} = \lambda_i + \lambda_i \Omega X_{it} + \pi_i f_t + \sum\nolimits_{t=2}^{T} \rho_i \Omega D_t + \mu_{it} \tag{13}$$

In the second stage, the AMG estimator is determined through the aggregation of individual estimates, delineated as:

$$\widehat{\lambda}_{AMG} = N^{-1} \sum_{i=1}^{N} \widehat{\lambda}_i \tag{14}$$

This structured approach ensures the incorporation of dynamic panel data specifics, facilitating a robust and nuanced understanding of the long-run elasticities that characterize the interrelations among the variables.

The CCEMG estimator represents an alternative estimation technique. Crafted by Pesaran (2006), the CCEMG methodology is adeptly utilized in econometric investigations to address the pervasive issue of CSD. It effectively resolves cross-correlation among cross-sections and heterogeneity, offering a robust solution to challenges such as CSD, unit root series, latent factors, and heterogeneous slopes (Pesaran, 2006).

Following the estimation of long-run elasticities, the subsequent econometric progression entails discerning the direction of causality. To this end, this study employs the Dumitrescu and Hurlin (DH) non-causality approach (Dumitrescu and Hurlin, 2012), a method predicated on Granger's causality framework (Granger, 1969). A significant advantage of the DH non-causality test lies in its capacity to navigate the complexities of CSD and slope heterogeneity. This method utilizes a system-wide Wald test statistic ($W_{N.T}^{HNC}$) across all variables and cross-sections, thereby providing a comprehensive assessment of causality within the panel data context.

Ensemble methods represent a fundamental class of ML techniques that improve predictive performance by combining multiple models. These methods are particularly effective in reducing variance, bias, or improving predictions over single-model approaches. Ensemble techniques such as bagging, boosting, and stacking are widely recognized for their robustness and accuracy across various applications and datasets (Mienye and Sun, 2022).

Bagging, short for bootstrap aggregating, is a robust ensemble technique that enhances the performance of ML models. It is particularly useful in regression contexts. Bagging aims to improve model stability and accuracy by averaging the predictions from multiple models trained on different subsets of the original dataset.

- **Bootstrap Sampling:** The first step in bagging is creating multiple bootstrap samples from the original training dataset. In bootstrap sampling, subsets are selected randomly with replacement, meaning each subset may contain repeated instances of the same data point. Each bootstrap sample is typically the same size as the original dataset, ensuring that each model has a comprehensive set of data to learn from. This method allows the ensemble to explore a variety of data scenarios, which is critical for building a robust model.
- **Model Training:** A regression model is trained independently on each bootstrap sample. The choice of model can vary, but regression trees are commonly used due to their sensitivity to changes in the training set, which makes them particularly effective when used in a bagging ensemble. The independence of training across different samples captures diverse patterns in the data, contributing significantly to the ensemble's robustness.
- **Aggregation of Predictions:** After training, the predictions from each model are averaged to produce a single final prediction. This averaging process reduces variance and helps smooth out prediction anomalies, leading to a more accurate and stable outcome. Averaging is particularly effective in regression, as it mitigates the impact of outliers and reduces the likelihood of overfitting, thus enhancing the predictive performance of the ensemble (Breiman, 1996).

Bagging is highly effective with regression models that exhibit high variance. The technique leverages the instability of these models by training multiple instances on varied subsets of data, thus capturing a broad spectrum of data behaviors. When their predictions are averaged, the ensemble often outperforms any single model in stability and accuracy, making Bagging a preferred method for regression problems where predicting continuous outcomes with high precision is critical (Dietterich, 2000). In regression tasks, bagging is a powerful ensemble method that significantly enhances model accuracy by averaging multiple predictions, which reduces variance and improves stability. This method is ideal for applications requiring precise continuous predictions, such as in financial modeling or environmental forecasting.

Boosting is an ensemble technique that enhances the performance of ML models, particularly in regression, by iteratively improving models based on the errors of previous ones. This method aggregates multiple weak learners to form a strong predictive model, focusing on reducing bias and variance, leading to more accurate predictions.

- **Initialization and Model Building:** Boosting starts with initializing weights for each data point in the training set, typically giving equal weights initially. A regression model, often referred to as a weak learner, is then trained on the dataset.

- **Error Evaluation and Model Updating:** After the first model is trained, its prediction errors are evaluated. These errors are used to update the weights of the data points. Points that are harder to predict (i.e., have larger errors) receive increased weights, whereas easier-to-predict points get their weights decreased. This iterative reweighting focuses the learning algorithm on the most difficult cases in the training dataset (Solomatine and Shrestha, 2004).
- **Model Addition and Aggregation:** A new model is then trained on the reweighted data, and the process repeats for a specified number of iterations or until improvements become negligible. Each model in the sequence focuses on correcting the residuals of the previous models. The final predictive model is a weighted combination of these weak learners, where more accurate predictors are given higher weights (Schapire, 2003).

Boosting is particularly effective in reducing bias and also helps reduce variance. This dual benefit is crucial in regression tasks where both underfitting and overfitting can degrade the model's performance. By focusing iteratively on the most difficult parts of the training data, boosting builds a more accurate and robust model, making it a powerful tool for regression problems that involve complex, non-linear relationships that are difficult to model with a single weak learner (Solomatine and Shrestha, 2004). Boosting offers a significant advantage in regression analysis by effectively combining multiple weak models to produce a highly accurate prediction. This method systematically focuses on reducing errors and enhancing the model's ability to generalize, which is particularly valuable in regression tasks where prediction accuracy is paramount.

Stacking, or stacked generalization, is an advanced ensemble learning technique designed to improve model predictions by combining multiple base models through a -learner. This technique effectively harnesses the strengths of various models, addressing their individual weaknesses to enhance the overall predictive accuracy.

- **Training Base Learners:** The process begins with the independent training of multiple base learners, each offering a unique approach to the problem. In this setup, we use Generalized Linear Models (GLM), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF). These models are chosen for their diverse capabilities in capturing different data patterns, from linear relationships in GLM to complex nonlinear interactions in RF. The individual predictions of these models reflect various aspects and structures within the data, providing a rich set of perspectives for the subsequent meta-learner (Xu et al., 2021).
- **Creation of Meta-Features:** Once the base models are trained, they predict outcomes on a holdout set or via cross-validation on the training set, creating a new dataset of predictions. These predictions, known as meta-features, serve as the input for the meta-learner. The meta-features encapsulate the predictive insights of each base model, effectively summarizing their individual assessments into a form that the meta-learner can use (Ding and Wu, 2020).
- **Training the Meta-Learner:** The meta-learner, which could be another regression model such as Logistic Regression, is trained on these meta-features. Its role is to discern the best way to integrate the base models' predictions. By training on the outputs rather than the original features, the meta-learner can focus on correcting the base models' errors and capitalizing on their successes. This step is crucial as it determines how the strengths of various base models are combined to achieve superior performance (Chatzimparmpas et al., 2021).

Stacking is particularly effective in complex prediction tasks where no single model uniformly excels across all dataset segments. It reduces both bias and variance by combining models that are differently biased and variably accurate, leading to improved prediction accuracy and robustness. Moreover, stacking has been shown to perform exceptionally well in both theoretical and practical applications, outstripping the performance of the individual models and other ensemble techniques in many cases (Tan and Luo, 2021). The stacking technique stands out as a sophisticated method in ensemble learning, known for its ability to integrate multiple predictive models into a coherent framework that improves upon the capabilities of its constituent elements. Through the strategic use of a meta-learner, stacking achieves a harmonious balance among diverse models, enhancing predictive performance across a wide range of applications.

6. Empirical results

The BRICS countries exhibit similar economic structures, which suggest the presence of financial and economic spillovers; these dynamics may lead to CSD and slope heterogeneity within their economies. Four CSD tests are employed to examine these phenomena in longitudinal data analysis, which are particularly well-suited for datasets where the time dimension exceeds the number of cross-sections (T > N). The results from the panel CSD tests are shown in Table 2. The empirical findings indicate a rejection of the null hypothesis of the absence of CSD, thereby affirming the existence of country-specific spillovers within the sample.

Moreover, the identification of a long-run association from the test facilitated the subsequent analysis of whether the slope parameters exhibit heterogeneity. As highlighted by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013), insights from the slope parameter analysis for longitudinal data are critical in guiding the selection of analytical methods and interpreting coefficient estimations. The results from these two tests are presented in Table 3, indicating a rejection of the null hypothesis that slope coefficients are homogeneous across the panel. This finding underscores the necessity for employing suitable long-run coefficient estimation techniques, such as the AMG and CCEMG estimators, to accurately capture the dynamics within the data.

Given the substantial intercorrelation, CSD, and slope heterogeneity observed, CADF and CIPS methodologies are utilized to determine the integration order of the tested variables. The results from the CADF unit root test, detailed in Table 4, indicate that for all selected variables, the null hypothesis of non-stationarity is not rejected. However, these variables achieve stationarity when differentiated under both conditions (intercept but also intercept and trend).

Table 2
CSD test results.

Variable	CSD (Pesaran 2015, 2021)	CSD_w (Juodis and Reese, 2022)	CSD_{w+} (Fan et al., 2015)	CSD* (Pesaran and Xie, 2021)
CFP	11.490***	−2.020**	34.320***	0.490
	(0.000)	(0.044)	(0.000)	(0.624)
TEC	9.150***	−1.300	27.640***	0.190
	(0.000)	(0.195)	(0.000)	(0.848)
FPI	2.820***	−1.750*	38.780***	0.360
	(0.000)	(0.079)	(0.000)	(0.723)
LU	1.820*	−2.210**	13.110***	1.550
	(0.069)	(0.027)	(0.000)	(0.121)
PAG	−2.290**	−1.330	32.070***	7.660***
	(0.022)	(0.183)	(0.000)	(0.000)
LU*TEC	5.140***	−1.440	15.260***	0.340
	(0.000)	(0.151)	(0.000)	(0.732)
LU*FPI	11.700***	−1.450	35.210***	0.400
	(0.000)	(0.148)	(0.000)	(0.686)
LU*AG	−2.610***	−2.570	38.520***	1.600
	(0.009)	(0.010)***	(0.000)	(0.110)

Notes: P-VALUES in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 3
Slope heterogeneity test results.

Test	Delta tilde ($\hat{\Delta}$)	Delta tilde $\hat{\Delta}_{Adj.}$
Blomquist and Westerlund (2013)	3.430*** (0.001)	3.092*** (0.002)
Pesaran and Yamagata (2008)	9.905*** (0.000)	10.989*** (0.000)

Notes: P-values in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Heteroscedasticity and Autocorrelation Consistent Kernel: Bartlett with average bandwidth 3.

Furthermore, the results derived from the CIPS test reveal that CFP and the interaction term LU*TEC are level-stationary, or I(0). For the remaining variables, stationarity is established at the first difference, or I (1). Consequently, it is established that CFP, TEC, FPI, LU, PAG, and the interaction terms LU*TEC, LU*FPI, and LU*PAG are treated as stationary time series data after first-order differencing, thereby confirming their non-stationary nature. This detailed analysis ensures that the econometric models applied later accurately reflect the dynamics inherent in the data.

The results of the panel cointegration test, as developed by Westerlund (2007), are documented in Table 5. This cointegration method conducts statistical analysis to ascertain the existence of long-run relationships, or cointegration, among the variables. The test outcomes provide compelling and statistically significant evidence of long-run associations as observed in both group and panel statistics datasets. Specifically, the Group τ-statistic (Gτ), Group α-statistic (Gα), Panel τ-statistic (Pτ), and Panel α-statistic (Pα) all demonstrate robust indications of cointegration within the ample, regardless of the deterministic specification. These findings again highlight the presence of an association between the variables.

To estimate the impact of the regressors on the dependent variable, AMG and CCEMG estimators have been implemented. The long-run coefficients are presented in Tables 6-7. The results indicate that technological advancements, land use dedicated to cereal productivity, and the food production index significantly enhance cereal food production in the BRICS region. However, methane and nitrous oxide emissions from the agricultural sector show a negative sign.

Technological innovations, according to Model 1, significantly boost cereal food productivity, with long-run coefficients ranging from 0.034 % to 0.089 % (at the 5 % level). This suggests that a 1 % increase in the adoption of technological innovations in agriculture could lead to an increase in cereal food productivity by approximately 0.034 % to 0.089 % in the long-run. In addition, the sign of the coefficients remains consistent across the different models. In the current era, technological innovations have played a pivotal role globally, particularly in developing countries, by broadening access to information and enhancing communication systems in rural areas (Wang et al., 2019; Min et al., 2020). The widespread use of technology has directly impacted agricultural output and rural household income in the BRICS countries; technology adoption depends on risk preference as well as it is interlinked with credit and insurance contracts (Wu and Li, 2023).

The food production index also shows a positive and significant correlation with cereal food production; a 1 % increase in the index results in a 1.368 % to 1.389 % increase in cereal production. This growth in cereal production can be supported by actions such as improving water and sanitation systems, natural fertilizer use, advanced crop breeding, and multiple cropping practices. These findings align with those of Koondhar et al. (2021), who noted that green advancements in cereal productivity in the BRICS region could significantly enhance the richness of the food production index.

Regarding CH_4 and NO_2 emissions, the negative coefficients indicate

Table 5
Westerlund's panel cointegration test results.

Statistics	Gτ	Ga	Pτ	Pa
Intercept				
Value	−3.481***	−11.200	−10.628***	−14.238**
Z-Value	−2.425	0.513	−5.377	−1.455
P-Value	0.008	0.696	0.000	0.073
Robust P-Value	0.003	0.103	0.000	0.023
Intercept and Trend				
Value	−3.544**	−9.364	−10.568***	−13.494*
Z-Value	−1.676	2.069	−4.696	0.103
P-Value	0.047	0.981	0.000	0.541
Robust P-Value	0.037	0.520	0.003	0.057

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 4
Panel unit root test results.

Variable	Intercept				Intercept and trend				Integration order
	Level		First difference		Level		First Difference		
	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	
CADF panel unit root test									
CFP	−1.814	0.468	−2.631*	0.022	−2.567	0.282	−4.834*	0.000	I(1)
TEC	−2.172	0.176	−2.920*	0.003	−2.496	0.345	−3.047**	0.036	I(1)
FPI	−2.256	0.129	−3.825*	0.000	−2.700	0.180	−4.940*	0.000	I(1)
LU	−1.754	0.525	−4.743*	0.000	−2.038	0.778	−4.582*	0.000	I(1)
PA	−2.303	0.107	−3.182*	0.000	−2.548	0.299	−3.696*	0.000	I(1)
LU*TEC	−2.041	0.268	−2.795*	0.008	−1.954	0.837	−3.179**	0.017	I(1)
LU*FPI	−2.165	0.180	−4.245*	0.000	−2.586	0.266	−4.907*	0.000	I(1)
LU*PAG	−1.752	0.527	−4.108*	0.000	−2.355	0.485	−4.101*	0.000	I(1)
CIPS panel unit root test									
CFP	−2.762*		−5.863*		−4.333*		−5.963*		I(0)
TEC	−2.087		−3.856*		−2.348		−4.174*		I(1)
FPI	−2.217***		−5.499*		−2.695		−6.248*		I(1)
LU	−2.362		−5.698*		−3.898**		−5.922*		I(1)
PAG	−2.180		−4.347*		−2.449		−4.778*		I(1)
LU*TEC	−2.559*		−4.478*		−2.275***		−4.579*		I(0)
LU*FPI	−2.240		−5.644*		−2.141		−6.136*		I(1)
LU*PAG	−1.438		−5.863*		−2.363		−5.867*		I(1)
Critical values	1 %		5 %		10 %		1 %	5 %	10 %
	−2.55		−2.33		−2.21		−3.06	−2.84	−2.73

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 6
AMG estimates.

Variable	Model 1				Model 2				Model 3				Model 4			
	Coeff.	Std. Ers.	Z stats.	P-Value	Coeff.	Std. Ers.	Z stats.	P-Value	Coeff.	Std. Ers.	Z stats.	P-Value	Coeff.	Std. Ers.	Z stats.	P-Value
TEC	0.034*	0.020	1.720	0.085	1.577***	0.349	4.520	0.000	0.034	0.023	1.520	0.129	0.029*	0.017	1.660	0.097
FPI	1.368**	0.547	2.500	0.012	1.395**	0.570	2.450	0.014	−2.672**	1.347	−1.980	0.047	1.396**	0.563	2.480	0.013
PAG	−0.483*	0.249	−1.940	0.052	−0.335	0.305	−1.100	0.271	−0.350	0.291	−1.200	0.229	−2.019***	0.439	−4.600	0.000
LU	1.077***	0.181	5.940	0.000												
LU*TEC					0.092***	0.021	4.430	0.000								
LU*FPI									0.231***	0.050	4.620	0.000				
LU*PAG													0.086***	0.015	5.550	0.000
Constant	−0.827	1.919	−0.430	0.667	16.161***	4.383	3.690	0.000	16.494***	4.268	3.860	0.000	18.353***	3.077	5.960	0.000
Trend	0.023*	0.012	1.910	0.056	0.032*	0.018	1.810	0.071	0.032*	0.020	1.660	0.096	0.023*	0.012	1.920	0.055
Wald χ^2	1018.47***			0.000	1.34e + 07***			0.000	560.45***			0.000	1496.97***			0.000
Obs.	160				160				160				160			
RMSE	0.0495				0.0506				0.5030				0.0497			

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7
CCEMG estimates.

Variable	Model 1				Model 2				Model 3				Model 4			
	Coeff.	Std. Ers.	Z stats.	P-Value	Coeff.	Coeff.	Std. Ers.	Z stats.	P-Value	Std. errs.	Coeff.	Std. Ers.	Z stats.	P-Value	Z stats.	Coeff.
TEC	0.089**	0.038	2.300	0.021	−1.633***	0.255	−6.410	0.000	0.085**	0.037	2.270	0.023	0.087**	0.036	2.390	0.017
FPI	1.389***	0.463	3.000	0.003	1.341***	0.492	2.720	0.006	−2.646**	1.030	−2.570	0.010	1.406***	0.475	2.960	0.003
PAG	−0.491**	0.249	−1.970	0.049	−0.438*	0.235	−1.860	0.062	−0.391*	0.223	−1.750	0.079	−1.873***	0.369	−5.080	0.000
LU	1.019***	0.129	7.920	0.000												
LU*TEC					0.097***	0.016	6.050	0.000								
LU*FPI									0.228***	0.037	6.130	0.000				
LU*PAG													0.080***	0.012	6.620	0.000
Constant	−4.753	6.880	−0.690	0.490	−5.858	15.682	−0.370	0.709	−3.693	14.893	−0.250	0.804	−3.714	15.089	−0.250	0.806
Trend	0.018***	0.006	3.060	0.002	0.023***	0.009	2.730	0.006	0.020***	0.007	2.950	0.003	0.019***	0.006	3.200	0.001
Wald χ^2	454.85***			0.000	2253.12***			0.000	2014.13***			0.000	193.27***			0.000
Obs.	160				160				160				160			
RMSE	0.0465				0.0476				0.0466				0.0467			

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

that increases in emissions from agriculture significantly diminish cereal food productivity, with a reduction ranging from 0.483 % to 0.491 %. This aligns with prior findings by Eshete et al. (2020) and Dimnwobi et al. (2022), who showed that environmental pollution adversely affects agricultural productivity due to changes in climate conditions such as precipitation patterns and temperature increases, which can negatively affect cereal crop growth. Furthermore, the positive coefficients related to land use under cereal production demonstrate a significant impact on cereal production, with a 1 % increase in land use leading to a 1.019 % to 1.077 % increase in productivity, validating findings by Yu et al. (2019) and Kibria et al. (2023). This suggests that non-climatic factors such as land significantly affect efficiency and production levels.

Lastly, the interaction effects of land use under cereal production with technological innovation (LU*TEC), food production index (LU*FPI), and emissions from the agriculture sector (LU*PAG) are also significant. These interactions underline the importance of integrating effective land use and technological advancements to boost cereal food productivity sustainably and efficiently in the BRICS economies. This holistic approach is essential for achieving SDGs and maintaining a balance in cereal food productivity, highlighting the transformative potential of minor adjustments in these areas.

Building upon the estimation of long-run coefficients for the relevant variables, causality analysis is run. The DH methodology provides a robust framework for identifying the causal relationships within the data. The results, detailed in Table 8, reveal the strength and direction of connections among the selected series.

Fig. 5 illustrates the Dumitrescu-Hurlin causality flows, mapping out the interactions between the variables. The causality analysis reveals unidirectional causality flows from PAG to CFP, from TEC to CFP, from PAG to TEC, from LU to PAG, from PAG to FPI, and from LU to FPI. These results suggest that emissions from agriculture not only impact cereal food production but also affect the sectors of technology adoption and food production efficiency, indicating a downstream influence of agricultural practices on these critical areas. Notably, the analysis shows that technological innovations and food production indices do not reciprocally influence the emission levels, pointing towards a primarily one-way impact from agricultural practices to these sectors.

Furthermore, the findings highlight bidirectional causality relationships between several pairs of variables. In fact, a feedback mechanism emerges between CFP and FPI, CFP and LU, LU and TEC, and TEC and FPI. These bidirectional interactions underline the interdependent nature of these variables, where changes in one invariably influence the other, reflecting a complex web of interrelations that govern agricultural productivity and sustainability.

These causal dynamics are consistent with the findings from previous studies (Dimnwobi et al., 2022, Kibria et al., 2023). That also underscored the intertwined nature of these variables within the agricultural sector. This coherence across studies reinforces the robustness of the current findings and emphasizes the critical importance of considering these interdependencies in policy formulations aimed at enhancing agricultural efficiency and sustainability. This nuanced understanding of causality not only informs theoretical perspectives but also provides actionable insights for policymakers seeking to optimize agricultural outputs while mitigating environmental impacts in the BRICS region.

Table 8
Pairwise Dumitrescu-Hurlin panel causality test results.

Null hypothesis	W Stat.	Zbar Stat.	P-value
TEC $\nLeftrightarrow$ CFP	5.58882	3.21930	0.0013***
CFP $\nLeftrightarrow$ TEC	2.08522	−0.08361	0.9334
FPI $\nLeftrightarrow$ CFP	8.38217	5.85264	0.0000***
CFP $\nLeftrightarrow$ FPI	6.47287	4.05271	0.0000***
PAG $\nLeftrightarrow$ CFP	4.24288	1.95045	0.0511*
CFP $\nLeftrightarrow$ PAG	2.98458	0.76423	0.4447
LU $\nLeftrightarrow$ CFP	6.19613	3.79182	0.0001***
CFP $\nLeftrightarrow$ LU	4.73355	2.41302	0.0158**
FPI $\nLeftrightarrow$ TEC	5.26471	2.91375	0.0036***
TEC $\nLeftrightarrow$ FPI	5.81390	3.43149	0.0006***
PAG $\nLeftrightarrow$ TEC	7.29153	4.82448	0.0000***
TEC $\nLeftrightarrow$ LAG	3.73626	1.47285	0.1408
LU $\nLeftrightarrow$ TEC	5.73356	3.35575	0.0008***
TEC $\nLeftrightarrow$ LU	5.50306	3.13845	0.0017***
PAG $\nLeftrightarrow$ FPI	5.76375	3.38421	0.0007***
FPI $\nLeftrightarrow$ PAG	3.31862	1.07914	0.2805
LU $\nLeftrightarrow$ FPI	8.41620	5.88473	0.0000***
FPI $\nLeftrightarrow$ LU	3.43093	1.18502	0.2360
LU $\nLeftrightarrow$ PAG	7.29567	4.82838	0.0000***
PAG $\nLeftrightarrow$ LU	2.78244	0.57367	0.5662

Notes: 2 lags. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

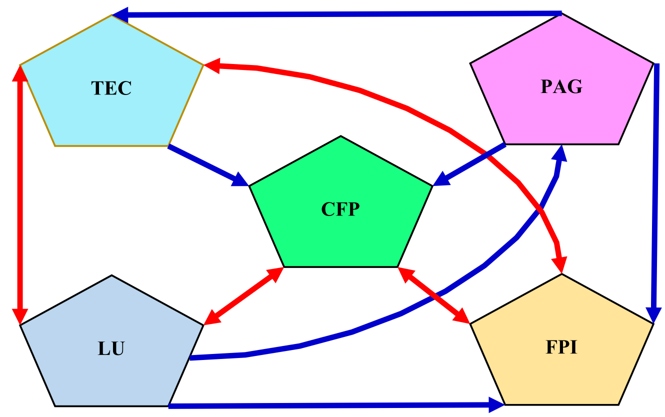

Fig. 5. Summary of causality test results.

7. Discussion

The analyses highlight a crucial intersection among technological innovations, effective land use, and agricultural practices that directly impact cereal food production in the BRICS region. Each of these factors, supported by robust empirical evidence, points towards a nuanced understanding of how targeted interventions can foster sustainable agricultural productivity.

Technological Innovation: The significant impact of technological innovations on cereal production underscores a transformative shift in agricultural methodologies. Technological tools not only enhance the efficiency of agricultural operations but also extend their benefits to broader socio-economic aspects by improving the information dissemination and resource management capabilities of rural households. The correlation between technology adoption and increased cereal production is consistent with previous findings (Min et al., 2020), which observed that technology had a substantial effect on the livelihoods and productivity of rural communities. This reflects a broader trend where technological interventions, such as precision agriculture, mobile technology, and genetically modified crops, contribute to increased agricultural outputs by enabling better crop monitoring, optimized resource use, and improved resistance to pests and diseases. Policymakers could incentivize the design, improvement, and maintenance of technologies that promote sustainable environmental development without causing ecological damage. Such innovative technologies should enable the planning of agricultural practices to promote the study of ecological processes that encourage the maintenance of functional biodiversity and their impacts (Rose et al., 2019). In this contest, therefore, BRICS governments should (Ma et al., 2024):

- impose a carbon tax on those technologies that lead to the degradation of environmental quality;
- encourage the diffusion of green technologies and the adaptation of energy frameworks;
- promote low-carbon technologies;
- stimulate green technologies.

Food Production Index: The positive association between the food production index and cereal food production further substantiates the role of enhanced agricultural productivity measures in fostering food security. This index, as an aggregate indicator, reflects the effectiveness of various agricultural inputs and practices, from crop diversification to advanced irrigation systems. The linkage between a higher food production index and increased cereal output resonates with the insights provided by Koondhar et al. (2021), who argued that sustainable practices within the agricultural sector could dramatically enhance food production capacities.

Intensive agriculture, with the creation of huge monocultural crops treated with large external inputs (Pretty, 2008), has caused huge environmental impacts, so much so that over time there has been a growing awareness of a shift to agricultural practices that not only ensure socio-economic equity and food security, but also build and protect the ecosystem services on which agriculture depends (Barrett, 2010; Godfray et al., 2010; Garnett et al., 2013; FAO; 2014; DeFries et al., 2015; UN, 2015). In such an approach, ecosystem services guaranteed by biodiversity, such as pollination and pest control, must be exploited in a way that avoids the use of external inputs like chemical fertilizers, pesticides, etc. (Cassman 1999; Garibaldi et al., 2011; Bommarco et al., 2013), as prescribed by the 2030 Agenda for Sustainable Development and the Intergovernmental Platform on Biodiversity and Ecosystem Services (Díaz et al., 2015a; Díaz et al., 2015b).

Agricultural Emissions: The adverse effects of methane and nitrous oxide emissions highlight the environmental challenges associated with agricultural expansion and intensity. The significant negative impact of these emissions on cereal productivity brings to the forefront the urgent need for sustainable farming practices that minimize environmental footprints while maintaining crop yields. This finding aligns with earlier research by Eshete et al. (2020), which linked environmental degradation from agricultural emissions to reduced crop productivity due to altered weather patterns and disrupted ecosystems. These insights advocate for integrated pest management, reduced reliance on chemical fertilizers, and the adoption of green technology in farming operations. To reduce pollutant emissions, helping the achievement of the SDGs, the BRICS countries could (Pata, 2021):

- encourage modern agricultural techniques, such as organic farming;
- increase farmers' awareness of environmental issues;
- promote low-carbon agricultural production;
- incentivizing the use of animal fertilizers;
- supplying clean inputs in agricultural activities.

Land Use: The analysis also confirms the critical role of land use in determining agricultural output. Effective land management practices that enhance land productivity without depleting its fertility are essential for sustainable agriculture (Magazzino et al., 2023a,b). The soil ecosystem plays a fundamental role not only in sustaining biological productivity, thus ensuring the life of living organisms such as plants and animals, but also in ensuring the livelihood of humans through its central role in agriculture by providing basic ecosystem services (Vanlauwe et al., 2010; Marinelli et al., 2021), like nutrient cycling and climate regulation (Dominati et al., 2010). In general, therefore, effective land management strategies, such as encouraging traditional agricultural practices, such as crop rotation, intercropping, farm-level diversification, and reduced agrochemical use (Kovács-Hostyánszki et al., 2017), could have direct consequences on the quality of this core ecosystem, influencing processes such as the regulation of water flows, biogeochemical cycles, as well as preserving biodiversity and ecosystem services. A further and fundamental target could be to halt land degradation and thus achieve the sustainability goal 'Land Degradation Neutrality'.

In particular, the increase in cereal production with expanded arable land emphasizes the need for policies that balance land use dynamics with agricultural needs. This is particularly important in the BRICS nations, where urbanization and industrialization pose continuous threats to agricultural land.

Interaction Effects: The study's exploration of interaction effects between land use and other variables like technological innovations and the food production index suggests that synergies between these factors can significantly enhance cereal productivity. This integrated approach is pivotal for not only maximizing land use efficiency but also for ensuring that technological and managerial improvements are effectively translated into agricultural output.

In conclusion, these findings underscore the complex and interconnected challenges facing the agricultural sector in the BRICS nations. Addressing these challenges requires a comprehensive approach that combines technological advancements, sustainable land use practices, and environmental considerations to enhance cereal productivity sustainably. Such strategies align with the SDGs and ensure long-run food security and economic stability in the region.

8. Robustness checks

Three different ensemble ML models were employed to validate the robustness of the panel data method results: Boosting, Bagging, and Stacking. These models are known for their efficacy in improving predictive performance. As ML analysis requires, all variables are normalized using the scale function.

Fig. 6 offers a comparative visual analysis of the performance metrics for the ensemble models. The figure is organized into three panels, one for each model type, with each panel depicting four key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). These metrics are represented on the y-axis, while the x-axis categorizes them. Each panel displays a set of colored dots that correspond to different models (Model 1, Model 2, Model 3, and Model 4), as indicated by the legend. In all three panels, the distribution of dots varies per metric, which allows for a quick assessment of how each model performs according to each specific metric.

For all models, the R^2 values appear to be high, suggesting a strong explanatory power. However, the specific performance of each model can only be evaluated by examining the corresponding numeric values. Overall, the graphic aims to facilitate the comparison of the three ensemble methods and ascertain the most accurate and reliable approach for the analysis.

Table 9 represents the importance scores derived from the Boosting and Bagging models.

As per Table 9, the importance scores reveal significant contributions from specific variables:

- TEC is highlighted as a predominant variable, particularly in Model 3 for the Boosting method, indicating a key driver of cereal food productivity.
- PAG registers the highest importance scores, reinforcing their significant impact on the models' outputs.
- The importance scores for LU and the interaction terms like LU*TEC highlight the intricate relationships between land use practices and technological innovations.

Table 10 provides an overview of the meta-learner coefficients for the Stacking ensemble models, highlighting the differential contributions of the base learners: GLM, SVM, KNN, and RF. The coefficients reveal how much each model influences the final prediction of the stacked model.

The results from Table 10 underscore the consistent dominance of the RF model, which exhibits the highest coefficients in all model configurations (1.22, 1.06, 1.17, and 1.10, respectively, for Models 1–4). This reflects its robustness and superior predictive accuracy, making RF the most reliable predictor among the incorporated base learners. The contributions from SVM and KNN, in contrast, display considerable

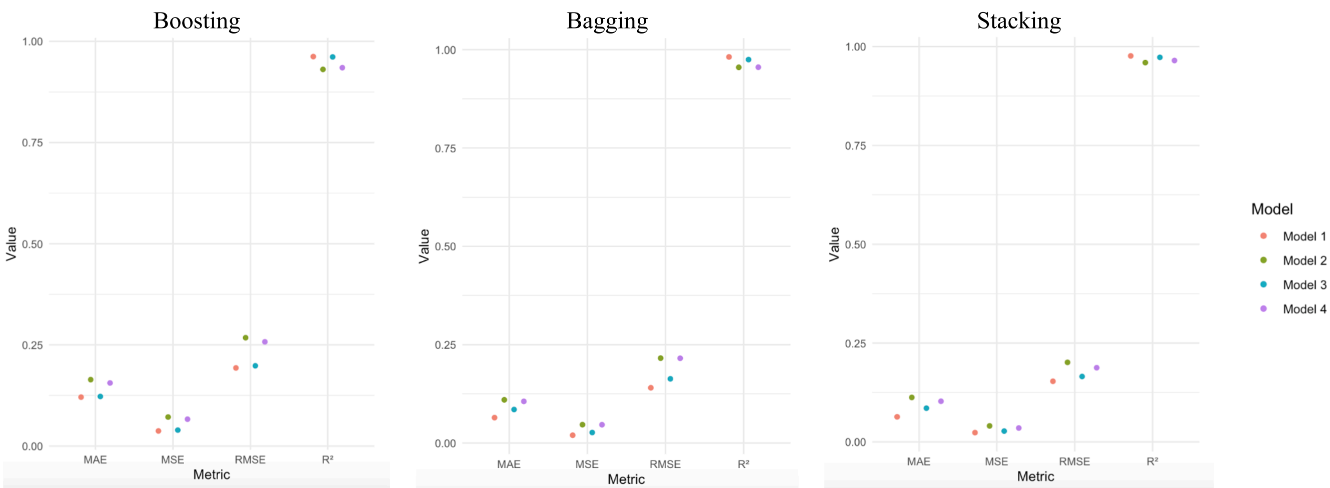

Fig. 6. Ensemble ML models' metrics.

Table 9
Boosting and bagging importance scores.

	Variable	Boosting	Bagging
Model 1	TEC	71.30	17.04
	FPI	7.77	1.50
	PAG	269.56	95.60
	LU	35.47	11.38
Model 2	TEC	51.94	10.80
	FPI	17.86	3.72
	PAG	242.13	97.77
	LU*TEC	26.10	14.13
Model 3	TEC	64.11	19.11
	FPI	13.21	1.49
	PAG	255.36	98.74
	LU*FPI	17.41	7.21
Model 4	TEC	85.55	18.56
	FPI	14.19	3.32
	PAG	229.68	79.02
	LU*PAG	35.09	25.70

Table 10
Stacking model meta-learner coefficients.

	(Intercept)	GLM	SVM	KNN	RF
Model 1	0.00	0.00	0.01	−0.22	1.22
Model 2	0.00	−0.03	0.26	−0.27	1.06
Model 3	0.00	−0.03	−0.15	0.01	1.17
Model 4	0.00	−0.09	0.14	−0.13	1.10

variability. SVM, for example, exerts a positive influence in Models 2 and 4 (coefficients of 0.26 and 0.14, respectively), yet a negative impact in Model 3 (−0.15). KNN's influence is similarly variable, contributing negatively in Models 1 and 2 (−0.22 and −0.27, respectively), but slightly positively in Model 3 (0.01). In conclusion, Model 1 demonstrates the most robust predictive capabilities within this specific stacking ensemble, attributable primarily to its high coefficient for RF.

The ensemble ML models applied here as robustness checks underscore the reliability of the study's main findings. The consistent performance across various metrics confirms the analytical soundness of the models, affirming the study's conclusions regarding the determinants of cereal food production in the BRICS economies. The application of ensemble ML methods serves as a robust validation of the key panel findings. The importance scores from the Boosting and Bagging models, alongside the meta-learner coefficients from the Stacking models, offer a quantifiable affirmation of the identified factors affecting cereal food production in the sample observed.

Technological Innovation: The ML models validate the significant role of technological innovations as reflected by their high importance scores. This concurs with the empirical analysis, where technological advances were shown to enhance cereal production efficiency and effectiveness. The ML results support the premise that technology is a key driver of productivity, which is consistent with the documented benefits to rural socio-economic conditions found in previous research.

Food Production Index: The positive relationship between the food production index and cereal output is reaffirmed by ML analyses, which echo the econometric evidence of this index's role in improving agricultural measures. The ensemble models corroborate the earlier findings that a higher food production index – indicative of efficient agricultural inputs and practices – is associated with increased cereal production.

Agricultural Emissions: The adverse impact of agricultural emissions on cereal productivity is distinctly captured by the ML models, where emissions variables exhibit a clear influence on the models' outcomes. This substantiates the empirical analysis and aligns with prior research that emphasizes the negative repercussions of environmental degradation on crop yields. The ML methods lend further credence to the call for sustainable farming practices.

Land Use: The ML models reinforce the importance of land use in agricultural output, which aligns with the econometric evidence indicating that land use under cereal productivity is a significant factor. Through their predictive power, these models support the need for balanced land use policies that contribute to increased cereal production.

Interaction Effects: Perhaps most compellingly, the ML methods validate the interaction effects identified in the empirical analysis. The importance scores for interaction terms such as LU*TEC in the ML models confirm that when technological innovations and efficient land use converge, cereal productivity has a substantial positive effect.

In conclusion, the ensemble methods confirm and enhance the reliability of the panel technique findings, providing computational proof of the significant influence of technological innovations, food production index, and land use on cereal food production while also recognizing the detrimental effect of agricultural emissions. These advanced analytical techniques not only corroborate the econometric evidence but also offer a sophisticated lens through which to interpret the complex dynamics at play, supporting a comprehensive approach to enhancing agricultural productivity in the BRICS region.

9. Conclusions and policy Implications

In the quest to meet the escalating food demands of a burgeoning global population amidst shrinking arable lands and rapid urbanization, cereal production is a vital cornerstone with its significant potential to augment this empirical evidence. Yet, the impact of environmental pollution from cereal production is a crucial factor that bears upon its own yield. This article delves into the strategies for amplifying cereal production within the BRICS nations, operating under the constraints of limited arable land and the overarching influence of agricultural pollution. It fills a gap in the existing literature by integrating technological innovations and a newly formulated food production index as regressors within the context of the BRICS economies over the 1990–2021 period.

To explore the effects of technological innovations, land use under cereal production, the food production index, and emissions from the agricultural sector on cereal food production, the study employed several panel data methodologies (CADF test, CIPS test, Westerlund's cointegration test, DH causality analysis, as well as AMG and CCEMG estimators), addressing significant CSD and slope heterogeneity. The long-run coefficients highlight that while technological innovations and the food production index exert a positive influence on cereal food production, emissions from the agriculture sector inversely affect production levels. Interaction terms further indicate a significant enhancement of cereal food production when combined with effective land use.

Causality analysis elucidates the directionality of these relationships, indicating unidirectional causality from emissions and technological innovations to cereal food production, and bidirectional causality among cereal production, land use, and the food production index. Robustness checks conducted via ensemble ML methods confirm these relationships, with model importance scores and meta-learner coefficients underscoring the significance of these variables in predicting cereal food production.

Based on this empirical evidence, the study offers several policy recommendations to support the attainment of SDGs 2, 8, 9, and 12 for BRICS countries:

Technological Innovations: Implementing precision agriculture technologies, supporting R&D in biotechnology for crop improvement, and promoting the adoption of modern machinery can enhance efficiency and reduce environmental impact while bolstering production.

Land Use Management: Sustainable land management practices, such as agroforestry and conservation agriculture, can improve soil health and biodiversity. Policies that ensure secure land tenure can encourage long-run sustainable investment by farmers (Magazzino et al., 2023a,b).

Crop Diversification: Diversifying cereal production by cultivating a range of crops can enhance food security and resilience to climate change, while sustainable practices like efficient irrigation can increase productivity and mitigate environmental harm.

Environmental Protection: Reducing water pollution through efficient irrigation and careful fertilizer application, encouraging Integrated Pest Management, and managing agricultural waste can help mitigate emissions and their detrimental effects on productivity.

Implementing these strategies calls for a collaborative approach among governments, policymakers, farmers, researchers, and other stakeholders, considering each BRICS nation's unique environmental, socio-economic, and local contexts, and fostering regional cooperation to promote sustainable agricultural practices.

Sustainable land use is one of the key conditions for ensuring the ecological resilience of agricultural practices in terms of providing ecosystem services. Indeed, these activities are increasingly aimed at satisfying an ever-growing demand for food. Integrating attention to the conservation of soil ecosystem services into production- and income-oriented agronomic perspectives ensures food production while reducing the environmental risks associated with the loss of soil ecosystem services. Effective strategies in this regard can include the enhancement of key ecological processes that support production, including nutrient cycling, pollination, and biotic regulation of pests. The result is diversified agricultural systems.

According to the 2030 Agenda for Sustainable Development and its goals, there is a strong call to sustain natural resources, food, and agriculture by improving local stakeholders' awareness of the role of soils in ecosystem services, and identifying farming systems that can produce various benefits while excluding negative impacts (Loos et al., 2014; Leifeld, 2016). Achieving the interlinked goals of nutrition, food security, poverty reduction, and local development requires extensive governmental efforts at the top level (MEA, 2005).

Despite the robustness of our findings, several limitations warrant consideration. First, the study relies on historical data from 1990 to 2021, which may not fully capture the rapidly evolving agricultural technologies and practices. Future research could focus on more recent data and emerging trends in cereal production. Additionally, while this study examines the BRICS nations, its applicability to other regions remains untested. Comparative studies involving different geographic and economic contexts could provide broader insights. Furthermore, the complex interactions between environmental pollution and cereal production merit deeper investigation, particularly regarding long-run sustainability and resilience under climate change scenarios. Future research should also explore the socio-economic impacts of proposed policy recommendations on smallholder farmers to ensure equitable and inclusive agricultural development.

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CRediT authorship contribution statement

Cosimo Magazzino: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Tulia Gattone:** Writing – review & editing, Visualization, Validation, Software, Data curation. **Muhammad Usman:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Donatella Valente:** Validation, Project administration, Funding acquisition.

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.

Data availability

Data will be made available on request.

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