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Driving Global Food Security: Determinants of Agricultural Productivity in Leading Producing Countries Worldwide

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ABSTRACT

Agricultural production is one of the most widespread economic activities in the world, yet understanding what actually drives productivity remains essential for addressing food security challenges. This study examines the determinants of cereal and soybean yields in the world's top-producing countries using panel-data fixed-effects regression to control for unobserved heterogeneity across countries. The analysis includes 520 observations for the top 20 cereal-producing countries (1994-2021) and 427 observations for the top 7 soybean-producing countries (1961-2021), subject to data availability. The results indicate that fertilizer use, GDP per capita, irrigation, pesticide application, precipitation, and temperature significantly influence cereal yield. For soybean yield, significant determinants involve fertilizer use, GDP per capita, temperature, and precipitation. The policy implications suggest that governments and stakeholders should prioritize targeted fertilizer subsidies, expand irrigation infrastructure, and invest in farmer education programs to optimize yield outcomes while ensuring sustainable agricultural practices.

Keywords: Agricultural productivity, food security, climate change, and panel data analysis

INTRODUCTION

Global food security faces growing challenges as the world population is projected to reach 9.8 billion by 2050, requiring a 70% increase in food production (UN, 2022). This demographic pressure, combined with the impacts of climate change and shrinking farmland, emphasizes the urgent need to understand and enhance the factors that influence agricultural productivity (Calvin et al., 2023). Agricultural productivity, defined as the efficiency with which resources are used to produce output, acts as the key link between production capacity and global food security (Dohlman et al., 2025). It remains the leading indicator of whether the global food system can meet the nutritional needs of a growing population (Silva et al., 2025). Food security, defined by the Food and Agriculture Organization as access to enough, safe, and nutritious food, is directly connected to productivity across major crop systems (FAO, 2023a).

According to the World Health Organization, about 733 million people experienced hunger or undernourishment in 2023. With global food demand expected to keep rising, stagnation in agricultural productivity presents a serious threat (WHO, 2024). A mere 1% increase in cereal yields could add approximately 28 million tons to global food supplies, significantly improving food availability for vulnerable populations (FAO, 2025). Likewise, improvements in soybean yields support global protein security and bolster livestock systems that provide essential nutrition to billions (Barboza Martignone et al., 2024). Yield gains in staple crops like cereals and soybeans are not only agricultural milestones but also critical factors for human well-being and economic resilience (OECD/FAO, 2021). When crop yields decline or stagnate, food prices tend to rise, hunger among vulnerable groups worsens, and broader economic instability can occur (World Bank, 2025; IMF, 2024).

The relationship between agricultural productivity and food security functions through several interconnected pathways: higher yields increase food availability, reduce production costs, stabilize market prices, and increase farmer incomes (IFPRI 2024). However, this relationship is influenced by complicated interactions among policy, technological, environmental, and socioeconomic factors, which differ significantly across countries and production systems (Bezner Kerr et al., 2023). Leading agricultural economies-such as the United States, China, India, and Brazil-have achieved significant productivity gains through various combinations of technological innovation, policy support, and effective resource management (FAO, 2023b).

Therefore, understanding the determinants of productivity in leading producing countries is essential for developing knowledge-based practices that can strengthen food security at local, national, and global scales (Herrero et al., 2020). This study addresses this gap by employing panel-data regression analysis to identify the key determinants of agricultural productivity in the world's leading cereal- and soybean-producing countries. Our analysis provides empirical evidence on how government policies, technological factors, environmental conditions, and socioeconomic variables interact to affect yield outcomes, recommending essential findings for policymakers and agricultural stakeholders.

LITERATURE REVIEW

Agricultural Productivity: Cereal and Soybean Yields

Agricultural productivity refers to the efficiency with which inputs are converted into outputs during the farm production process (FieldBee, 2022). It is usually expressed as a ratio, such as output per unit of land (yield per hectare), output per worker (labor productivity), or output per unit of capital investment (Nolte & Ostermeier, 2017). These productivity indicators provide an understanding of how effectively agricultural resources are utilized and reflect technological progress, management practices, and systemic efficiency (Bocean, 2024). Among these, output per unit of land, usually measured in tons per hectare, serves as a widely accepted indicator of agricultural productivity because land remains one of the most critical and limited factors in agricultural production (Hamada, 2025). Yield-based measures also allow standardized comparisons across farms, regions, and countries by accounting for differences in farm size (Rada & Fuglie, 2019). Cereal production, including wheat, buckwheat, oats, rice, maize, rye, millet, sorghum, barley, and mixed grains, is vital to global food security (Albahri et al., 2023). Maize, wheat, and rice are the most widely grown cereals worldwide, and production must increase by an estimated 70% by 2050 to meet future food demand (Bahar et al., 2020).

Global cereal production has generally increased over time, though some years have seen sharp fluctuations (Erenstein et al., 2022). The significance of cereal production goes beyond food supply; it also plays an important role in promoting economic growth and reducing poverty (Mughal & Fontan Sers, 2020). As shown in Figure 1, global cereal production has followed a steady upward trend, with significant surges around 1990 and 2000 (Iizumi et al., 2014). However, this growth has coincided with environmental challenges, such as climate change, pest infestations, and plant diseases, which have disrupted production patterns (Bajwa et al., 2020). The factors affecting cereal production vary significantly across countries due to differences in agroecological conditions, technology adoption, and policy environments (Neupane et al., 2022).

China, the United States, and India are the world's three leading cereal producers, with China alone accounting for 21% to 23% of global output (Deng, 2023). Along with these top producers, countries such as Russia, Brazil, Argentina, Indonesia, and Canada have experienced notable, though more gradual, increases in cereal production (USDA, 2025). Other nations such as Bangladesh, France, Ukraine, Pakistan, Vietnam, Germany, Thailand, Mexico, Ethiopia, and Nigeria have also experienced changes in cereal production, with results ranging from uncertain growth to declines depending on local circumstances (OECD/FAO, 2024). Various factors contribute to fluctuations in global cereal production, including climate change, pest and disease outbreaks, and agricultural practices (Rubayet & Hossain, 2024).

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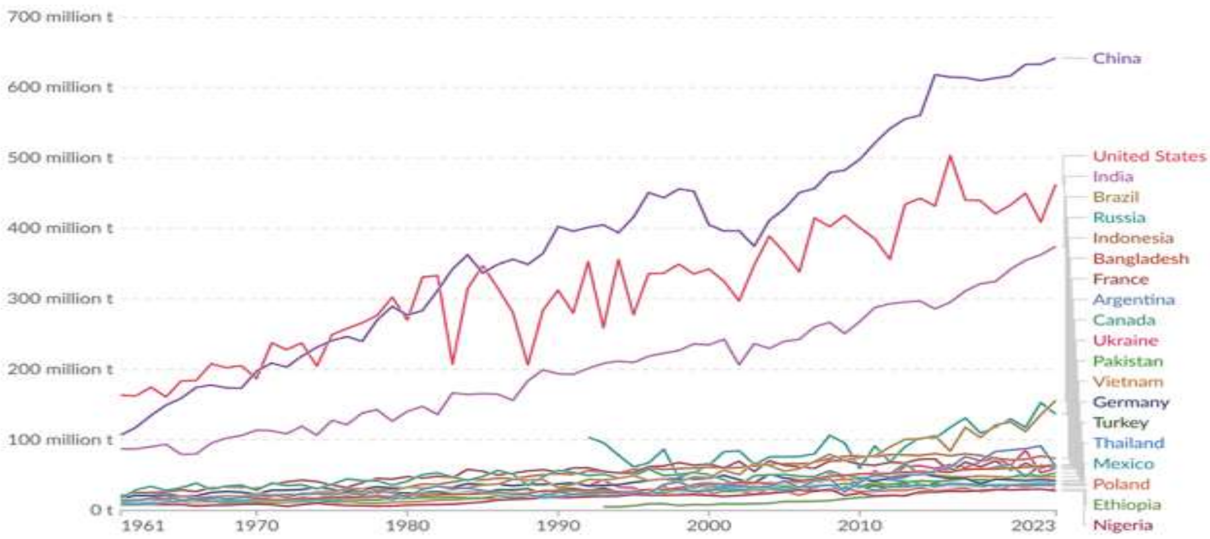

Figure 1 - Trend of Cereal Production

Source: Food and Agriculture Organization of the UN (2025) - processed by Our World in Data

Figure 2 illustrates the trend in cereal yields among the top 20 cereal-producing countries worldwide, measured as output per unit of land area (tons per hectare). Yield serves as a clear indicator of how efficiently countries convert available farmland into food (Movilla-Pateiro et al., 2021). Especially, countries such as the United States, France, and Germany consistently report the highest cereal yields, even though they are not the largest producers by total volume. This suggests that these countries use advanced technologies, improved crop varieties, and effective management practices to maximize productivity (Sanyaolu & Sadowski, 2024). Highlighting yield is especially important for improving global food security because it emphasizes producing more food from the same land rather than expanding agricultural areas at the expense of forests and natural ecosystems (Hannah et al., 2022). Yield improvements are closely linked to agricultural innovation and sustainable intensification, both of which are vital for feeding a growing global population while reducing environmental impact (Fusco et al., 2023). The adoption of improved irrigation systems and balanced fertilization has been shown to increase cereal yields significantly (Zuber et al., 2025). Yet, unsustainable practices can harm soil quality and reduce productivity in the long term (De Corato et al., 2024). Technological innovation, including precision agriculture and biotechnology, is expected to be crucial for increasing cereal productivity and adapting farming systems to environmental challenges (Chen, 2025).

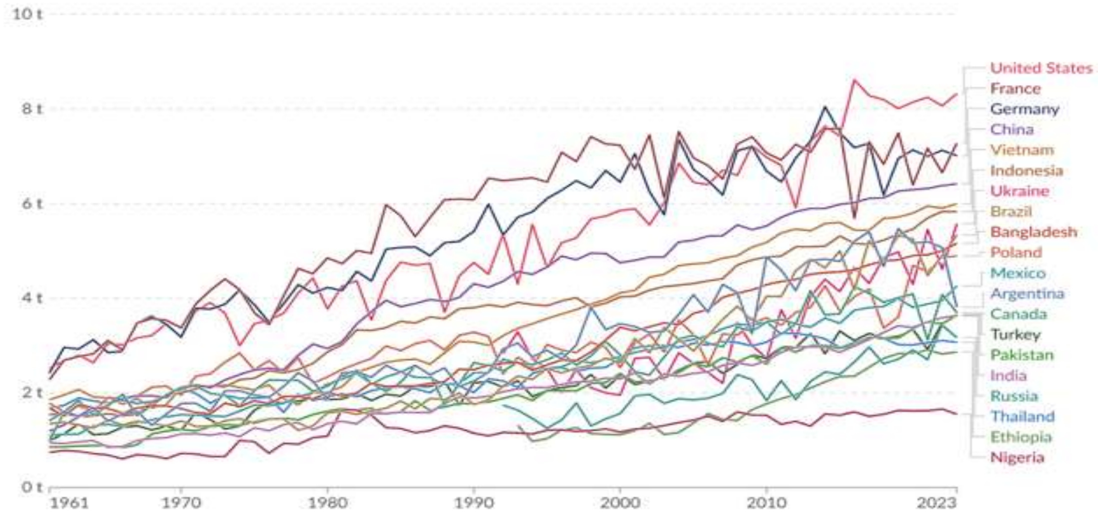

Figure 2 - Trend of Cereal Yield

Source: Food and Agriculture Organization of the UN (2025) - processed by Our World in Data

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Soybean Production and Yield

Besides cereal production, soybean farming is important for maintaining global food security (Yadav et al., 2023). The top seven soybean-producing countries—Brazil, the United States, Argentina, China, India, Paraguay, and Canada—account for nearly 95% of global soybean production (Volkova & Smolyaninova, 2024). According to the United States Department of Agriculture (USDA), Brazil led global soybean production in 2023, followed by the United States, Argentina, China, India, Paraguay, and Canada (USDA, 2023). A growing number of studies identify Brazil as the world's top soybean producer, overtaking the United States after years as the second-largest producer (Langemeier, 2024; Ali et al., 2022; Voora et al., 2020). According to Colussi et al. (2023), Brazil is close to surpassing its previous production records, while Argentina is going through its worst soybean harvest in over two decades.

Furthermore, soybean production has become one of the fastest-growing agricultural sectors worldwide, primarily due to the crop's high nutritional value and associated health benefits (Siamabele, 2021). According to the Food and Agriculture Organization (FAO), global soybean production was estimated at 393.5 million metric tons for the 2023–2024 period (FAO, 2023c). The total area of soybean cultivation worldwide is about 134 million hectares, producing 348.86 million metric tons in 2022 (AMIC, 2024). Figure 3 illustrates the production trends of these seven leading soybean-producing countries. Soybean production is affected by various biophysical and socioeconomic factors that differ by country (Qiao et al., 2023). The major challenges facing soybean production include the constantly changing weather and climate conditions, poor soil quality, farmers' resistance to adopting new agricultural practices and technologies, lack of diverse genetic varieties leading to increased vulnerability to pests and diseases, and insufficient economic policies and support for farmers (Amoanimaa-Dede et al., 2022). However, some solutions that could improve this situation include developing and distributing improved, resilient soybean varieties, adopting sustainable, climate-smart farming practices, integrating digital and precision technologies, and improving market access and incentives for farmers (Asewar et al., 2022).

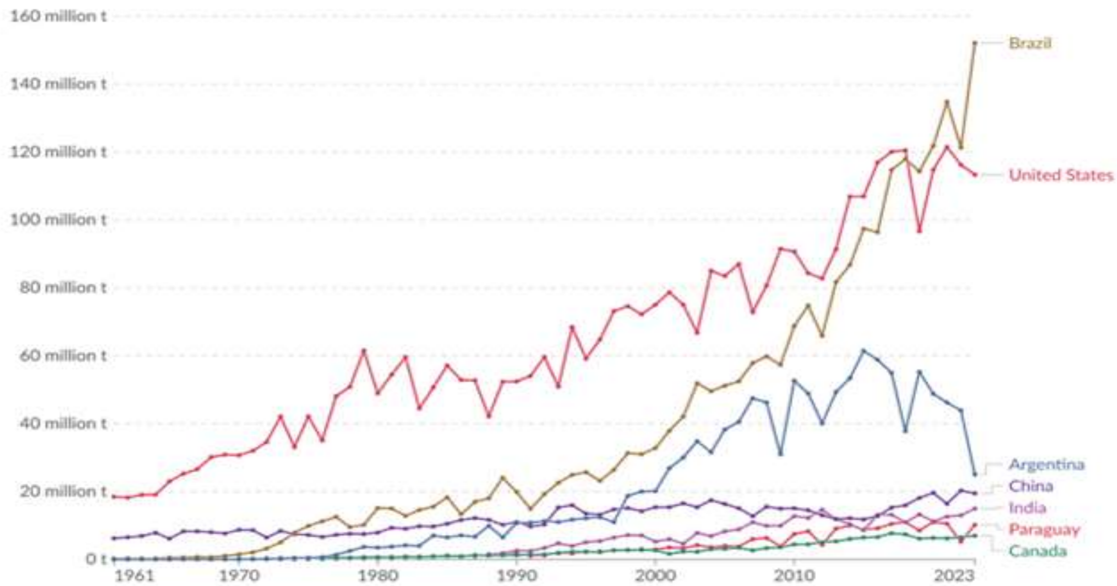

Figure 3 - Trend of Soybean Production

Source: Food and Agriculture Organization of the UN (2025) - processed by Our World in Data

Figure 4 below shows why yield is a more understandable metric than absolute production volumes for assessing sustainable agricultural development (de la Cruz et al, 2023). Although Brazil leads in total soybean production with approximately 150 million metric tons, yield data reveal that Brazil, the United States, Canada, and Paraguay all achieve yields of 2.5 to 3.5 tons per hectare. This convergence shows that high production can come from either the expansion of cultivated land (extensive growth) or from increased productivity per unit area (intensive growth) (Zhang et al., 2023).

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China's case clearly highlights the importance of yield efficiency. Although it ranks as the fourth-largest soybean producer, with approximately 20 million metric tons, China's yield remains low at 1 to 2 tons per hectare—less than half that of leading producers. This suggests that China needs to use much more land, water, labor, and inputs to produce each ton of soybeans, making its production system economically and environmentally unsustainable (Wu et al., 2020). If China could reach Brazil's yield levels, it might potentially double its production without using more resources (Colussi et al., 2025). India provides an even clearer example; despite significant efforts in production, its yields consistently stay below 1.5 tons per hectare. This low productivity results in higher input costs per unit of output, undermining both farm profitability and national food security (Das et al., 2022). These findings confirm that countries with higher yields show better resource-use efficiency, which is vital for sustainable agricultural growth (Yuan et al., 2021).

Soybean yield directly determines sustainable food security (Chaplin-Kramer et al., 2023). Countries achieving yields of over 3 tons per hectare can support more people with less land, helping preserve natural ecosystems and reduce environmental stress (Dreoni et al., 2022). The significant yield gaps between top producers—those exceeding 3 tons per hectare—and lower-yielding countries with yields of only 1–2 tons per hectare highlight a considerable opportunity to improve global food security. Bridging these gaps through targeted improvements in the productivity drivers identified in this study could yield significant gains in both food availability and sustainability (Ray et al., 2022).

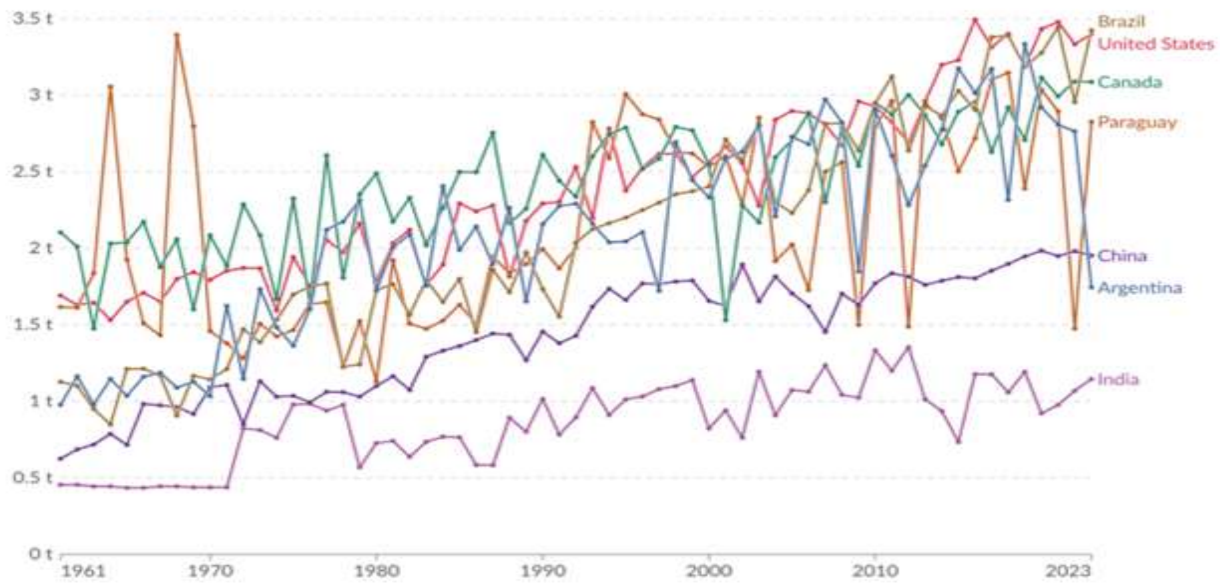

Figure 4 - Trend of Soybean Yield

Source: Food and Agriculture Organization of the UN (2025) - processed by Our World in Data

Conceptual Framework

Agricultural productivity is mainly influenced by several interconnected factors that fall into the socioeconomic, technological, and environmental categories (Sam et al., 2021). Socioeconomic factors include GDP per capita, a proxy for educational levels and overall economic development, and government subsidies that provide vital resources for farmers (Sarma & Rahman, 2020). This reflects a country's ability to invest in agriculture, education, and technology adoption, creating a supportive environment for increasing productivity (Yaganandham, 2024). Technological determinants include irrigation systems that improve water security and drought resilience, enabling farmers to sustain consistent production under different climatic conditions (Gautam et al., 2024). Material inputs, especially fertilizer and pesticide applications, supply vital nutrients and support pest control, with studies showing yield increases of 12.5-30.9% for fertilizers and 11.2% for pesticides. However, excessive use can cause environmental harm and reduce returns. Climatic variability, particularly in precipitation patterns, directly affects water availability and crop growth cycles, while environmental factors, such as temperature, influence plant physiological processes and determine optimal growing conditions for different crops (Yuan et al., 2024).

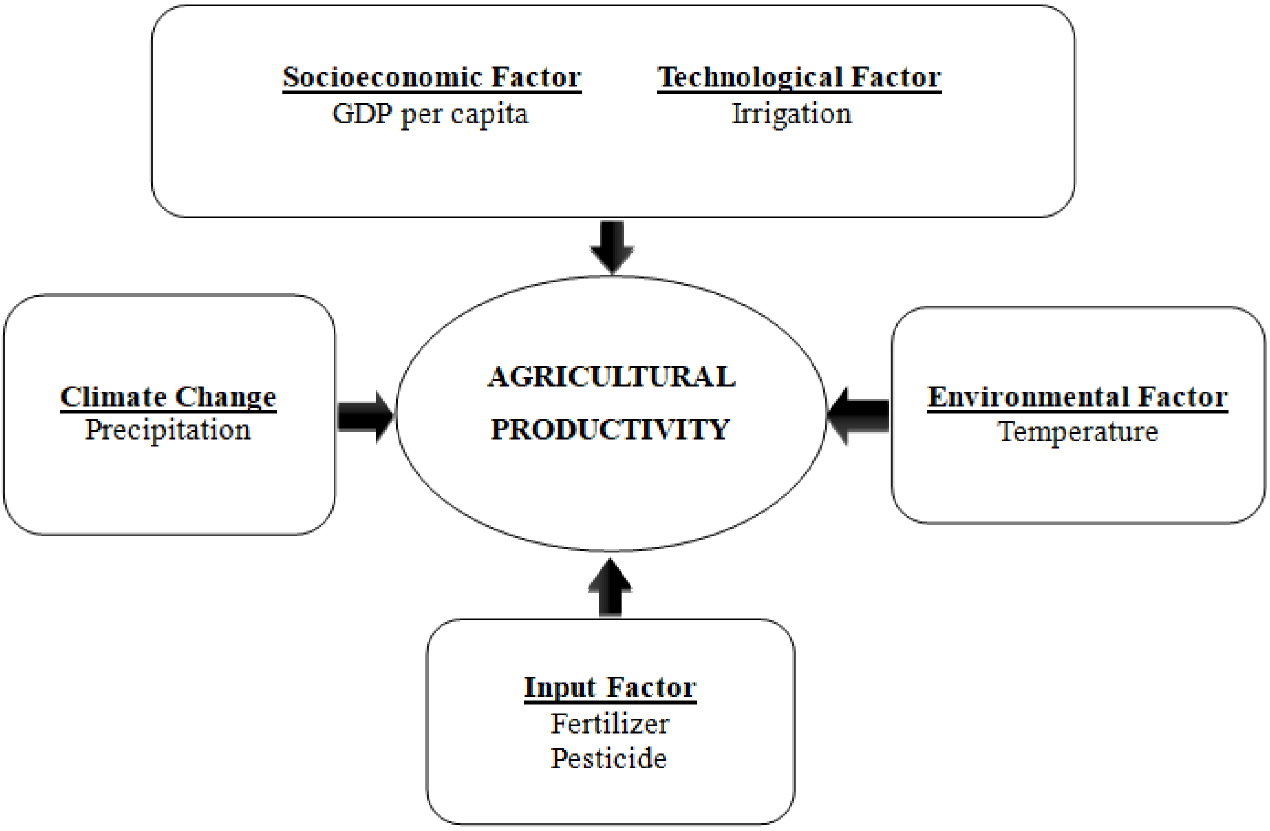

Figure 5 - Conceptual Framework

Source: Authors' Conception

This multidimensional framework acknowledges that agricultural productivity results from the complex interaction of human capital, economic resources, technological capabilities, input management strategies, and environmental constraints, with the significance of each factor differing across crops, countries, and production systems (Ndidiamaka et al., 2025).

DATA AND METHODOLOGY

Data Sources and Description

Data for this study were obtained from multiple sources, including the FAO Statistics Division for crop production, yield, fertilizer, temperature, and precipitation data; World Bank Development Indicators for the per capita GDP variable; and OECD Agricultural Statistics for government subsidies information. The dataset includes cereal data from 520 observations across the top 20 producing countries (1994-2021) and soybean data from 427 observations across the top 7 producing countries (1961-2021). The time period varies between crops due to differences in data availability, the evolution of international reporting standards, and the historical development of each crop's role in global agricultural systems.

For cereals, the analysis is restricted to 1994-2021 because comprehensive, standardized, and internationally comparable data on key production and management variables—particularly irrigation, pesticide application rates, and fertilizer use—only became consistently available across developing and developed countries from the mid-1990s onward. This improvement is closely linked to the implementation of WTO agricultural agreements, structural adjustment programs, and the subsequent strengthening of national statistical systems, which collectively improved both the coverage and management of cereal production statistics. Focusing on the post-1994 period allows the cereal model to incorporate a set of explanatory variables measured with more consistency, thereby reducing measurement error and improving the reliability of cross-country comparisons.

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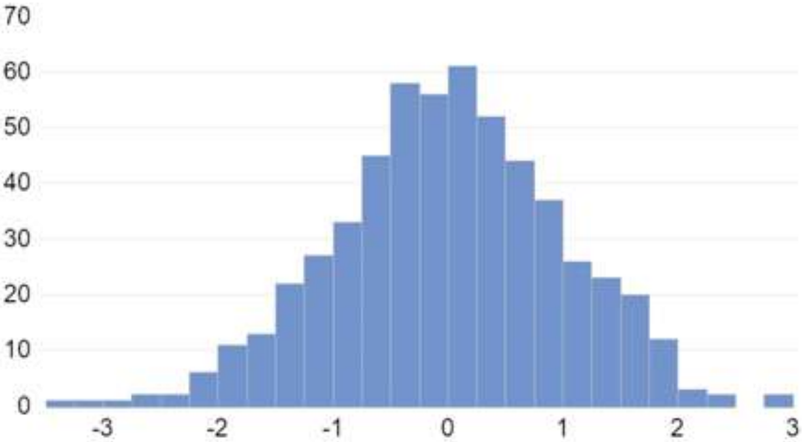
However, this shorter cereal period implies that some structural changes in agricultural production prior to 1994-such as early phases of the Green Revolution, the initial diffusion of high-yielding varieties, the expansion of basic irrigation infrastructure, and the gradual adoption of chemical inputs—are not directly captured within the cereal dataset. As a result, the cereal analysis primarily reflects the behavior of agricultural systems in a more "mature" phase of intensification, where many transformative technologies and practices are already in place. This has implications for comparability across the cereal and soybean models: differences in estimated relationships may partly reflect the fact that soybeans are observed over both early and later structural periods, whereas cereals are observed mainly during the later, post-1994 period.

For soybeans, the analysis covers 1961-2021. The longer time horizon is because the top seven soybean-producing countries began collecting systematic and relatively standardized data earlier, driven by soybeans' strategic role in international trade, the geographically concentrated nature of production (dominated by a small group of major exporters), and strong export-market requirements for consistent reporting of production, yields, and input use since the 1960s. These conditions facilitated comparability across countries over a longer historical period. Thus, the soybean model captures both the initial expansion and globalization of soybean production and the subsequent intensification and technological upgrading, covering multiple structural phases in the evolution of global soybean markets. Therefore, cereal and soybean crops were analyzed separately, not for comparison, but to identify the determinants of productivity for each crop.

Standardized residuals for the cereal yield model in Figure 5 demonstrate good model performance, with near-perfect normality. The distribution shows a mean close to zero (1.71e-15), indicating unbiased predictions, and a standard deviation close to one (0.98), confirming proper standardization. The slight negative skewness (-0.11) and moderate excess kurtosis (3.02) result in a Jarque-Bera test statistic of 1.15 with a p-value of 0.56, indicating a failure to reject normality at standard significance levels. This indicates that the model assumptions are correctly satisfied and that the statistical inferences from the cereal yield regression are dependable.



Series: Standardized Residuals	
Sample 1994 2021	
Observations 560	
Mean	-3.29e-16
Median	0.011786
Maximum	2.894996
Minimum	-3.265598
Std. Dev.	0.981398
Skewness	-0.110867
Kurtosis	3.015439
Jarque-Bera	1.152776
Probability	0.561924

Figure 6 – Data Normality Test for Cereal

Source: Authors' Construct, 2026

Soybean yield model residuals are acceptable but less ideal than the cereal model, with a near-zero mean (2.18e-16), appropriate standard deviation (0.99), slight negative skewness (-0.10), and notably high kurtosis (3.29). The Jarque-Bera test yields a statistic of 2.22 and a p-value of 0.33, indicating normality but hinting at some deviation from an ideal normal distribution. Higher kurtosis (fat tails) indicates more extreme residuals, reflecting greater complexity and diversity in modeling cereal production across 20 countries compared to the more uniform group of 7 major soybean producers. Despite minor deviations, the residuals confirm the models' accuracy and the reliability of the coefficients.

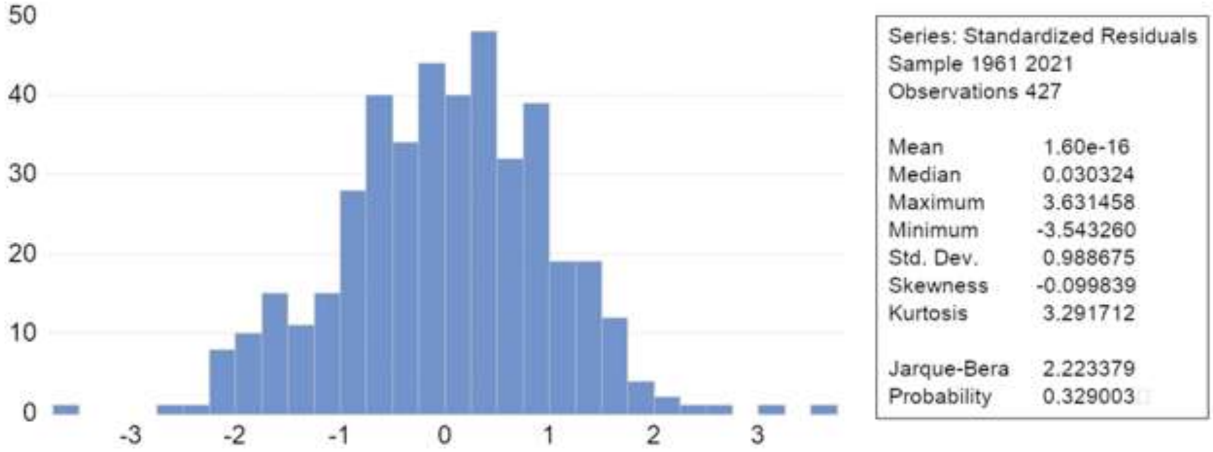


Figure 7 – Data Normality Test for Soybean

Source: Authors' Construct, 2026

Empirical Framework

Given the importance of yield in determining food security, this section uses panel data regression models to identify the key factors influencing cereal and soybean yields. Panel data regression is a statistical method used to analyze datasets that follow the same units—such as countries, individuals, or organizations—across multiple time periods (Wooldridge, 2016). This type of data, also known as longitudinal data, combines cross-sectional and time-series aspects, enabling a more thorough analysis of dynamic relationships (Hsiao, 2022). Panel regression models are commonly used across fields such as economics, sociology, and marketing to examine how time-varying variables affect a dependent outcome (Hill et al., 2020).

One of the main advantages of panel data regression models is their ability to account for unobserved heterogeneity—that is, individual-specific factors that affect the dependent variable but are not directly included in the model (Coakley, 2006). Ignoring these factors can produce biased and inconsistent estimates (Fernández-Val & Weidner, 2018). Panel data models handle this by including individual-specific fixed or random effects, which help isolate the influence of explanatory variables more accurately (Qin & Al Amin, 2022). As a result, these models generate more accurate, dependable estimates and stronger inferences (Benfratello, 2024).

Model Specification

The general panel data model is defined as shown in equation 1 below, along with additional specifications using fixed effects to control for country-specific heterogeneity.

$$AY_{it} = \beta_0 + \beta_1 Fert_{it} + \beta_2 Temp_{it} + \beta_3 Precip_{it} + \beta_4 Pest_{it} + \beta_5 GDP_{it} + \beta_6 Comm\ Price_{it} + \beta_7 Govt\ Sub_{it} + \beta_8 Irrig_{it} + \varepsilon_{it} \quad (1)$$

Where:

AY – Agricultural productivity; cereal yield and soybean yield (total output in tons/ha)

$Fert$ – Fertilizer (total number in kg/ha)

$Temp$ – Temperature (temperature change on land in ℃)

$Precip$ – Precipitation (average millimeters per year)

$Pest$ – Pesticide (total number in kg/ha)

GDP – GDP per capita (thousands in \$)

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$Comm\ price$ – Commodity price (producer price per ton in $)

$Gov't\ Sub$ – Government subsidy (% of gross farm receipt)

$Irrig$ – Irrigation (water withdrawn for agriculture as a % of the total water withdrawn)

β_0 – Global leading producing country-specific fixed effect

ε_{it} – Error term

i – Global producing countries

t – Time (years)

We included commodity price and government subsidy in equation 1 as potential explanatory variables, reflecting their theoretically important role in influencing production decisions and input use. However, these variables do not appear in the final set of regression models because on the data side, although we obtained price and subsidy information from FAO and OECD Agricultural Statistics, as well as related macroeconomic indicators from the World Bank, the coverage and consistency of these variables are substantially weaker than for the core agronomic and climatic variables. In particular, the price series and subsidy data are frequently missing, discontinuous, or redefined following major policy reforms, leading to breaks in the series. These issues are especially distinct for developing countries and earlier years in the panel, which introduces potential measurement error and compromises cross-country comparison.

Also, preliminary estimations that included commodity price and government subsidy in the regression models revealed serious multicollinearity with other covariates, especially per capita GDP, fertilizer use, and climate-related variable. Variance inflation factors (VIFs) increased significantly when price and subsidy were added, and several key coefficients became unstable in both sign and magnitude. This indicates that, in our model, price and subsidy are strongly correlated with broader economic development and policy environments already captured by other variables, making it difficult to separately identify their independent effects without inflating standard errors and reducing the accuracy of the estimates.

The irrigation variable is an indirect proxy for irrigation intensity and does not measure irrigated area directly. We use this proxy because it is consistently available across countries and over time, whereas irrigated area as a share of cropland is not available for the full sample. Therefore, irrigation should be interpreted as a broad indicator of agricultural water use rather than a precise measure of irrigated land coverage. Similar caution applies to the climate variables, which are country-level aggregates rather than field-level growing-season measures.

Model Selection Justification: Fixed Effect vs Random Effects

The decision between fixed- and random-effects models was made using the Hausman test. The Hausman test evaluates whether the unique errors are correlated with the regressors (Obeid, 2025), with the null hypothesis that a random effects model is preferred and the alternative hypothesis that a fixed effects model is preferred. In mathematics contexts:

$$H_{Null}: E[\varepsilon_{it}/X_{it}] = 0 \quad \Rightarrow \quad \text{Random effect model is preferred}$$

$$H_{Alt}: E[\varepsilon_{it}/X_{it}] \neq 0 \quad \Rightarrow \quad \text{Fixed effect model is preferred}$$

The Hausman test results strongly support the use of fixed effects models for both cereal and soybean models. The cereal model is statistically significant at the 1% level, and the soybean model is also significant at the 1% level, as shown in Table 1. Both tests reject the null hypothesis (a random effects model is preferred), indicating that country-specific unobserved characteristics—such as socioeconomic factors, technological inputs, resource inputs, environmental conditions, and climatic variability—are correlated with the explanatory variables. This correlation violates the random effects assumption and would lead to biased and inconsistent estimates if ignored (Antonakis et al., 2021).

Table 1 – Hausman Test Results

	Chi-sq. statistic	*P-value*
Cereal model	38.387987	0.0001
Soybean model	549.94999	0.0000

Source: Authors' Construct, 2026

The fixed effects approach accounts for these time-invariant country-specific factors, allowing us to identify the true causal effects of climatic factors (precipitation and temperature), socioeconomic conditions (per capita GDP), technological inputs (irrigation), and production inputs (fertilizer and pesticides) on agricultural productivity (Millimet & Bellemare, 2023), while maintaining the validity of our statistical inferences.

While fixed effects and extensive controls help minimize some sources of endogeneity, they do not address time-varying unobservable that may jointly influence input decisions and yields. We did not implement instrumental variables or dynamic panel methods because suitable, reliably measured instruments are not available for our cross-country, multi-crop dataset, and introducing more complex identification strategies would substantially increase the methodological burden relative to the primary goals of the paper. As a result, our estimates should be interpreted as informative correlations conditional on observed controls, rather than fully identified causal effects.

Cross-sectional Dependence Test with Correction

Cross-sectional dependence is a critical concern in panel data analysis of agricultural productivity, as countries may be affected by common global shocks, such as international commodity price fluctuations, climate patterns, technological spillovers, and global economic crises, which can simultaneously impact agricultural outcomes across nations (Terefe *et al*., 2024). The detected cross-sectional dependence violates the assumption of independent errors across units, which can bias standard errors and invalidate inference (Liu & Xu 2024); we identified this issue in our analysis and corrected for it. To address these cross-sectional dependencies, we employ cross-sectional SUR (Seemingly Unrelated Regression) correction, and the diagnostic test results show substantial improvement in both the cereal and soybean models. The Cross-Sectional SUR tests assess the presence of cross-sectional dependence within the panel data (Baltagi *et al*., 2016), which is crucial for ensuring the validity and robustness of our econometric models.

Table 2 – Cross Sectional Dependence Test Results

Test	*Statistic*	*P-value*
Cereal Model		
Breusch-Pegan LM	16.81285	1.0000
Pesaran CD	0.503348	0.6147
Soybean Model		
Breusch-Pegan LM	3.150132	1.0000
Pesaran CD	0.575534	0.5649

Source: Authors' Construct, 2026

The Breusch-Pagan LM test is particularly appropriate when the time dimension (T) exceeds the cross-sectional dimension (N) (Pesaran, 2015), which is the case in our data. Accordingly, LM-based diagnostics are well-suited to our setting and provide reliable evidence on cross-sectional dependence. To reinforce robustness, we also complement the LM test with CD-type diagnostics, ensuring our conclusions about residual dependence are not test-specific. From our results, the Breusch-Pagan LM test is no longer significant for either the cereal or soybean models, indicating that spatial correlation has been effectively removed. The Pesaran CD test likewise finds no residual cross-sectional dependence. Although the SUR adjustment greatly reduced the magnitude of cross-sectional correlation, the now-insignificant CD test indicates that the most important spatial dependence has been addressed, supporting the validity of our statistical inference for agricultural productivity determinants.

RESULTS AND DISCUSSIONS

Determinants of Cereal Yield in the Top Twenty-Producing Countries Worldwide

Table 3 shows the estimation results, including estimated coefficients, standard errors, and p-values for each explanatory variable and the fixed effects for the top twenty-producing countries in the world (China, United States, India, Brazil, Russia, Argentina, Canada, Indonesia, France, Ukraine, Bangladesh, Vietnam, Germany, Pakistan, Turkey, Mexico, Thailand, Poland, Ethiopia, and Nigeria). The R^2 value of 0.9975 indicates that the model explains approximately 99.75% of the variation in the cereal yield.

Fertilizer application significantly increases cereal yield (Yokamo et al., 2022; Kostić et al., 2021). Holding other factors constant, increasing fertilizer by one kilogram per hectare (1 kg/ha) leads to an average increase of 0.02887 tons per hectare (tons/ha) in cereal yield. This finding supports the idea of fertilizer-responsive agriculture, which shows that fertilizer use can significantly boost crop yields (Tamagno et al., 2024). Furthermore, previous studies have shown that fertilizer application not only boosts crop yields but also enhances soil fertility and decreases soil erosion (Change, 2016). However, the quadratic term for fertilizer use in the model is negative and significant, indicating that beyond a certain point, additional fertilizer application results in diminishing returns. This pattern illustrates the law of diminishing returns, which indicates that the additional benefit of fertilizer decreases as more is applied (Good & Beatty, 2011; Cobb & Douglas, 1928).

GDP per capita has a positive and significant impact on cereal yield (Asfew & Bedemo, 2022). In this study, the coefficient for GDP per capita is both positive and statistically significant, indicating that higher GDP per capita is associated with higher cereal yields. Specifically, increasing the GDP per capita by one thousand dollars ($1,000) results in a rise of cereal yield by 0.00006 tons/ha, assuming all other variables remain constant. Supporting findings include Baldos (2023), who found strong correlations between agricultural R&D intensity and national income, leading to significant productivity gains, and Ruane & Ramasamy (2023), who showed high returns to agrarian research investments in developed countries. This is attributed to better access to resources, infrastructure, and investment in agriculture (Malec et al., 2024). Research by Ruzzante et al. (2021) demonstrated that countries with higher GDP per capita can afford advanced agricultural technologies and improved inputs, thereby increasing productivity. Contradictory findings, such as Tavilode & Moon (2025), argue that institutional factors sometimes outweigh income levels in determining agricultural productivity. In some low-income countries experiencing rapid GDP growth, yield improvements may lag due to institutional or infrastructural bottlenecks (Kaplinsky & Kraemer-Mbula, 2022).

GDP per capita is a reliable indicator of education and technological progress in agriculture, as wealthier countries typically invest more in human capital development and technological advancement (Nin-Pratt, 2021). Higher-income countries invest more heavily in educational systems that develop skilled agricultural technicians, extension workers, and farmers capable of applying advanced farming practices, while also funding agricultural research and development programs that create improved crop varieties, precision agriculture technologies, and efficient farming equipment (Raji et al., 2024). The economic capacity associated with higher GDP per capita enables countries to build strong infrastructure, including storage facilities, transportation systems, and processing plants, while also providing farmers with access to modern inputs such as high-quality fertilizers, improved seeds, and advanced equipment (FAO, 2017). Wealthier nations tend to have stronger institutional frameworks that facilitate technology transfer, support agricultural innovation, and promote the adoption of best practices. This makes GDP per capita a comprehensive indicator that captures both the educational capacity to use advanced farming techniques and the technological resources needed to implement them effectively (Quan et al., 2024).

Irrigation has a positive and significant effect on cereal yield (Peterson et al., 2023). Assuming all other factors remain constant, a 1% increase in irrigation is associated with a 0.021950-ton/ha increase in cereal yield. Numerous studies have demonstrated that irrigation not only increases yields but also enhances water use efficiency and helps reduce soil salinization (Cuevas et al., 2019; Machado & Serralheiro, 2017; De Pascale et al., 2011). However, the quadratic term for irrigation is negative and statistically significant, suggesting that excessive irrigation may reduce cereal yield. This aligns with findings that the marginal benefit of irrigation declines as irrigation levels increase (Fontes et al., 2021). Over-irrigation can cause waterlogging, nutrient leaching, and increased soil salinity—factors that harm crop performance (Priyadharshini & Babu, 2023). These adverse effects are especially noticeable in cereals like wheat and barley, which are vulnerable to waterlogging and saline environments (Zeeshan et al., 2020). Therefore, implementing efficient irrigation management practices is crucial to prevent over-irrigation and maximize yield outcomes for cereal crops (Nikolskii & Aidarov, 2023). The interaction term provides strong support for how factors interact to influence cereal yield. The Irrigation × GDP per capita coefficient of 0.000002 shows that the productivity benefits of irrigation increase with higher GDP per capita. Thus, holding all other variables constant, when irrigation coverage increases by 1%, each additional $1,000 in GDP per capita results in an extra 0.000002 tons/ha of cereal production yield. This finding aligns with prior research emphasizing that the advantages of GDP per capita in agricultural production depend on the context and can be improved with additional inputs (Fukase & Martin, 2020).

Pesticide application has a strong and statistically significant positive effect on cereal yield (Tudor et al., 2023). The positive coefficient indicates that increasing pesticide use is associated with higher cereal yields. Specifically, a 1 kg/ha increase in pesticide use leads to a 0.15143 tons/ha rise in cereal yield, assuming all other variables remain constant. This finding is consistent with pest management principles, which emphasize the importance of pesticides in reducing pest populations and increasing crop yields (Peshin & Zhang, 2014). Pesticide use has been shown to enhance yields, improve crop quality, and suppress pest infestations (Tudi et al., 2021). However, the quadratic term for pesticide use is also negative and significant, indicating diminishing returns to pesticide application and suggesting that excessive use can decrease cereal yields (Liu et al., 2015). Skevas and Lansink (2014) similarly note that the marginal benefit of pesticide application decreases as usage increases. Overreliance on chemical pesticides has been associated with negative effects, including the development of pesticide-resistant pests, soil deterioration, and the destruction of beneficial insects and soil microbes, all of which can harm crop yields (Qasim et al., 2024). For instance, Khan et al. (2023) report that pesticide use harms soil microbial communities, thereby reducing soil fertility and, consequently, crop yield. Supporting this, a study in the United States found that pesticide use on wheat farms reduced soil organic carbon, leading to lower cereal yields (West & Marland, 2002).

Precipitation has a positive and significant impact on cereal yield (Chandio et al., 2022). Implying that a one-millimeter (1mm) increase in precipitation will lead to a 0.10986 ton/ha increase in cereal yield, assuming all other variables remain constant. Our finding matches the extensive empirical evidence from agricultural productivity research worldwide. Lobell & Gourdji (2012) showed that precipitation is one of the most important factors affecting crop yields worldwide, with a 1% increase in rainfall during the growing season linked to a 0.45-0.65% rise in cereal productivity in major producing regions. Likewise, Qin et al. (2023) discovered that sufficient rainfall during main growth stages greatly improves grain filling and biomass production in wheat, rice, and maize systems. The positive effect of precipitation is especially noticeable in semi-arid and temperate regions, where water availability is the main limiting factor for crop growth. This supports our findings that increased rainfall directly leads to higher cereal productivity by boosting soil moisture, improving nutrient uptake, and reducing water stress during basic stages of plant development. The negative coefficient on the squared precipitation term confirms the well-known idea of diminishing marginal returns to water inputs in farming systems. Mohammadi et al. (2023) discovered similar quadratic patterns across different crops, indicating that optimal precipitation levels vary depending on the crop and region. However, yields consistently decrease beyond certain thresholds due to anaerobic soil conditions and delayed planting or harvesting activities. Schlenker & Roberts (2009) documented that the precipitation-yield relationship follows a clear inverted U-shape, with peak productivity occurring at moderate rainfall levels (typically 400-800mm annually for cereals), after which additional precipitation becomes harmful.

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Temperature has a positive and statistically significant effect on cereal yield (Ben Mariem et al., 2021). Precisely, a one-degree Celsius (1°C) increase in temperature is linked to a 0.14469 tons per hectare (tons/ha) rise in cereal production yield. This result aligns with the findings by Zhao et al. (2017), which recommend that a moderate temperature increase can enhance crop productivity. Though the quadratic term for temperature is negative and significant, indicating that beyond a certain threshold, further increases in temperature negatively impact yield. This decline results from the disruptive effects of high temperatures on key metabolic processes, such as photosynthesis and respiration, which are crucial for plant growth and development (Morales et al., 2020). Several studies support this conclusion. For example, Asseng et al. (2011) found that the optimal temperature range for wheat cultivation is 15°C to 5°C, while temperatures above 30°C can cause yield losses of up to 20%.

The cross-section fixed effects represent country-specific intercepts in the panel regression models. They can be interpreted as capturing systematic, time-invariant differences in average yield levels across countries after controlling for the observed explanatory variables (fertilizer, irrigation, pesticides, climate, GDP per capita, and interaction terms). In other words, each country's fixed effect shows how its baseline yield level differs from the overall reference level implied by the omitted intercept, holding the included covariates constant.

The magnitude and sign of these fixed effects thus reflect unobserved, country-specific factors that are not explicitly modeled but are persistent over time. The relatively large negative fixed effects for Thailand (−97.60) and Vietnam (−96.97), compared with a smaller negative effect for Russia (−43.58), indicate that Thailand and Vietnam have substantially lower baseline cereal yields than Russia, even after accounting for input use, climate, and income.

Table 3 – Panel Data Regression Results for Cereal Yield Determinants with Cross-Sectional Dependency Correction

Variable	*Coefficient*	*Standard Error*	*P-Value*
Fertilizer	0.028874	0.000825	0.0000***
Fertilizer^2	-0.000083	0.000003	0.0000***
GDP per capita	0.000064	0.000010	0.0000***
Irrigation	0.021950	0.004756	0.0000***
Irrigation^2	-0.000231	0.000032	0.0000***
Irrigation × GDP per capita	0.000002	0.000000	0.0000***
Pesticide	0.151428	0.014416	0.0000***
Pesticide^2	-0.001483	0.000847	0.0805*
Precipitation	0.109857	0.028851	0.0002***
Precipitation^2	-0.000031	0.000008	0.0002***
Temperature	0.144689	0.024410	0.0000***
Temperature^2	-0.042053	0.010275	0.0000***
Cross-section Fixed Effects			
Country	*Effect*		
Argentina	-54.05469		
Bangladesh	-74.17702		
Brazil	-98.59947		
Canada	-51.84116		
China	-56.86190		
Ethiopia	-70.00740		
France	-71.33277		
Germany	-60.58702		
India	-82.66773		
Indonesia	-71.62378		
Mexico	-66.08791		
Nigeria	-85.55371		

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Pakistan	-46.47348
Poland	-54.56212
Russia	-43.57588
Thailand	-97.60471
Turkey	-56.98097
Ukraine	-50.64694
USA	-65.43056
Vietnam	-96.96998

Source: Authors' Construct, 2026

*** and * are significant levels at 1% and 10% respectively

$R^2 = 0.9975$

Determinants of Soybean Yield in the Top Seven-Producing Countries Worldwide

The top seven soybean-producing countries analyzed in this study are Brazil, the United States, Argentina, China, India, Paraguay, and Canada. The R^2 value of 0.9313 shown in Table 4 suggests that about 93.13% of the variation in soybean yield is explained by the model, which includes fertilizer use, GDP per capita, precipitation, and temperature.

The fertilizer coefficient is 0.00971, indicating a positive relationship between fertilizer use and soybean yield. Specifically, increasing fertilizer application by one kilogram per hectare (1 kg/ha) results in a soybean yield increase of 0.00971 tons per hectare (tons/ha), assuming all other variables remain constant. In other words, increased fertilizer use is linked to higher soybean yields (Hua et al., 2020). This effect mainly results from fertilizer's role in improving soil fertility, thereby promoting better crop growth and development (Pagano & Miransari, 2016). Khan et al. (2022) also discovered that fertilizer application significantly enhances various growth parameters and boosts soybean grain yield. The quadratic term for fertilizer is statistically significant, showing a non-linear relationship. This indicates that while moderate fertilizer usage increases soybean yield, excessive application decreases it (Hamed et al., 2021). Thus, excessive nitrogen (N) use has been shown to reduce yields by promoting excessive vegetative growth at the expense of reproductive development, resulting in smaller seeds and lower pod set (Mahboob et al., 2023). These findings highlight the significance of balanced, targeted fertilizer management in soybean cultivation.

The coefficient for GDP per capita is −0.00008, indicating that, all other variables being equal, an increase in GDP per capita is associated with a decrease in soybean yield by 0.00008 tons per hectare (tons/ha). This could be due to the sample being limited to the seven largest producers, which might introduce selection bias, as these countries represent mature agricultural economies where yield improvements encounter natural biological and economic limits (Jones et al., 2017). Additionally, the negative relationship might indicate the "Dutch disease" phenomenon in agricultural settings, where economic growth in other sectors pulls resources away from agriculture (Lauvsnes & Ingulfsvann, 2023). Countries such as Argentina and Brazil have experienced periods when rapid growth in the mining and manufacturing sectors led to a decline in agricultural investment and labor shifts, potentially explaining the negative coefficient observed (Graña-Colella & Silva Neira, 2024). Several studies have documented similar inverse relationships between national wealth and specific crop yields, especially in developed agricultural economies (Fei et al., 2023). Research by Sedibe et al. (2023) found that as countries grow economically, they often experience declining marginal productivity in traditional commodity crops such as soybeans due to land constraints and opportunity costs. Analysis of OECD countries showed that higher GDP per capita is associated with limits to agricultural intensification, where further yield increases are no longer economically viable (OECD/FAO, 2021). Likewise, FAO (2018) demonstrated that as economies develop and GDP per capita increases, the agricultural sectors usually shrink as a share of total economic output, leading to decreased investment in traditional crop productivity improvements. Countries like the United States and Brazil, despite being major soybean producers, have experienced periods in which economic growth coincided with stagnating or declining yield growth rates (Valdes et al., 2023). Some literature contradicts this negative relationship, arguing that higher GDP per capita should, in theory, enhance agricultural productivity through multiple channels (Şen et al., 2024). According to Oli et al. (2025), higher-income countries consistently demonstrate faster adoption rates of yield-enhancing technologies, including genetically modified soybean varieties, precision agriculture tools, and advanced fertilizer management systems. Studies by Akpabio et al. (2025) also showed that countries with higher per capita GDP tend to have better-educated farmers who can more effectively adopt complex agricultural technologies, resulting in higher yields.

The positive and significant coefficient (0.04765) on the quadratic term for temperature indicates an accelerating positive relationship between temperature and soybean yield, suggesting that the marginal benefits of higher temperatures increase as temperature rises. This finding contrasts with the typical inverted U-shaped temperature-yield relationships documented in some agricultural literature. Alsajri et al. (2020) found that most crops, including soybeans, have optimal temperature ranges beyond which yields decrease due to heat stress, often showing a negative quadratic trend. Nonetheless, our positive squared term may reflect the specific geographic and climatic conditions of the top seven soybean producers—mainly temperate regions like the US Midwest, Brazil's Cerrado, and Argentina's Pampas—where current temperatures might still be below the optimal level for soybean growth (de LT Oliveira & Hecht, 2017). Chebrolu et al. (2016) observed that soybeans have relatively high heat tolerance compared to other major crops, with optimal growing temperatures between 20-30°C, and Ntiamoah et al. (2022) found that some soybean-producing areas might actually benefit from moderate warming. This positive acceleration may also indicate adaptation mechanisms, as Butler & Huybers (2013) demonstrated that soybean varieties have been successfully bred for higher temperature tolerance, potentially shifting the optimal temperature range upward over time.

The negative main effect of precipitation (-0.008807) combined with the positive precipitation × GDP per capita interaction (0.000002) reveals a distinguished relationship that critically depends on levels of economic development. The negative main precipitation effect indicates that, holding all other variables constant, higher precipitation will decrease soybean yield by 0.00881 tons per hectare (tons/ha). This contradicts the typical positive relationship observed in most agricultural studies (Zhao et al., 2025; Thomasz et al., 2024; Gagné et al., 2022; Tsekhmeistruk et al., 2021), but this apparent contradiction is resolved when considering the interaction term (precipitation × GDP per capita).

That being said, the negative effect of precipitation becomes less severe as GDP per capita rises. Holding all other factors fixed, for every millimeter (1mm) rise in precipitation, an extra $1,000 in GDP per capita is associated with a further 0.000002 tons per hectare (tons/ha) increase in soybean yield. This shows that precipitation benefits only in wealthier or more economically developed countries, likely due to superior drainage infrastructure, flood management systems, and precision agriculture technologies that can handle excess moisture (Shen et al., 2025). This finding aligns with Ibrahim et al. (2014), who demonstrated that the impact of weather shocks varies significantly with adaptive capacity and infrastructure quality. The negative precipitation effect in lower-income contexts may reflect inadequate drainage systems that lead to waterlogging, as documented by Gangana Gowdra (2025). In contrast, wealthier countries can turn excess precipitation into useful resources through advanced irrigation management and soil conservation practices (Dhillon et al., 2025).

Similarly, Brazil (16.08) and Paraguay (11.60) show higher positive fixed effects than other countries, indicating more favorable baseline conditions for soybean production that are not fully explained by the observable variables in the model. Substantively, these unobserved country-specific components may reflect differences in institutional quality, infrastructure and market access, land tenure systems, research and extension services, historical patterns of agricultural development, soil characteristics, or long-standing policy periods that are not directly measured in our dataset but systematically influence yield levels. The fixed-effects framework allows us to control for these time-invariant factors when estimating the coefficients on the observed variables, thereby reducing omitted-variable bias.

Table 4 – Panel Data Regression Results for Soybean Yield Determinants with Cross-Sectional Dependency Correction

Variable	*Coefficient*	*Standard Error*	*P-Value*
Fertilizer	0.009714	0.000702	0.0000***

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$Fertilizer^2$	-0.000025	0.000003	0.0000***
GDP per capita	-0.000083	0.000007	0.0000***
Temperature	0.001736	0.036967	0.6390
$Temperature^2$	0.047651	0.019700	0.0160**
Precipitation	-0.008807	0.002456	0.0004***
Precipitation × GDP per capita	0.000002	0.000000	0.0000***
Cross-section Fixed Effects			
Country	***Effect***		
Argentina	7.017832		
Brazil	16.08537		
Canada	6.624701		
China	6.277355		
India	9.911978		
Paraguay	11.59502		
USA	6.728889		

Source: Authors' Construct, 2026

*** and ** are significant levels at 1% and 5% respectively

$R^2 = 0.9313$

CONCLUSION

By 2050, the world's population is expected to reach around 9.8 billion. This expected growth creates major challenges for the global food system, making it more urgent to boost agricultural productivity to secure food supply. One effective way to tackle this challenge is to focus on the world's top agricultural producers—countries that already play a key role in feeding the global population. Ensuring these countries maintain and improve their productivity is essential for meeting future food demands. This study analyzed the factors affecting cereal yield from 1994 to 2021 because comprehensive, standardized data for all explanatory variables across the top twenty producing countries became consistently available only from 1994 onward. Earlier data showed inconsistent reporting standards, especially for variables like irrigation percentages and pesticide application rates in developing countries within our sample. The study demonstrated that fertilizer use, GDP per capita, irrigation, pesticide application, precipitation, and temperature all significantly affect cereal yield. These results emphasize the complicated nature of agricultural performance, where material inputs (such as fertilizer and pesticide), socioeconomic factors (like GDP per capita), technological inputs (such as irrigation), climatic variability (like precipitation), and environmental conditions (such as temperature) all work together to influence outcomes.

Meanwhile, soybean productivity was examined from 1961 to 2021. This is because the top seven soybean-producing countries developed more systematic agricultural data-collection systems earlier, given the strategic importance of soybean trade in international markets. Also, the soybean industry's development experienced rapid global expansion starting in the 1960s, driven by livestock feed demand and protein security concerns, necessitating longer-term analysis to capture complete development cycles and structural changes in the determinants of productivity. The results show that fertilizer use, GDP per capita, temperature, and precipitation significantly impact soybean yield. These findings emphasize the importance of a wide range of drivers—including material inputs (fertilizer), socioeconomic capacity (GDP per capita), environmental conditions (temperature), and climatic variability (precipitation)—in influencing soybean productivity outcomes. In a nutshell, both cereal and soybean yields are affected by complex interactions among environmental, economic, technological, and institutional factors. Targeted policies that strengthen these areas in major producing countries are essential to ensuring global food security amid growing demand and climate uncertainty.

The presence of substantial fixed-effect differences across countries highlights an important limitation of the fixed-effects approach: while it absorbs these unobserved, country-specific influences, it does not identify them or allow us to convey which institutional, historical, or biophysical factors are most important. As a result, our analysis explained how changes in observed inputs, technological, environmental, socioeconomic, and climate change relate to yields within countries over time, but it did not fully account for all cross-country productivity gaps. This is an interpretive constraint when for cross-country differences and causal implications of the estimated relationships.

While it is theoretically possible to compute the fertilizer rate at which marginal returns become negative, and to compare this with current application rates in major producing countries, we chose not to present such exact thresholds in this manuscript. Given the high degree of heterogeneity across countries, the aggregate nature of our data, and the absence of explicit cost in our models, we consider that reporting precise "optimal" levels might overstate the precision and policy specificity of our estimates. Instead, we focus on documenting the presence and direction of nonlinearities and on discussing their general implications for input efficiency and climate sensitivity.

Incomplete and heterogeneous data on price and subsidy prevent us from fully exploiting these variables in a cross-country panel framework. Therefore, future research should focus more detailed, consistent information on commodity price, input subsidy, and broader agricultural policy instruments which would allow for a more complete assessment of how economic incentives interact with climate and management factors in shaping crop yields and environmental outcomes. We also acknowledge all limitations explicitly and view the development of more sophisticated identification strategies-influencing micro-level data, natural experiments, or policy shocks-as an important direction for future work.

RECOMMENDATIONS

The estimated determinants help explain why yields rise or stall over time within a given country (e.g., through changes in fertilizer, irrigation, or climate conditions) and why persistent gaps remain between leading and lagging top producers, even after controlling for observable factors. For cereals, the significant role of fertilizer, irrigation, and GDP per capita indicates that continued investments in these areas can help countries move closer to the yield frontier, narrowing within-country and some cross-country gaps. For soybeans, however, the negative association with GDP per capita and the importance of climate interactions indicate that yield gaps are more closely linked to structural and institutional factors—such as land expansion patterns and crop-specific management practices—rather than to general economic development alone. Based on these findings, we provide the following recommendations to enhance cereal and soybean yields in the top-producing countries worldwide.

- ***Invest in Education and Extension Services for Farmers***

  Education improves farmers' ability to adopt and effectively apply modern agricultural technologies, which can result in higher cereal yields—including wheat, buckwheat, oats, rice, maize, rye, millet, sorghum, barley, and mixed grains—in the top twenty producing countries (China, United States, India, Brazil, Russia, Argentina, Canada, Indonesia, France, Ukraine, Bangladesh, Vietnam, Germany, Pakistan, Turkey, Mexico, Thailand, Poland, Ethiopia, and Nigeria). Similarly, soybean yields in major producers like the United States can improve through more informed and skilled farmers. Policymakers should provide funding for farmer education via seminars, workshops, and ongoing extension services. Strengthening agricultural extension systems will improve the dissemination of technical knowledge, promote the adoption of better practices, and enhance the provision of financial support. In developing countries among the top cereal producers (e.g., China, India, Brazil, Indonesia, and Nigeria), mobile-based learning platforms can be particularly effective in delivering content on crop rotation, pest control, soil health, and efficient water use. Encouraging farmer-based organizations can also improve peer learning and offer practical, community-driven training opportunities.

- ***Expand Irrigation Infrastructure***

  To reduce reliance on rain-fed agriculture and stabilize production, especially in drought-prone areas, irrigation investment is essential. Drip irrigation, sprinkler systems, rainwater harvesting, and flood irrigation are effective methods for boosting cereal yields in leading agricultural countries.

Policymakers should promote the expansion of irrigation systems through public investment and policies that encourage farmers to adopt them. In resource-limited settings—such as many developing countries in the top twenty—low-cost irrigation options, including small reservoirs, gravity-fed systems, and solar-powered pumps, should be encouraged as practical solutions.

- ***Promote Efficient Fertilizer Use and Soil Management***

Fertilizer use significantly increases cereal and soybean yields, but its efficiency depends on the context. In the top soybean-producing countries (Brazil, the United States, Argentina, China, India, Paraguay, and Canada), promoting precision agriculture can optimize fertilizer use and reduce environmental impact. Governments can promote adoption by funding farmer training, subsidizing access to technology, and encouraging soil testing. Where precision agriculture is less practical due to limited infrastructure, integrated soil fertility management—combining locally available organic inputs with targeted use of mineral fertilizers—can serve as a useful alternative. These methods are vital for developing countries, where access to advanced technology is limited.

- ***Reevaluate Input Subsidy Policies to Ensure Sustainability and Competitiveness***

Instead of relying on blanket subsidies, governments should shift to smart subsidies that reward farmers for adopting climate-smart, resource-efficient practices. This involves combining subsidized inputs with sustainable methods, such as conservation agriculture or precision farming, to maximize yield while reducing input waste and environmental impact. Well-targeted subsidies can improve competitiveness in global markets and support long-term food security and rural development.

REFERENCES

1. Ahmad, M. I., Oxley, L., & Ma, H. (2020). What makes farmers exit farming: A case study of Sindh Province, Pakistan. *Sustainability*, 12(8), 3160.
2. Akpabio, E. S., Akeju, K. F., & Omotoso, K. O. (2025). E-agriculture and food security in developing countries: Beaming the searchlight on Nigeria. Smart Agricultural Technology, 10, 100689. https://doi.org/10.1016/J.atech.2024.100689
3. Albahri, G., Alyamani, A. A., Badran, A., Hijazi, A., Nasser, M., Maresca, M., & Baydoun, E. (2023). Enhancing essential grains yield for sustainable food security and bio-safe agriculture through latest innovative approaches. *Agronomy*, 13(7), 1709.
4. Ali, T., Zhou, B., Cleary, D., & Xie, W. (2022). The impact of climate change on China and Brazil's soybean trade. *Land*, 11(12), 2286.
5. Alsajri, F. A., Wijewardana, C., Irby, J. T., Bellaloui, N., Krutz, L. J., Golden, B., & Reddy, K. R. (2020). Developing functional relationships between temperature and soybean yield and seed quality. *Agronomy Journal*, *112*(1), 194-204.
6. AMIC. (2024). Soyabean outlook – October 2024. https://www.pjtau.edu.in/files/AgriMkt/2024/October/Soyabean-October-2024.pdf
7. Amoanimaa-Dede, H., Su, C., Yeboah, A., Zhou, H., Zheng, D., & Zhu, H. (2022). Growth regulators promote soybean productivity: a review. *PeerJ*, 10, e12556.
8. Antonakis, J., Bastardoz, N., & Rönkkö, M. (2021). On ignoring the random effects assumption in multilevel models: Review, critique, and recommendations. *Organizational Research Methods*, *24*(2), 443-483.
9. Arends-Kuenning, M., Kamei, A., Garcias, M., Romani, G. E., & Shikida, P. F. A. (2021). Gender, education, and farm succession in Western Paraná State, Brazil. *Land use policy*, 107, 105453.
10. Asewar, B., Jagtap, M., Shinde, G., Mehetre, S., & Pendke, M. (2022). Climate-Resilient Technologies for Enhancing Productivity of Soybean in India. In *Soybean-Recent Advances in Research and Applications*. IntechOpen.
11. Asfew, M., & Bedemo, A. (2022). Impact of climate change on cereal crops production in Ethiopia. *Advances in Agriculture*, *2022*(1), 2208694.
12. Asseng, S., Foster, I. A. N., & Turner, N. C. (2011). The impact of temperature variability on wheat yields. *Global change biology*, 17(2), 997-1012.

13. Awika, J. M. (2011). Major cereal grains production and use around the world. In *Advances in cereal science: implications to food processing and health promotion* (pp. 1-13). American Chemical Society.
14. Bajwa, A. A., Farooq, M., Al-Sadi, A. M., Nawaz, A., Jabran, K., & Siddique, K. H. (2020). Impact of climate change on biology and management of wheat pests. *Crop Protection*, 137, 105304.
15. Baldos, U. L. C. (2023). Impacts of US Public R&D Investments on Agricultural Productivity and GHG Emissions. *Journal of Agricultural and Applied Economics*, *55(3)*, 536–550. doi:10.1017/aae.2023.29.
16. Baltagi BH, Kao C, Peng B. (2016). Testing Cross-Sectional Correlation in Large Panel Data Models with Serial Correlation. *Econometrics*. 2016; 4(4):44. https://doi.org/10.3390/econometrics 4040044
17. Barboza Martignone, G. M., Ghosh, B., Papadas, D., & Behrendt, K. (2024). The rise of Soybean in international commodity markets: A quantile investigation. Heliyon, 10(15), e34669. https://doi.org/10.1016/j.heliyon.2024.e34669
18. Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. (2012). Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global environmental change*, 22(1), 223-235.
19. Ben Mariem, S., Soba, D., Zhou, B., Loladze, I., Morales, F., & Aranjuelo, I. (2021). Climate change, crop yields, and grain quality of C3 cereals: A meta-analysis of [CO2], temperature, and drought effects. *Plants*, 10(6), 1052.
20. Benfratello, L. (2024). Random effects regression for panel data. In *Encyclopedia of quality of life and well-being research* (pp. 5811-5813). Cham: Springer International Publishing.
21. Bezner Kerr, R., Hasegawa, T., Lasco, R. D., Bhatt, l., Deryng, D., Farrell, A., & Tschakert, P. (2023). *Climate change and agriculture: Impacts, adaptation and mitigation*. In Climate Change 2023: Synthesis Report. Contribution of Working Groups I, Il and Ill to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 85-86). PCC. https://www.ipcc.ch/report/sixth-assessment-report-cycle/
22. Bocean, C. G. (2024). A cross-sectional analysis of the relationship between digital technology use and agricultural productivity in EU countries. *Agriculture*, *14*(4), 519.
23. Butler, E. E., & Huybers, P. (2013). Adaptation of US maize to temperature variations. *Nature Climate Change*, *3*(1), 68-72.
24. Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P. W., Trisos, C., & Hauser, M. (2023). IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland. (No Title).
25. Chandio, A. A., Yu, B., Noor, S., Magsi, H., Ali, A., & Ahmad, F. (2022). Impact of Climate Change on Cereal Crops Production in Ethiopia. *Journal of Functionally Graded Materials*, *2022*, 2208694
26. Change, C. (2016). Agriculture and Food Security. *The State of Food and Agriculture; FAO (Ed.) FAO: Rome, Italy*.
27. Chaplin-Kramer, R., Chappell, M. J., & Bennett, E. M. (2023). Un-yielding: Evidence for the agriculture transformation we need. *Annals of the New York Academy of Sciences*, *1520*(1), 89-104.
28. Chebrolu, K. K., Fritschi, F. B., Ye, S., Krishnan, H. B., Smith, J. R., & Gillman, J. D. (2016). Impact of heat stress during seed development on soybean seed metabolome. *Metabolomics*, *12*(2), 28.
29. Chen, X. (2025). The role of modern agricultural technologies in improving agricultural productivity and land use efficiency. *Frontiers in Plant Science*, *16*, 1675657.
30. Coakley, J., Fuertes, A. M., & Smith, R. (2006). Unobserved heterogeneity in panel time series models. *Computational Statistics & Data Analysis*, *50*(9), 2361-2380.
31. Cobb, C. W., & Douglas, P. H. (1928). A theory of production. *The American economic review*, 18(1), 139-165.
32. Colussi, J., Paulson, N., Schnitkey, G., & Cabrini, S. (2023). Record in Brazil, Drop in Argentina: Contrasting Soybean Harvests in South America. *farmdoc daily*, 13(59).
33. Colussi, J., Schnitkey, G., Paulson, N., & Coppess, J. (2025). Brazil and China's strong ag relationship: Opportunity or overdependence? farmdoc daily (15):85. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

https://farmdocdaily.illinois.edu/2025/05/brazil-and-chinas-strong-ag-relationship-opportunity-or-overdependence.html
34. Cuevas, J., Daliakopoulos, I. N., del Moral, F., Hueso, J. J., & Tsanis, I. K. (2019). A review of soil-improving cropping systems for soil salinization. *Agronomy*, 9(6), 295.
35. Das, B. S., Wani, S. P., Benbi, D. K., Muddu, S., Bhattacharyya, T., Mandal, B., Santra, P., Chakraborty, D., Bhattacharyya, R., Basak, N., & Reddy, N. N. (2022). Soil health and its relationship with food security and human health to meet the sustainable development goals in India. Soil Security, 8, 100071. https://doi.org/10.1016/j.soisec.2022.100071
36. De Corato, U., Viola, E., Keswani, C., & Minkina, T. (2024). Impact of the sustainable agricultural practices for governing soil health from the perspective of a rising agri-based circular bioeconomy. *Applied Soil Ecology*, *194*, 105199.
37. de la Cruz, V. Y. V., Tantriani, Cheng, W., & Tawaraya, K. (2023). Yield gap between organic and conventional farming systems across climate types and sub-types: A meta-analysis. Agricultural Systems, 211, 103732. https://doi.org/10.1016/j.agsy.2023.103732
38. de LT Oliveira, G., & Hecht, S. B. (2017). Sacred groves, sacrifice zones and soy production: globalization, intensification and neo-nature in South America. In *Soy, Globalization, and Environmental Politics in South America* (pp. 1-35). Routledge.
39. De Pascale, S., Dalla Costa, L., Vallone, S., Barbieri, G., & Maggio, A. (2011). Increasing water use efficiency in vegetable crop production: from plant to irrigation systems efficiency. *HortTechnology*, 21(3), 301-308.
40. Deng, Y., & Zeng, F. (2023). Sustainable path of food security in China under the background of green agricultural development. *Sustainability*, *15*(3), 2538.
41. Dhillon, R., Das, S., Shedekar, V. S., & Sharma, V. (2025). Assessing the impact of soil water deficit and supplemental irrigation scenarios on Ohio's maize and soybean yields using machine learning models. *Agricultural Water Management*, *320*, 109834.
42. Dohlman, E., Hansen, J., Chambers, W., & Interagency Agricultural Projections Committee. (2025). USDA Agricultural Projections to 2034.
43. Dreoni, I., Matthews, Z., & Schaafsma, M. (2022). The impacts of soy production on multi-dimensional wellbeing and ecosystem services: A systematic review. Journal of Cleaner Production, 335, 130182. https://doi.org/10.1016/j.jclepro.2021.130182
44. Erenstein, O., Jaleta, M., Mottaleb, K. A., Sonder, K., Donovan, J., & Braun, H. J. (2022). Global trends in wheat production, consumption and trade. In *Wheat improvement: food security in a changing climate* (pp. 47-66). Cham: Springer International Publishing.
45. FAO & UNICEF. (2020). WFP and WHO. 2020. *The state of food security and nutrition in the world*, 619.
46. FAO. (2017). The future of food and agriculture - Trends and challenges. Rome.
47. FAO. (2018). The future of food and agriculture – Alternative pathways to 2050. Rome. 224 pp. Licence: CC BY-NC-SA 3.0 IGO.
48. FAO. (2021). The State of Food and Agriculture 2021: Making agrifood systems more resilient to shocks and stresses. FAO. https://doi.org/10.4060/cb4476en
49. FAO. (2023a). The state of food security and nutrition in the world 2023: Urbanization, agrifood systems transformation and healthy diets across the rural-urban continuum. Agriculture Organization of the United Nations: Rome, Italy.
50. FAO. (2023b). The State of Food and Agriculture 2023: Leveraging innovation to drive sustainable productivity growth. Food and Agriculture Organization of the United Nations.
51. FAO. (2023c). World Food and Agriculture -Statistical Yearbook 2023. Rome. https://doi.org/10.4060/cc8166en
52. FAO. (2025). FAO Cereal Supply and Demand Brief. Food and Agriculture Organization of the United Nations. Retrieved from https://www.fao.org/worldfoodsituation/csdb/en
53. Fei, C., Jägermeyr, J., McCarl, B., Mencos Contreras, E., Mutter, C., Phillips, M., Ruane, A. C., Sarofim, M. C., Schultz, P., & Vargo, A. (2023). Future climate change impacts on U.S. agricultural yields, production, and market. Anthropocene, 42, 100386. https://doi.org/10.1016/j.ancene.2023.100386

54. Fernández-Val, I., & Weidner, M. (2018). Fixed effects estimation of large-T panel data models. *Annual Review of Economics*, 10(1), 109-138.
55. FieldBee. (2022). Measuring agricultural productivity on a farm. https://www.fieldbee.com/blog/measuring-agricultural-productivity-on-a-farm
56. Fontes, F., Gorst, A., & Palmer, C. (2021). Threshold effects of extreme weather events on cereal yields in India. *Climatic Change*, 16*5*(1), 26.
57. Fukase, E., & Martin, W. (2020). Economic growth, convergence, and world food demand and supply. World Development, 132, 104954. https://doi.org/10.1016/j.worlddev.2020.104954
58. Fusco, G., Campobasso, F., Laureti, L., Frittelli, M., Valente, D., & Petrosillo, I. (2023). The environmental impact of agriculture: An instrument to support public policy. *Ecological Indicators*, *147*, 109961.
59. Gagné, G., Lorenzetti, F., Cogliastro, A., & Rivest, D. (2022). Soybean performance under moisture limitation in a temperate tree-based intercropping system. *Agricultural Systems*, *201*, 103460.
60. Gangana Gowdra, V. M., Lalitha, B. S., Halli, H. M., Senthamil, E., Negi, P., Jayadeva, H. M., & Reddy, K. S. (2025). Root growth, yield and stress tolerance of soybean to transient waterlogging under different climatic regimes. *Scientific Reports*, *15*(1), 6968.
61. Gautam, T. K., Paudel, K. P., & Guidry, K. M. (2024). Determinants of irrigation technology adoption and acreage allocation in crop production in Louisiana, USA. *Water*, 16(3), 392.
62. Good, A. G., & Beatty, P. H. (2011). Fertilizing nature: a tragedy of excess in the commons. *PLoS biology*, 9(8), e1001124.
63. Graña-Colella, S., & Silva Neira, I. (2024). *Export manufacture competitiveness and commodity dependence: An empirical analysis of the Dutch Disease on Argentina and Chile during the commodity price boom* (No. 232-2024). Working Paper.
64. Hamada, K. (2025). Crop Yield per Hectare/Acre – Insights. https://khalidhamada.com/crop-yield-per-hectare-acre/
65. Hamed, R., Van Loon, A. F., Aerts, J., & Coumou, D. (2021). Impacts of compound hot-dry extremes on US soybean yields. *Earth System Dynamics*, 12(4), 1371-1391.
66. Hannah Ritchie, P. R., & Max R. (2022). “Crop Yields” Published online at OurWorldinData.org. Retrieved from: 'https://ourworldindata.org/crop-yields' [Online Resource]
67. Herrero, M., Thornton, P. K., Mason-D’Croz, D., Palmer, J., Benton, T. G., Bodirsky, B. L., & West, P. C. (2020). Innovation can accelerate the transition towards a sustainable food system. Nature Food, 1(5), 266-272.
68. Hill, T. D., Davis, A. P., Roos, J. M., & French, M. T. (2020). Limitations of fixed-effects models for panel data. *Sociological Perspectives*, 63(3), 357-369.
69. Hsiao, C. (2022). Analysis of panel data (No. 64). Cambridge university press.
70. Hua, W., Luo, P., An, N., Cai, F., Zhang, S., Chen, K., & Han, X. (2020). Manure application increased crop yields by promoting nitrogen use efficiency in the soils of 40-year soybean-maize rotation. *Scientific reports*, 10(1), 14882.
71. Ibrahim, F. D., Ibrahim, P. A., Odine, A. I., Jirgi, A. J., Usman, R. K., Ogaji, A., & Gbanguba, A. U. (2016). Impact of Climate Change on Soyabean Production in Lapai Local Government Niger State, Nigeria.
72. IFPRI. (2024). The 2024 Global food policy report: Food Systems for Healthy Diets and Nutrition. International Food Policy Research Institute.
73. Iizumi, T., Yokozawa, M., Sakurai, G., Travasso, M. I., Romanenkov, V., Oettli, P., & Furuya, J. (2014). Historical changes in global yields: major cereal and legume crops from 1982 to 2006. *Global ecology and biogeography*, *23*(3), 346-357.
74. IMF. (2024). World Economic Outlook: Steady but slow, amid divergence. Washington, DC: International Monetary Fund.
75. Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., & Wheeler, T. R. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. Agricultural Systems, 155, 269-288. https://doi.org/10.1016/j.agsy.2016.09.021

76. Kaplinsky, R., & Kraemer-Mbula, E. (2022). Innovation and uneven development: The challenge for low- and middle-income economies. Research Policy, 51(2), 104394. https://doi.org/10.1016/j.respol.2021.104394
77. Khan, B. A., Nadeem, M. A., Nawaz, H., Amin, M. M., Abbasi, G. H., Nadeem, M., & Ayub, M. A. (2023). Pesticides: impacts on agriculture productivity, environment, and management strategies. In *Emerging contaminants and plants: Interactions, adaptations and remediation technologies* (pp. 109-134). Cham: Springer International Publishing.
78. Khan, Z., Ahmad, B., Khan, M. N., Khan, M. A., Ahmad, S., Baloch, A., & Rahim, H. U. (2022). Stand Establishment, Growth, and Yield Enhancement Response of Soybean to Inoculation and NPK Compound and Organic Fertilizers. *Gesunde Pflanzen,* 74(1), 1123-1135.
79. Kostić, M. M., Tagarakis, A. C., Ljubičić, N., Blagojević, D., Radulović, M., Ivošević, B., & Rakić, D. (2021). The effect of N fertilizer application timing on wheat yield on chernozem soil. *Agronomy*, 11(7), 1413.
80. Kvartiuk, V., Petrick, M., Bavorova, M., Bednaříková, Z., & Ponkina, E. (2020). A brain drain in Russian agriculture? Migration sentiments among skilled Russian rural youth. *Europe-Asia Studies*, 72(8), 1352-1377.
81. Langemeier, M. (2024). International Benchmarks for Soybean Production. *farmdoc daily*, 14(43).
82. Lauvsnes, S. O., & Ingulfsvann, A. S. (2023). Dutch disease and agriculture in Norway revisited: The oil price, food imports, resource and sustainability nexus. *Journal of Cleaner Production*, *425*, 138934.
83. Liu, L., Wang, Y., & Xu, Y. (2024). A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. *American Journal of Political Science*, *68*(1), 160-176.
84. Liu, Y., Pan, X., & Li, J. (2015). A 1961-2010 record of fertilizer use, pesticide application and cereal yields: a review. *Agronomy for sustainable development*, 35, 83-93.
85. Lobell, D. B., & Gourdji, S. M. (2012). The influence of climate change on global crop productivity. *Plant physiology*, *160*(4), 1686-1697.
86. Machado, R. M. A., & Serralheiro, R. P. (2017). Soil salinity: effect on vegetable crop growth. Management practices to prevent and mitigate soil salinization. *Horticulturae*, 3(2), 30.
87. Mahboob, W., Yang, G., & Irfan, M. (2023). Crop nitrogen (N) utilization mechanism and strategies to improve N use efficiency. *Acta Physiologiae Plantarum*, 45(4), 52.
88. Malec, K., Rojík, S., Maitah, M., Abdu, M., & Abdullahi, K. T. (2024). Impact of investments in agricultural innovation on food security in sub-Saharan Africa. *Heliyon, 10(16)*, e35913. https://doi.org/10.1016/j.heliyon.2024.e35913
89. May, D., Arancibia, S., Behrendt, K., & Adams, J. (2019). Preventing young farmers from leaving the farm: Investigating the effectiveness of the young farmer payment using a behavioural approach. *Land use policy*, 82, 317-327.
90. Millimet, D., & Bellemare, M. F. (2023). Fixed effects and causal inference.
91. Mohammadi, S., Rydgren, K., Bakkestuen, V., & Gillespie, M. A. (2023). Impacts of recent climate change on crop yield can depend on local conditions in climatically diverse regions of Norway. *Scientific Reports*, *13*(1), 3633.
92. Morales, F., Ancín, M., Fakhet, D., González-Torralba, J., Gámez, A. L., Seminario, A., & Aranjuelo, I. (2020). Photosynthetic metabolism under stressful growth conditions as a basis for crop breeding and yield improvement. *Plants*, 9(1), 88.
93. Movilla-Pateiro, L., Mahou-Lago, X. M., Doval, M. I., & Simal-Gandara, J. (2021). Toward a sustainable metric and indicators for the goal of sustainability in agricultural and food production. *Critical Reviews in Food Science and Nutrition*, *61*(7), 1108-1129.
94. Mughal, M., & Fontan Sers, C. (2020). Cereal production, undernourishment, and food insecurity in South Asia. *Review of Development Economics*, 24(2), 524-545.
95. Ndidiamaka, E. V., Durokifa, A., Obi, V. Y. M., Ukeje, I. O., & Arinze, A. I. (2025). A multidimensional framework for sustainable agriculture: Integrating human capital, stakeholder dynamics, and governance to overcome policy barriers in achieving sdgs. *Journal of Law and Sustainable Development*, *13*(4), e04312-e04312.

96. Neupane, D., Adhikari, P., Bhattarai, D., Rana, B., Ahmed, Z., Sharma, U., & Adhikari, D. (2022). Does climate change affect the yield of the top three cereals and food security in the world? *Earth*, 3(1), 45-71.
97. Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: implications for climate change damages. *Journal of Environmental Economics and Management*, *108*, 102445.
98. Nikolskii, Y., & Aidarov, I. (2023). Over-Irrigation and Adverse Effects. In *Handbook of Irrigation Hydrology and Management* (pp. 389-404). CRC Press.
99. Nin-Pratt, A. (2021). Agricultural R&D investment intensity: A misleading conventional measure and a new intensity index. Agricultural Economics, 52, 317-328. https://doi.org/10.1111/agec.12620
100. Nolte, K., & Ostermeier, M. (2017). Labour market effects of large-scale agricultural investment: Conceptual considerations and estimated employment effects. World Development, 98, 430-446. https:// doi.org/10.1016/j.worlddev. 2017.05.012
101. Ntiamoah, E. B., Li, D., Appiah-Otoo, I., Twumasi, M. A., & Yeboah, E. N. (2022). Towards a sustainable food production: modelling the impacts of climate change on maize and soybean production in Ghana. *Environmental Science and Pollution Research*, *29*(48), 72777-72796.
102. Obeid, R. (2025). A Novel Hybrid Approach to Hausman's Specification Test for Fixed vs. Random Effects in Panel Data Models. *Random Effects in Panel Data Models*
103. OECD/FAO. (2021). OECD-FAO Agricultural Outlook 2021-2030. OECD Publishing, Paris. https://doi.org/10.1787/19428846-en
104. OECD/FAO. (2024). OECD-FAO Agricultural Outlook 2024-2033.
105. Oli, D., Gyawali, B., Acharya, S., & Oshikoya, S. (2025). Factors influencing learning attitude of farmers regarding adoption of farming technologies in farms of Kentucky, USA. *Smart Agricultural Technology, 10*, 100801. https://doi.org/10.1016/j.atech.2025.100801
106. Pagano, M. C., & Miransari, M. (2016). The importance of soybean production worldwide. In *Abiotic and biotic stresses in soybean production* (pp. 1-26). Academic Press.
107. Pekane, Z. T. (2018). *Migration and brain drain in secondary cities: A case study of the Madibeng Municipality* (Doctoral dissertation, Stellenbosch: Stellenbosch University).
108. Perry, E. D., Ciliberto, F., Hennessy, D. A., & Moschini, G. (2016). Genetically engineered crops and pesticide use in US maize and soybeans. *Science advances*, 2(8), e1600850.
109. Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric reviews*, *34*(6-10), 1089-1117.Peshin, R., & Zhang, W. (2014). *Integrated pest management and pesticide use* (pp. 1-46). Springer Netherlands.
110. Peterson, C. A., Pittelkow, C. M., & Lundy, M. E. (2023). Targeted irrigation expands scope for winter cereal production in water-limited areas of California's San Joaquin Valley. *Agricultural Systems*, *210*, 103696.
111. Priyadharshini, M. P., & Babu, S. (2023). Sub-Surface Drainage System for Management of Waterlogged Saline Soils. *Emerging Trends in Agriculture and Allied sciences*, 44.
112. Qiao, C., Cheng, C., & Ali, T. (2023). How climate change and international trade will shape the future global soybean security pattern. *Journal of Cleaner Production*, 422, 138603.
113. Qin, M., Zheng, E., Hou, D., Meng, X., Meng, F., Gao, Y., & Xu, T. (2023). Response of wheat, maize, and rice to changes in temperature, precipitation, CO2 concentration, and uncertainty based on crop simulation approaches. *Plants*, *12*(14), 2709.
114. Qin, Y., & Al Amin, M. (2022). Panel data using R: Fixed-effects and Random-effects. *Princeton University. Retrieved February*, *1*, 2023.
115. Quan, T., Zhang, H., Quan, T., & Yu, Y. (2024). Unveiling the impact and mechanism of digital technology on agricultural economic resilience. Chinese Journal of Population, Resources and Environment, 22(2), 136-145. https://doi.org/10.1016/j.cjpre.2024.06.004
116. Rada, N. E., & Fuglie, K. O. (2019). New perspectives on farm size and productivity. *Food Policy*, *84*, 147-152.
117. Raji, E., ljomah, T., & Eyieyien, O. (2024). Improving agricultural practices and productivity through extension services and innovative training programs. International Journal of Applied Research in Social Sciences, 6, 1297-1309. https://doi.org/10.51594/ijarss.v6i7.1267
118. Ray, D. K., Sloat, L. L., Garcia, A. S., Davis, K. F., Ali, T., & Xie, W. (2022). Crop harvests for direct food use insufficient to meet the UN's food security goal. *Nature Food*, *3*(5), 367-374.

119. Ruane, J., & Ramasamy, S. (2023). Global investments in agricultural research: Where are we and where are we going? Rome: Food and Agriculture Organization of the United Nations. https://openknowledge.fao.org/server/api/core/bitstreams/64cdae9c-d160-4809-8c6a-62f94d48b6f6/content
120. Rubayet, M. T., & Hossain, M. M. (2024). Climate Change and Its Impacts on Disease Dynamics in Major Cereal Crops. In *Climate Change and Soil-Water-Plant Nexus: Agriculture and Environment* (pp. 265-295). Singapore: Springer Nature Singapore.
121. Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development, 146*,105599. https://doi.org/10.1016/j.worlddev.2021.105599
122. Sam, A. S., Abbas, A., Padmaja, S. S., Sathyan, A. R., Vijayan, D., Kächele, H., & Müller, K. (2021). Flood vulnerability and food security in eastern India: A threat to the achievement of the Sustainable Development Goals. *International journal of disaster risk reduction*, 66, 102589.
123. Sanyaolu, M., & Sadowski, A. (2024). The role of precision agriculture technologies in enhancing sustainable agriculture. *Sustainability*, *16*(15), 6668.
124. Sarma, P., & Rahman, M. (2020). Impact of government agricultural input subsidy card on rice productivity in rajbari district of Bangladesh: application of endogenous switching regression model. *Agricultural Research*, 8(5), 131-145.
125. Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), 15594-15598.
126. Sedibe, M. M., Mofokeng, A. M., & Masvodza, D. R. (2023). Soybean production, constraints, and future prospects in poorer countries: a review. *Production and Utilization of Legumes-Progress and Prospects*.
127. Şen, A., Akpolat, A. G., & Balkan, İ. (2024). Commodity prices and economic growth: Empirical evidence from countries with different income groups. *Heliyon*, *10*(13). e34038. https://doi.org/10.1016/J.heliyon.2024.e34038
128. Shaner, W. W. (2019). *Farming systems research and development: guidelines for developing countries*. Routledge.
129. Shen, Y., Guo, Q., Liu, Z., Shen, Y., Jia, Y., & Wei, Y. (2025). Prediction of drought-flood prone zones in inland mountainous regions under climate change with assessment and enhancement strategies for disaster resilience in high-standard farmland. *Agricultural Water Management*, *309*(C).
130. Siamabele, B. (2021). The significance of soybean production in the face of changing climates in Africa. *Cogent Food & Agriculture*, 7(1), 1933745.
131. Silva, J. C. F., de Godoy Machado, K. L., de Souza Silva, A. F., Dias, R., Bodnar, V. R., Vieira, W. O., & Costa, L. C. (2025). Challenges and Opportunities for New Frontiers and Technologies to Guarantee Food Production: A Broad Systematic Perspective.
132. Skevas, T., & Lansink, A. O. (2014). Reducing pesticide use and pesticide impact by productivity growth: the case of Dutch arable farming. *Journal of agricultural economics*, *65*(1), 191-211.
133. Tamagno, S., Maaz, T. M., van Kessel, C., Linquist, B. A., Ladha, J. K., Lundy, M. E., & Pittelkow, C. M. (2024). Critical assessment of nitrogen use efficiency indicators: Bridging new and old paradigms to improve sustainable nitrogen management. *European Journal of Agronomy*, 159, 127231.
134. Terefe, A. T., Aredo, M. K., Workagegnehu, A. M., & Tesfaye, W. M. (2024). Effect of climate shocks on rural household welfare dynamics in Ethiopia: evidence from panel data. *Cogent Food & Agriculture*, *10*(1), 2356936.
135. Thomasz, E. O., Pérez-Franco, I., & Garcia-Garcia, A. (2024). Assessing the impact of climate change on soybean production in Argentina. Climate Services, 34, 100458. https://doi.org/10.1016/j.cliser.2024.100458
136. Tovilode, A. J., & Moon, W. (2025). Impact of Institutional Quality and Research and Development (R&D) on Agricultural Productivity in Low-and Middle-Income Countries. Journal of Economic Analysis, 4(2), 36-53. https://doi.org/10.58567/jea04020003

137. Tsekhmeistruk, M., Pankova, O., Kolomatska, V., Kobyzieva, L., Artiomov, M., & Sirovitskiy, K. (2021). Influence of weather and climatic conditions on soybean yield. *Ukrainian Journal of Ecology*, *11*(4), 11-17.
138. Tudi, M., Daniel Ruan, H., Wang, L., Lyu, J., Sadler, R., Connell, D., & Phung, D. T. (2021). Agriculture development, pesticide application and its impact on the environment. *International journal of environmental research and public health*, 18(3), 1112.
139. Tudor, V. C., Stoicea, P., Chiurciu, I. A., Soare, E., Iorga, A. M., Dinu, T. A., & Dumitru, E. A. (2023). The use of fertilizers and pesticides in wheat production in the main European Countries. *Sustainability*, 15(4), 3038.
140. UN. (2022). World population Prospects 2022: Highlights. Department of Economic and Social Affairs, Population Division. Retrieved from https://www.un.org/development/desa/publications/world-population-prospects-2022-highlights.html
141. USDA. (2023). Top soybeans producing countries. USDA Foreign Agricultural Services. Retrieved from https://fas.usda.gov/data/production/commodity/2222000
142. USDA. (2025). Russia wheat: General review (Commodity Intelligence Report). https://ipad.fas.usda.gov/highlights/2025/09/Russia/index.pdf
143. Valdes, C., Gillespie, J., & Dohlman, E. (2023). *Soybean production, marketing costs, and export competitiveness in Brazil and the United States* (Report No. EIB-262). U.S. Department of Agriculture, Economic Research Service.
144. Volkova, E., & Smolyaninova, N. (2024). Analysis of world trends in soybean production. In *BIO Web of Conferences* (Vol. 141, p. 01026). EDP Sciences.
145. Voora, V., Larrea, C., & Bermudez, S. (2020). Global market report: soybeans.
146. Wang, H., Guohui, S., Zizhong, S., & Xiangdong, H. (2023). Effects of climate and price on soybean production: Empirical analysis based on panel data of 116 prefecture-level Chinese cities. *PLoS One*, *18*(3), e0273887.
147. West, T. O., & Marland, G. (2002). A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: comparing tillage practices in the United States. *Agriculture, Ecosystems & Environment*, 91(1-3), 217-232.
148. WHO. (2024). Hunger numbers stubbornly high for three consecutive years as global crises deepen: UN report. Joint News Report, 24.
149. Wooldridge, J. M. (2016). *Introductory econometrics a modern approach*. South-Western cengage learning.
150. World Bank. (2025). Food Security Update: Latest Food Security Data. World Bank Group. Retrieved May 19, 2025, from https://www.worldbank.org/en/topic/agriculture/brief/ food-security-update.
151. Wu, F., Geng, Y., Zhang, Y., Ji, C., Chen, Y., Sun, L., & Fujita, T. (2020). Assessing sustainability of soybean supply in China: Evidence from provincial production and trade data. *Journal of Cleaner Production*, *244*, 119006.
152. Yadav, F. A., Farooq, G. M., & Fujimori, S. H. (2023). CLIMATE CHANGE AND FOOD PRODUCTION; A CASE STUDY OF SOYBEAN PRODUCTION IN BRAZIL. *African Journal of Emerging Issues*, 5(14), 1-12.
153. Yoganandham, G. (2024). Reforming India's Agricultural Sector: Enhancing Sustainability, Market Access, And Economic Growth Through Policy Innovations, Technology and Strategic Investments-A Theoretical Assessment. *Degrés*, *9*(12).
154. Yokamo, S., Jiao, X., Jasper, K., Gurmu, F., Jahan, M. S., & Jiang, R. (2022). Grain yield and nitrogen use efficiency vary with cereal crop type and nitrogen fertilizer rate in Ethiopia: A meta-analysis. *Agricultural Sciences*, 13(4), 612-631.
155. Yuan, S., Linquist, B. A., Wilson, L. T., Cassman, K. G., Stuart, A. M., Pede, V., Miro, B., Saito, K., Agustiani, N., Aristya, V. E., Krisnadi, L. Y., Zanon, A. J., Heinemann, A. B., Carracelas, G., Subash, N., Brahmanand, P. S., Li, T., Peng, S., & Grassini, P. (2021). Sustainable intensification for a larger global rice bowl. Nature Communications, 12, Article 7163. https://doi.org/10.1038/ S41467-021-27424-z
156. Yuan, X., Li, S., Chen, J., Yu, H., Yang, T., Wang, C., & Ao, X. (2024). Impacts of global climate change on agricultural production: a comprehensive review. *Agronomy*, 14(7), 1360.

157. Zeeshan, M., Lu, M., Sehar, S., Holford, P., & Wu, F. (2020). Comparison of biochemical, anatomical, morphological, and physiological responses to salinity stress in wheat and barley genotypes deferring in salinity tolerance. *Agronomy*, 10(1), 127.
158. Zhang, Y., Long, H., Chen, S., Ma, L., & Gan, M. (2023). The development of multifunctional agriculture in farming regions of China: Convergence or divergence? *Land Use Policy*, *127*, 106576.
159. Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., & Asseng, S. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of sciences*, 114(35), 9326-9331.
160. Zhao, J., Wang, Y., Zhao, M., Rodriguez, D., de Voil, P., Tan, Z., & Chu, Q. (2025). Anticipated changes in soybean drought stress and yield stability under future climates in Northeast China. *npj Sustainable Agriculture*, *3*(1), 14.
161. Zuber, M., Kalauni, N., Shrestha, N., Pandey, V. P., & Pokharel, B. (2025). Cereal yield and water requirements in response to irrigation and soil fertility management in a changing climate: a case of Tulsipur, Western Nepal. *Journal of Water and Climate Change*, *16*(3), 837-859.