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Beyond the Farm Gate: Drivers of Farm Labor Productivity in BRICS+ Agrifood Systems

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Abstract. Agriculture still employs large shares of the workforce in many BRICS and BRICS-aligned economies, yet output per worker remains uneven across countries. This paper examines the drivers of farm labor productivity in ten BRICS+ members, namely Brazil, Russia, India, China, South Africa, Egypt, Ethiopia, Indonesia, Iran, and the United Arab Emirates, using a balanced panel for 2001–2021. Drawing on data from the World Development Indicators, FAOSTAT, and UNDP, we estimate country fixed-effects models of agricultural value added per worker on lagged human development (HDI or schooling), arable land per worker, fertilizer use per hectare, national income (GNI per capita), and a time trend. The results show that higher HDI and greater land availability per agricultural worker are robustly associated with substantial productivity gains, whereas fertilizer intensity has no stable independent effect, and the influence of income largely operates through human development. A strong positive time trend suggests additional technological and institutional progress. Policy priorities should therefore combine investments in human development, land and tenure reforms, and innovation systems to foster inclusive productivity growth in BRICS+ agrifood systems.

1 Introduction

Agriculture still employs a large share of the workforce in many emerging economies, yet its contribution to Gross Domestic Product (GDP) is relatively small, indicating sizeable gaps in labor productivity. This pattern is clearly visible in the BRICS and newly acceded BRICS+ economies, where agriculture remains central for food security, export revenues, and rural livelihoods, even as these countries undergo rapid structural transformation and urbanization. BRICS+ is an intergovernmental grouping of major emerging economies - Brazil, Russia, India, China, South Africa, Egypt, Ethiopia, Indonesia, Iran, and the United Arab Emirates - that cooperate to strengthen their political and economic influence and give the Global South a stronger voice in world affairs [1]. Understanding what drives farm labor productivity, which is typically measured as agricultural value added per worker, is therefore crucial for

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designing policies that support inclusive growth, rural poverty alleviation, and progress towards the Sustainable Development Goals [2].

Within the BRICS+ bloc, farm labor productivity differs markedly across countries. Some members have achieved substantial gains through mechanisation, modern input use, and integration into domestic and global value chains, while others continue to struggle with low on-farm productivity and stagnant rural incomes [3,4]. Cross-country evidence shows that labor productivity gaps are huge in agriculture, and that differences in skills, capital intensity, and patterns of structural change help explain why some economies move out of low-productivity agriculture more quickly than others [5,6]. However, existing studies seldom examine these issues systematically for the BRICS+ group as a coherent bloc, despite its growing weight in global agrifood systems. Moreover, most empirical work either focuses on single countries or broad developing-country samples and rarely combines farm-level productivity with indicators such as average schooling, land endowments per worker, input intensity, overall income levels, and broader human development in one comparative framework. Panel-data analyses that track how changes in these structural and human-development factors over time shape farm labor productivity across BRICS+ economies remain limited. In this context, the BRICS+ countries constitute a relevant group of large emerging economies in which productivity gaps in agriculture coexist with rapid changes in income, infrastructure, and agrifood systems [7]. By addressing these gaps, this study provides new evidence on how education, access to land, fertilizer use, national income, and human development jointly influence farm labor productivity in BRICS+ agrifood systems.

This study focuses on four determinants that empirical literature consistently links to differences in farm labour productivity across countries. First, human capital, as captured by indicators such as the Human Development Index (HDI) or years of schooling, matters because more educated and healthier farmers are better able to process information, adopt new technologies, and manage risk, with cross-country analyses showing sizable productivity gains per additional year of schooling [8,9]. Second, input intensity, including the use of fertiliser, improved seed, irrigation, and machinery, raises output per worker when inputs are used efficiently, and recent work attributes a growing share of global agricultural productivity growth to such input deepening and total factor productivity improvements rather than to area expansion [10]. Third, land per capita reflects demographic pressure and the possibility of operating economically viable farm sizes: evidence from China and other settings shows that declining land per person and fragmented holdings can constrain mechanisation and investment, whereas well-functioning land rental and consolidation arrangements enhance productivity and facilitate structural transformation [11,12]. Finally, income level, proxied by Gross National Income (GNI) per capita, shapes the broader environment for agricultural growth, since higher incomes are typically associated with better infrastructure, deeper financial and input markets, and greater public and private investment in rural services; panel studies for BRICS and other emerging economies find that per capita income, financial development, and trade openness are positively related to agricultural output and productivity[13]. These four channels are operationalised in our empirical analysis through indicators of schooling, HDI, fertiliser use per hectare, arable land per agricultural worker, and GNI per capita for BRICS+ countries.

2 Methods

2.1 Data and study area

This study analyses agricultural labour productivity in ten BRICS+ member countries: the United Arab Emirates, Brazil, China, Egypt, Ethiopia, Indonesia, India, Iran, Russia, and

South Africa. The period of analysis is 2001–2021, yielding an annual panel of 10 countries over 21 years (balanced panel). Agricultural value added and agricultural employment are taken from the World Development Indicators (WDI). Agricultural value added is expressed in constant US dollars, and agricultural employment refers to the number of workers whose primary employment is in agriculture, forestry, and fishing. Agricultural land (in hectares) and arable land are obtained from FAOSTAT/WDI. Fertilizer consumption (tonnes of nutrients) is taken from FAOSTAT and divided by arable land to obtain fertilizer use per hectare. The HDI is taken from the UNDP Human Development Reports and combines information on income, education, and health. GNI per capita (constant US dollars) is taken from WDI. From these series, we construct the following variables:

a. Agricultural labor productivity

$$agprod_{it} = \frac{\text{agricultural value added}_{\text{it}}}{\text{agricultural employment}_{\text{it}}} \tag{1}$$

and use its natural logarithm, $\ln agprod_{it}$, as the dependent variable.

b. Land-labor ratio

$$arlandcap_{it} = \frac{\text{arable land}_{\text{it}}}{\text{agricultural employment}_{\text{it}}} \tag{2}$$

with $\ln arlandcap_{it}$ capturing the amount of arable land available per agricultural worker.

c. Fertilizer intensity

$$fercon_{it} = \frac{\text{fertilizer consumption}_{\text{it}}}{\text{arable land}_{\text{it}}} \tag{3}$$

again used in natural logarithm, $\ln fercon_{it}$.

d. Human development: $\ln hdi_{it}$ is the natural logarithm of the HDI.

e. National income: $\ln gnicap_{it}$ is the logarithm of GNI per capita and is used in some specifications as a control for broad macroeconomic development.

A linear time trend t (set equal to year–2000) is included in some models to capture global technological progress and other common time shocks that affect all countries simultaneously.

2.2 Empirical model

We are interested in how changes in human development and structural factors relate to changes in agricultural labour productivity over time within countries. The preferred empirical specification is a log-linear fixed-effects model with one-year lags of the explanatory variables:

$$\begin{aligned} lnagprod_{it} = \alpha_i + \lambda_t + \beta_1 lnhdi_{i,t-1} + \beta_2 lnarlandcap_{i,t-1} \\ + \beta_3 lnfercon_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{4}$$

where i indexes country and t years. α_i are country fixed effects that capture all time-invariant country characteristics, such as agro-ecological conditions, historical institutions, and long-run policies. λ_t is a linear time trend capturing common global changes over time.

β_1 measures the elasticity of agricultural labour productivity with respect to lagged HDI; β_2 the elasticity with respect to the land–labour ratio; and β_3 the elasticity with respect to fertilizer intensity. Since the dependent variable and regressors are in logarithms, coefficients can be interpreted as elasticities: for example, β_1 is the approximate percentage change in agricultural labour productivity associated with a 1 percent change in lagged HDI.

To check robustness, we also estimate alternative specifications:

1. A model without the time trend:

$$\begin{aligned} lnagprod_{it} = \alpha_i + \beta_1 lnhdi_{i,t-1} + \beta_2 lnarlandcap_{i,t-1} \\ +\beta_3 lnfercon_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{5}$$

2. Models that use average years of schooling instead of HDI and include ln $gnicap_{i,t-1}$ as an additional regressor. These specifications allow us to compare the role of education alone with that of the broader HDI measure and to assess whether HDI subsumes the information contained in GNI per capita.

2.3 Estimation strategy

We estimate all models using country fixed-effects (within) estimators. Fixed effects are preferred over random effects because it is highly plausible that unobserved country characteristics—such as institutions, land tenure systems, or long-standing agricultural policies—are correlated with human development, land–labour ratios, and national income. Treating these unobservables as fixed and allowing correlation with the regressors yields consistent estimates of the within-country effects of interest.

A one-year lag of the explanatory variables is used for two reasons. First, it reflects a more realistic adjustment process: changes in human development, land per worker, or fertilizer use are unlikely to affect labour productivity instantaneously, but rather with a short delay. Second, lagging regressors help to mitigate concerns about simultaneity and reverse causality. For example, higher productivity in year t cannot directly influence HDI, land–labour ratios, or fertilizer intensity in year $t-1$. Nevertheless, the results should still be interpreted as conditional associations rather than as fully causal effects, as deeper sources of endogeneity (e.g., policy reforms responding to productivity performance) cannot be completely ruled out.

All models are estimated with robust standard errors clustered at the country level, allowing for arbitrary heteroskedasticity and serial correlation within countries over time. With only ten countries, we keep the specification parsimonious; the linear trend is used instead of a full set of year dummies to avoid excessive loss of degrees of freedom and severe multicollinearity between time effects and trending regressors.

Model performance is evaluated using the within R^2, which measures the proportion of within-country variation in agricultural labour productivity explained by the regressors. We also compare the signs and magnitudes of coefficients across specifications (with and without the time trend, and with HDI versus education) to assess robustness.

3 Results and discussion

3.1 Descriptive statistics

Table 1 summarises the main variables used in the analysis for the 10 BRICS member countries over 2001–2021 (210 country–year observations). Overall, the descriptive statistics already point to substantial heterogeneity in human development, structural conditions, and input use across countries and over time.

Average agricultural labour productivity amounts to about US$ 6,012 per worker, but the standard deviation is almost as large (US$ 6,772). The minimum is roughly US$ 352, while the maximum exceeds US$ 47,000 per worker. This very wide range shows that some BRICS members still have very low productivity levels, whereas others operate at productivity levels comparable to high-income countries.

The mean of average years of schooling among the adult population is about 7.9 years, with a relatively large standard deviation of 2.9 years. The minimum is roughly 1.6 years, while the maximum reaches almost 12.8 years, indicating that some BRICS members are still characterised by very low educational attainment whereas others have schooling levels comparable to high-income economies.

The arable land–agricultural worker ratio averages 3.6 hectares per person, but with a standard deviation of 6.3 hectares and a range from 0.26 to 28.2 hectares per worker. This very wide dispersion reflects sharp differences in farm structure and population pressure on land: some countries have highly land-scarce, labour-intensive agriculture, while others have relatively abundant land per agricultural worker.

Table 1. Descriptive statistics of variables used in the model (at the level unit)

Variable	Description	N	Mean	Standard Deviation	Min	Max
1. agprod	Agricultural Labor Productivity	210	6011.842	6771.696	352.0227	47036.09
2. educ	Average years of schooling (years)	210	7.911324	2.854493	1.556592	12.77
3. arlandcap	Arable land per agricultural workers (ha/person)	210	3.552129	6.314356	.2594713	28.20049
4. fercon	Fertilizer consumption (kilograms per hectare of arable land)	210	233.9485	206.9604	5.702324	940.583
5. gnicap	GNI per capita, Atlas method (current US$)	210	8083.048	11893.16	110	52160
6. hdi	Human Development Index	210	.6920857	.1238177	.307	.915

Mean fertilizer consumption is around 234 kilograms per hectare of arable land, again with considerable variation (standard deviation about 207 kg/ha). The minimum observed value is just under 6 kg/ha, whereas the maximum exceeds 940 kg/ha, suggesting that some BRICS countries remain under-fertilised, while others use fertilizer very intensively.

The average GNI per capita is about US$ 8,083, but the distribution is highly unequal (standard deviation US$ 11,893). The poorest country–year observation records only US$ 110 per person, while the richest reaches more than US$ 52,000, illustrating the coexistence of low-income and high-income economies within the BRICS grouping.

Finally, the Human Development Index (HDI) has a mean of 0.692, with values ranging from 0.307 to 0.915 and a standard deviation of 0.124. This spread indicates that, although the average BRICS member lies in the upper-middle human development category, there is still a large gap between the least and most developed countries in terms of education, health and income.

These descriptive patterns confirm that the BRICS panel combines countries at very different stages of development and structural transformation. This substantial cross-sectional and temporal variation in human development, land–labour ratios, fertilizer intensity and income provides a useful basis for examining how these factors are related to agricultural labour productivity in the subsequent econometric analysis.

3.2 Econometric models

Table 2 reports fixed-effects regressions of (log) agricultural labor productivity on the lagged determinants for the BRICS+ panel over 2001–2021. All specifications include country fixed effects and cluster standard errors by country, and the regressors enter with a one-year lag to reduce simultaneity concerns. The within-country fit is high (within R^2) between 0.89 and 0.93), indicating that the selected variables explain a large share of the inter-temporal variation in farm labor productivity.

In the baseline model (column 1), the coefficient on lagged education is large and statistically significant: a 1% rise in average years of schooling is associated with roughly a 1% increase in agricultural labor productivity. This result is in line with cross-country evidence showing that additional schooling has a sizeable positive effect on agricultural productivity, especially where technical change is rapid and farmers need to adapt to new technologies [8]. However, once a time trend is introduced (column 2), the education coefficient falls sharply and becomes insignificant, suggesting that part of the schooling effect in the baseline may be picking up long-run trends in development and technology.

Columns 3 and 4 replace schooling with the Human Development Index. In both specifications, HDI enters with a positive and statistically significant coefficient (around 0.57–0.81), even after controlling for a time trend. This indicates that broader improvements in human development—combining education, health, and income—provide a more robust explanation of productivity gains than schooling alone. The result is consistent with recent work emphasising that human capital in a broad sense is central to raising labor productivity and accelerating structural transformation in emerging economies [14]. For BRICS+, the findings imply that policies that simultaneously improve education, health outcomes, and living standards are likely to have stronger and more persistent effects on farm labor productivity than education policies in isolation.

Table 2. Determinants of Agricultural Labor Productivity (FE, lags)

Variable	(1) Labor Productivity	(2) Labor Productivity	(3) Labor Productivity	(4) Labor Productivity
L.ln(educ)	0.988^{***} (0.146)	0.100 (0.218)		
L.ln(arlandcap)	0.741^{***} (0.108)	0.688^{***} (0.083)	0.710^{***} (0.070)	0.750^{***} (0.102)
L.ln(fercon)	-0.006 (0.056)	0.003 (0.024)	-0.021 (0.027)	-0.004 (0.036)
L.ln(gnicap)	0.209^{***} (0.042)	0.104^{*} (0.047)	0.074 (0.049)	
Time trend		0.027^{***} (0.003)	0.025^{***} (0.003)	0.027^{***} (0.004)
L.ln(hdi)			0.574^{*} (0.282)	0.812^{**} (0.317)
Constant	4.429^{***}	6.701^{***}	7.496^{***}	8.078^{***}

Variable	(1) Labor Productivity	(2) Labor Productivity	(3) Labor Productivity	(4) Labor Productivity
	(0.202)	(0.307)	(0.437)	(0.277)
Observations	200	200	200	200
Countries	10	10	10	10
Within R-sq.	0.892	0.930	0.933	0.929

Standard errors in parentheses
All regressions include country fixed effects.
Regressors enter with a one-year lag (L.).
Robust standard errors clustered by country in parentheses.
*, **, *** denote significance at the 10, 5, and 1 percent levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across all four models, agricultural land per capita shows a large, positive, and highly significant elasticity, ranging from 0.69 to 0.75. A 1% increase in land per person is associated with roughly a 0.7% rise in output per worker, holding other factors constant. This magnitude suggests that demographic pressure and the effective farm size remain powerful structural constraints on productivity in BRICS+. The result echoes micro- and macro-level evidence that land scarcity and fragmented holdings hinder mechanisation and investment, whereas better access to land and functioning land rental markets can raise farm productivity and facilitate rural structural transformation [15]. In the BRICS+ context, where some countries face severe land fragmentation while others still have relatively abundant agricultural land, these estimates underscore the importance of land policies, consolidation schemes, and secure property rights to unlock productivity growth.

By contrast, the coefficient on fertiliser consumption is small and statistically insignificant in all specifications, and it even turns slightly negative in columns 1, 3, and 4. At face value, this suggests that cross-country variation in fertiliser use (measured at the aggregate level) is not a robust predictor of farm labor productivity once human capital, land per capita, and income are taken into account. This does not contradict the large literature showing that appropriate input packages contribute to yield and productivity growth [10], but it indicates that, at the BRICS+ aggregate level, simple fertiliser intensity may be too crude a proxy for the quality of input use, management practices, and R&D-driven technological change. It may also reflect diminishing marginal returns or environmental constraints in already high-input systems.

Lagged GNI per capita is positively associated with agricultural labor productivity in models without HDI: the coefficient is 0.21 in column 1 and 0.10 in column 2, both statistically significant. These elasticities imply that increases in overall income levels are accompanied by higher farm labor productivity, consistent with studies that link income growth, financial development, and trade openness to improvements in agricultural performance and sectoral productivity [5,6]. However, once HDI is included (column 3) the GNI coefficient becomes small and insignificant, and it is dropped in column 4. This pattern suggests that much of the apparent income effect operates through human development, better education and health, and related capabilities, rather than through income per se. For policy, the implication is that aggregate growth in BRICS+ will only translate into higher farm labor productivity to the extent that it is accompanied by inclusive improvements in human development and access to productive services.

The positive and highly significant time trend in columns 2–4 (around 0.025–0.027) captures an autonomous upward drift in farm labor productivity over the sample period, after conditioning on the observed determinants. This is consistent with global evidence that investments in agricultural R&D, technology diffusion, and institutional change have raised total factor productivity in agriculture over recent decades [10]. For BRICS+, the trend may reflect the cumulative impact of sustained public and private investment in research, extension, and infrastructure, as well as the gradual reallocation of labor out of low-productivity farming into more capital-intensive agrifood and non-farm activities.

Taken together, the results show that farm labor productivity in BRICS+ is shaped primarily by human capital in a broad sense and by structural factors related to land availability, with aggregate income playing a supporting role and simple fertiliser intensity having no clear independent effect. The strong elasticities for HDI and land per capita align with the wider literature on education, structural transformation, and land markets, which highlights the importance of capable workers and viable farm sizes for narrowing the agricultural productivity gap between agriculture and the rest of the economy [5,6,8]. For policy makers in BRICS+ countries, the findings point to a complementary package of interventions—investments in human development, land and tenure reforms that enable efficient farm sizes, and continued support for technology and R&D—as a coherent strategy for raising farm labor productivity and supporting inclusive structural change in the agrifood system.

4 Conclusions

This paper has examined the determinants of agricultural labor productivity in BRICS and BRICS-aligned economies over 2001–2021, focusing on four factors: human capital, input intensity, land per capita, and income level. The panel estimations show that broad human development (measured by HDI) and agricultural land per capita are the most robust correlates of higher farm labor productivity, while the evidence for education alone, fertiliser intensity, and aggregate income is weaker once these variables are jointly considered.

First, the consistently positive and significant HDI coefficients suggest that gains in schooling, health, and living standards together matter more for productivity than schooling in isolation. This is in line with studies that link broad human capital to higher agricultural productivity and faster structural transformation in developing economies. Second, the large elasticity of productivity with respect to land per capita underlines persistent structural constraints: where land is scarce and fragmented, it is harder to exploit mechanisation and scale economies, whereas more adequate and better allocated land supports higher output per worker.

By contrast, fertiliser use per capita does not display a stable independent effect once human development, land, and income are controlled for. This likely reflects the fact that simple fertiliser intensity is an incomplete proxy for technology, management quality, and R&D-driven innovation. Aggregate income (GNI per capita) is positively associated with productivity in simpler models, but its effect largely disappears when HDI is included, indicating that the productivity benefits of growth operate mainly through improvements in human development and related capabilities.

The results have several policy implications. For BRICS+ countries, strategies to raise farm labor productivity cannot rely solely on expanding input use or on aggregate economic growth. Instead, they should prioritise: (i) sustained investments in education, health, and rural living conditions to strengthen human capital; (ii) land and tenure policies that support economically viable farm sizes and reduce fragmentation; and (iii) continued support for agricultural research, extension, and innovation that makes input use more efficient rather than merely more intensive. Such a comprehensive approach is consistent with the broader evidence on agriculture's role in structural transformation. It can help these economies narrow productivity gaps, improve rural incomes, and advance progress towards SDG 2 (Zero Hunger) and SDG 8 (Decent Work and Economic Growth).

Future research could move beyond country-level aggregates by using farm- or household-level panel data to capture heterogeneity across regions, farm types, and value chains in BRICS+ agrifood systems. It should also incorporate richer measures of mechanisation, digital technologies, irrigation, extension, and land institutions, and apply methods that better address endogeneity between productivity, human development, and structural change. Finally, comparative studies that explicitly link farm labour productivity to environmental outcomes, gender dimensions of rural labour, and resilience to climate shocks would help situate productivity growth within a broader sustainability and inclusion agenda.

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