Comparing the Effects of Information Globalization on Agricultural Producer Prices in Developing and Developed Countries

Agus Dwi Nugroho

Faculty of Agriculture, Universitas Gadjah Mada, Yogyakarta, Indonesia

Abstract

Existing studies claim that the Internet of Things (IoTs) raises agricultural producer prices while others claim the contrary. Meanwhile, no studies have been conducted to investigate the impact of IoTs at the macro level, as represented by information globalization. The main objective of this study is to determine the impact of information globalization on agricultural producer prices in developing and developed countries. This study used time series data from 1991 to 2020 and cross-section data from 66 developing and 26 developed countries. The data was analyzed using two-stage least squares. The first stage of analysis shows that pesticides and farm machinery increase agricultural production in developing and developed countries, while employment in agriculture, forestry, and fishing has the opposite effect. Meanwhile, nutrient nitrogen, manure, and irrigation have differing effects on agricultural production in the two areas. The second stage of analysis shows that agricultural producer prices in developing and developed countries will rise when agricultural production, agricultural import, and human capital increase. Agricultural value-added, food consumer price inflation and population growth have varying impacts on agricultural producer prices. Meanwhile, the main variable investigated in this study, information globalization, has been proven to increase agricultural producer prices in both developing and developed countries.

Keywords

Agricultural production, agricultural import, agricultural value added, food consumer price, population, human capital.

Nugroho, A. D. (2024) "Comparing the Effects of Information Globalization on Agricultural Producer Prices in Developing and Developed Countries", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 3, pp. 93-107. ISSN 1804-1930. DOI 10.7160/aol.2024.160307.

Introduction

Agriculture is one sector that has been severely impacted by many disruptions. Food production and supply chains are disrupted, resulting in higher food prices and reduced food access. Many countries are putting in place various strategies and regulations to counteract these disruptions and increase agricultural yield (Saboori et al., 2023). This is consistent with the Cobb-Douglas production theory, which states that the production function is attained using two inputs, capital and labor. Based on the needs, some of these factors can change and others remain constant in the short run, while all production factors can change in the long run (Pindyck and Rubinfeld, 2013). The combination of production factors has been shown to increase food yield in the long run (Chandio et al., 2023).

The Cobb-Douglas production theory also emphasizes the importance of technology to accelerate agricultural production growth (Pindyck and Rubinfeld, 2013). Technology is an instrumental action design that eliminates uncertainty in the cause-effect linkages involved in reaching a desired outcome. According to Rogers' innovation adoption theory, these numerous technologies will be adopted by agricultural participants (Rogers, 2003). The adoption of technology in agriculture has succeeded in speeding up the production process, improving product quality, and overcoming labor shortages (Sun et al., 2023).

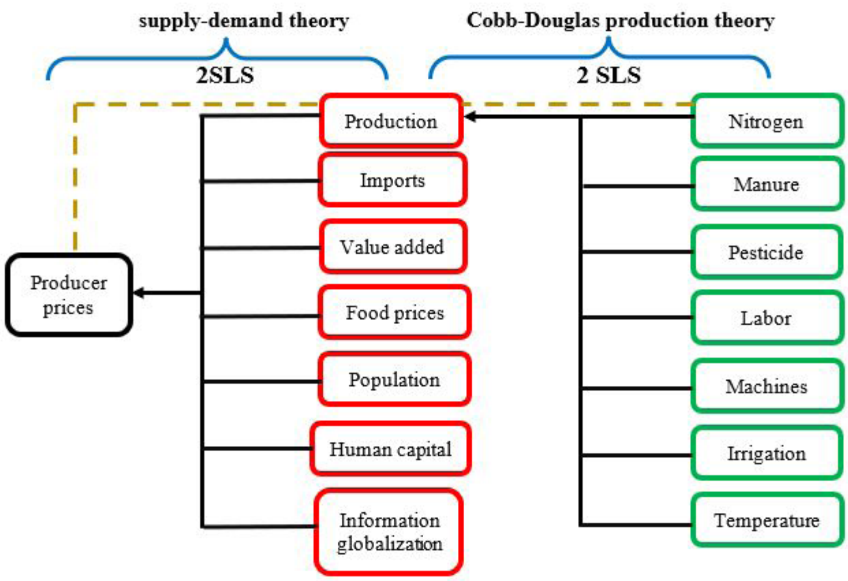
One of the most important packages of technological innovation that has influenced the world over the previous five decades is the green revolution. This technological package combined with irrigation and intense use of chemical fertilizers, herbicides, and agricultural equipment in various crops, is the primary source of global agricultural growth (Jeder, 2023). Agriculture has now embraced the smart and precise integration of technologies like the Internet of Things (IoTs), sensors, robotics, artificial intelligence, intelligent supply chains, big data analysis, and blockchain. The primary goal of technological integration is to increase agricultural productivity and efficiency (Chandio et al., 2023; Jararweh et al., 2023). The technology also addresses information issues that impede farmers' market access, introduces new methods of offering extension services, and enhances agricultural supply chain management (Deichmann et al., 2016).

In the macro aspect, IoTs can be linked to information globalization, which means the ability to share information across countries. It is measured by the number of television sets per capita and the number of individuals who have access to the Internet. Furthermore, the press freedom index measures the accessibility of news-related information (Gygli et al., 2019).

IoTs can improve agribusiness buyer recognition and be more helpful to farmers by increasing product prices (Jararweh et al., 2023). Much research on the impact of IoTs on producer prices has been carried out but most of this research was carried out at the micro level (Chandio et al., 2023; Deichmann et al., 2016; Subejo et al., 2019). Meanwhile, no investigations at the macro level have been conducted and this is the novelty of this study. Existing studies also produce different findings, with some claiming that IoTs raise agricultural producer prices (Chandio et al., 2023) while others claim that IoTs have no significant impact on agricultural producer prices (Deichmann et al., 2016). This is a research gap and encourages us to conduct studies at the macro level. So, the main objective of this study is to determine the impact of information globalization on agricultural producer prices in developing and developed countries.

Research framework

This study uses two main interrelated theories, namely aggregate supply-demand and Cobb-Douglas production (Figure 1). The supply-demand theory relates to price changes in the market, including the producer level. The concept of supply and demand is at the foundation of current economic theory, describing how the total output amount and aggregate price level can be established to reach equilibrium. This approach emphasizes the importance of demand in influencing prices. Demand is measured by the quantity of consumers, their purchasing power, and their characteristics (Pindyck and Rubinfeld, 2013). Hence, this study attempts to characterize demand using variables such as population size, consumer food prices, and consumer education quality. On the other hand, supply influences prices, particularly those of goods produced by producers, as well as the quality of these goods and the ability to supply goods from abroad. This study represents this circumstance with numerous explanatory variables: production, value added, and imports.



Source: Authors identification, 2024

Figure 1: Research framework

Another key consideration is the function of technology in accelerating the flow of information between producers (supply) and consumers (demand). Currently, macro-level information can be represented as information globalization. Globalization of information aims to measure the flow of ideas, knowledge, and pictures. Information globalization is quantified using various variables: 1) Internet bandwidth measures the used international internet bandwidth capacity and serves as a proxy for international incoming and outgoing digital information; 2) high technology exports describe the flow of technological and scientific information; 3) the number of television sets per capita; 4) the number of people with internet access; and 5) the press freedom index measures the availability of news-related information (Gygli et al., 2019).

Meanwhile, Cobb Douglas' theory suggests that supply (in this case agricultural production) is influenced by a variety of production inputs utilized by farmers, including fertilizer, pesticides, manpower, and agricultural equipment. The utilization of these production inputs has the potential to increase agricultural production in both developed and developing countries (Pindyck and Rubinfeld, 2013).

These conditions demonstrate that agricultural production has an impact on farm prices, but it is also influenced by the usage of production inputs. If this condition is evaluated using econometrics, it will create a problem known as endogeneity, which will bias the analysis results. To address this, a particular technique is required, specifically the use of simultaneous least squares analysis (Greene, 2003).

Material and methods

Data source

This study used time series data from 1991 to 2020 and cross-section data from 66 developing and 26 developed countries (Appendix A1). We classified countries using IMF indicators, which included developing and developed countries. There are 23 developing countries in Africa, 18 countries in Asia, 18 countries in Latin America and the Caribbean, and the rest are in Europe and Oceania. The developed countries for this study sample are spread across America, Asia, Europe, and Oceania. As stated in Table 1, this study will also use several other explanatory variables and data sources.

Effective chemical fertilizer management is very important to increase agricultural productivity, while improving water and air quality and mitigating climate change (Gourevitch et al., 2018). The main obstacle of using chemical fertilizers is that they are expensive and impact soil degradation, nutrient depletion, and are one of the main sources of greenhouse gas (GHG) emissions. As a result, many farmers are switching from conventional fertilizers to organic fertilizers. Organic fertilizer reduces GHG intensity greatly

Variable	Symbol	Source
Gross production index number (2014-2016 = 100)	GPI	FAO
Agricultural producer price index (2014-2016 = 100)	PPI	FAO
Nutrient nitrogen N (total)	NIT	FAO
Manure applied to soils (ton)	MAN	FAO
Pesticides (litre)	PES	FAO
Employment in agriculture, forestry, and fishing (000 persons)	EMP	ILO
Farm machinery per unit of agricultural land	MAC	Our data in World
Land area equipped for irrigation (000 ha)	IRRI	FAO
Temperature change	TEMP	FAO
Agricultural import value index (2014-2016 = 100)	IMP	FAO
Agricultural value added (million US$)	AVA	FAO
Food consumer price inflation (%)	FCPI	World Bank
Population growth (%)	POP	World Bank
Human capital index	HCI	Penn World Table
Information globalization index	IGI	KOF Globalization Index

Source: Authors identification, 2024

Table 1: Variable and data source.

as compared to conventional fertilizer. Furthermore, the usage of organic fertilizer helps to prevent crop losses caused by bio-physical stress to a certain extent and increases crop production and economic profitability (Gholkar et al., 2022).

Hypothesis 1: The use of nitrogen fertilizer will increase agricultural production.

Hypothesis 2: The use of manure will increase agricultural production.

Like chemical fertilizers, pesticides have the potential to significantly boost global agricultural production and technical efficiency. Global pesticide use continues to increase due to the increasing number of pest species following climate change and land degradation (de Souza et al., 2023). However, their excessive usage has put water resources and individual health at risk. Water contaminated with pesticides causes chronic toxicity, carcinogenic, and detrimental environmental impacts (Singh et al., 2023). This shows the importance of human resource capabilities in managing the use of agricultural inputs.

Hypothesis 3: The use of pesticides will increase agricultural production.

An increase in agricultural labor quality will lead to an increase in agricultural production, value-added, and competitiveness (Dait, 2022). Human capital is also a key part of agricultural research and development innovation. Innovation has the potential to boost food availability and accessibility, economic development, and well-being (Usman et al., 2021). However, several issues still exist in agriculture, including the gender gap. Women are still rarely involved in agricultural activities and receive lower wages than men (Zaman et al., 2022). The next issue is the shift of labor from the agricultural sector to the non-agricultural sector. Agriculture is considered not an attractive sector since it cannot provide a decent income for labors (Usman et al., 2021). The decline in the share of employment in the agricultural sector encourages modern production factors in this sector and there is a continuous increase in the combination of modern and traditional factors (agricultural modernization) (Liu and Wang, 2022). Many modern machine tools are used in agriculture today such as tractors, pumps, threshers, harvesters, and power tillers. Robots and artificial intelligence are no longer limited to typical agricultural production tasks (such as plowing and combined harvesting) but are also used to conduct non-standard tasks (such as fruit picking, selective weeding, and plant sensing) (Marinoudi et al., 2019).

Hypothesis 4: The use of labor will increase agricultural production.

Hypothesis 5: The use of machines will increase agricultural production.

Agricultural production is also vulnerable to climate change. This increases floods and droughts, soil degradation, water shortages, pests and diseases; jeopardizes agricultural productivity; disrupts production efficiency; and declines in GDP, consumption, household income across all economic sectors, and food security (Liu and Wang, 2022). The worst thing is water scarcity puts a strain on agricultural production. Hence, it can be overcome by implementing innovative water management technology and effective water consumption. One of which is the use of smart irrigation technology to increase crop yields, overcome water scarcity and climatic challenges, conserve water and soil, mitigate soil salinity, and manage groundwater quantity and quality (Usman et al., 2021).

Hypothesis 6: The use of irrigation will increase agricultural production.

Hypothesis 7: The increasing temperature will disrupt agricultural production.

According to supply theory, the abundance of products in the market causes the price to fall and vice versa. This theory outlines the rational behavior of producers seeking to maximize profits by altering production volumes in response to price changes (Pindyck and Rubinfeld, 2013). Excessive growth in agricultural production leads to market saturation, a fall in domestic producer profitability, and a worsening of the industrial sector's financial status (Yakovenko et al., 2018). Aside from quantity, producer prices are also influenced by product quality which can be represented as value-added. The rise of value-added has a favorable impact on product prices and producer incomes (Bassett et al., 2018).

Hypothesis 8: the increase in agricultural production will reduce producer prices.

Hypothesis 9: the increase in agricultural value-added will increase producer prices.

Consumer prices are the next factor that drives producer pricing, as consumer prices cause price rises at the producer level (Levin and Vimefall, 2015). Inflation raises production costs and prices while decreasing product competitiveness (Amiri et al., 2021). The final economic factor that influences producer prices is economic openness. The entry of imported products causes excessive supply in the domestic market and product prices will fall. Meanwhile, the imposition of tariffs raises the price of imported products, which in turn raises the price of domestic products (Krugman and Obstfeld, 2003).

Hypothesis 10: the increase in food price inflation will increase producer prices.

Hypothesis 11: the increase in agricultural imports will reduce producer prices.

Apart from economic factors, producer prices are also influenced by non-economic factors. The first is population, both quantity and quality. Population growth raises the demand for food products. In these circumstances, producers have the opportunity to increase prices to meet market demand (Pindyck and Rubinfeld, 2013). Population quality or human capital has also an important role in reducing transaction costs, increasing the effectiveness of managerial decisions in agricultural businesses, and ensuring the sustainability of the agricultural food supply chain (Oliveira and Turčínková, 2019).

Hypothesis 12: the increase in population growth will increase producer prices.

Hypothesis 13: the increase in human capital will increase producer prices.

The second is related to the information globalization. This is critical because agricultural market participants, especially farmers, often do not receive information. The oligopsony agricultural market structure makes some market participants hide market information. The use of information and communication technologies (ICTs) makes it easy for farmers to access agricultural information, from upstream to downstream. As a result, farmers will get a decent price (Nugroho, 2021).

Hypothesis 14: the increase in information globalization will increase producer prices.

Data analysis

The empirical analysis begins with Augmented Dicky Fuller (ADF) unit root test to eliminate spurious regression due to the usage of nonstationary time-series data throughout the period (Levin et al., 2002):

$$\Delta Y_{it} = \alpha Y_{it-1} + \sum \beta_{it} \Delta Y_{it} - j + X_{it}\delta + v_{it} \qquad (1)$$

Y_{it} is the pooled variable, X_{it} is an exogenous variable, v_{it} is the error term.

Following that, we ran the two-stage least squares (2SLS). The 2SLS model was chosen because the study model, particularly the GPI, has an endogeneity issue. Endogeneity occurs when the GPI is supposed to influence PPI; while other variables also influence the GPI (Batmunkh et al., 2022). The conventional least squares model cannot solve the endogeneity problem because it cannot eliminate the error terms and correlate with one another.

The 2SLS model employs an instrumental variable technique to integrate calculations. The residuals from step 1 are then utilized to estimate the covariance matrix of the disturbance equation consistently. Finally, it estimates the correlation structure in each equation using the generalized least squares (GLS) model (Greene, 2003).

Equation 2 based on Cobb Douglas or constant elasticity of substitution (CES) production functions:

$$GPI = \beta_0 + \beta_1 NIT + \beta_2 MAN + \beta_3 PES + \beta_4 EMP + \\ + \beta_5 MAC + \beta_6 IRRI + \beta_7 TEMP + \mu \qquad (2)$$

Equation 3:

$$PPI = \gamma_0 + \gamma_1 GPI + \gamma_2 IMP + \gamma_3 AVA + \gamma_4 FCPI + \\ + \gamma_5 POP + \gamma_6 HCI + \gamma_7 IGI + \sigma \qquad (3)$$

The reformulation of Equations (2) and (3) is called the reduced form of the structural equations system. The reduced form is obtained by substituting TEMP Equation (2) into Equation (3):

$$PPI = \gamma_0 + \gamma_1 (NIT + MAN + PES + EMP + \\ + MAC + IRRI + TEMP) + \gamma_2 IMP + \gamma_3 AVA + \\ + \gamma_4 FCPI + \gamma_5 POP + \gamma_6 HCI + \gamma_7 IGI + \sigma \qquad (4)$$

$$PPI = \gamma_0 + \gamma_1 NIT + \gamma_1 MAN + \gamma_1 PES + \gamma_1 EMP + \\ + \gamma_1 MAC + \gamma_1 IRRI + \gamma_1 TEMP + \gamma_2 IMP + \\ + \gamma_3 AVA + \gamma_4 FCPI + \gamma_5 POP + \gamma_6 HCI + \\ + \gamma_7 IGI + \sigma \qquad (5)$$

Abbreviations are explaned below the Table 3.

The 2SLS model must pass several post-estimation tests to be valid. Post-estimation tests for the 2SLS model include (Greene, 2003): 1) the Hausman method was used as an endogeneity test, 2) the Stock & Yogo method was used as a weak instrument test, and 3) the Sargan method was used as an identification restriction test.

Results and discussion

Results

We ran two-unit the Augmented Dicky Fuller (ADF) root tests, one for developing countries and one for developed countries. Unit root test for developing countries shows that *GPI, PPI, NIT, MAN, PES, EMP, MAC, IRRI, TEMP, IMP, AVA, FCPI, POP, HCI*, and *IGI* are stationary at level (Table 2). Meanwhile, unit root tests for developed countries show that *GPI, PPI, MAN, MAC, TEMP, IMP, FCPI, POP, HCI*, and *IGI* are stationary at level. At the same time, *NIT, PES, EMP, IRRI*, and *AVA* are stationary at the first-difference level.

The 2SLS model was used to assess all variables after the data became stationary. Equation (2) demonstrates that the endogeneity test has a significance level of 0.038 in developing countries and 0.030 in developed countries, but Equation (3) has a significance level of 0.043 in developing countries and 0.021 in developed countries (Table 3). Both models exhibit endogeneity significance levels lower than the 5% alpha level, indicating that endogeneity issues exist in their respective structural equations. Both the overidentification and weak instrument tests show a significant value at the 5% alpha level, indicating that the structural model is over-identified and that each equation contains a strong instrument variable.

The Cobb-Douglas function is used in this study to depict the technological relationship between the amounts of two or more inputs (especially physical capital and labor) and the quantity of output that those inputs can produce. Nutrient nitrogen (NIT), pesticides (PES), farm machinery (MAC), and irrigation (IRRI) are some inputs that can boost agricultural production (GPI) in developing countries. According to our findings, NIT, PES, MAC, and IRRI boosted agricultural output by 0.000002, 0.00008, 4.2834, and 0.0006, respectively. Two inputs cause a decline in GPI in developing countries, namely manure (MAN) and employment in agriculture, forestry and fishing (EMP) of -0.00002 and -0.0001. Meanwhile, temperature change (TEMP) does not have a significant effect on GPI in developing countries. In developed countries, MAN, PES, and MAC are inputs that can raise GPI by 0.000006, 0.0003, and 0.7873 respectively. On the other hand, GPI will decrease by -0.000009, -0.0063, and -0.0012 due to increases in NIT, EMP, and IRRI in developed countries. TEMP does not have a significant effect on GPI in developed countries, as it does in developing countries.

Following that, we examine the determinants influencing agricultural producer prices (PPI) in both developing and developed countries. PPI in developing countries experienced an increase when GPI, agricultural import (IMP), agricultural

Symbol	Developing countries		Developed countries	
	Stage	Statistic	Stage	Statistic
GPI	At level	-12.351***	At level	-5.734***
PPI	At level	-40.482***	At level	-8.369***
NIT	At level	-6.782***	1st difference	-9.219***
MAN	At level	-6.612***	At level	-6.025***
PES	At level	-7.369***	1st difference	-9.263***
EMP	At level	-7.300***	1st difference	-9.758***
MAC	At level	-6.598***	At level	-3.922***
IRRI	At level	-6.699***	1st difference	-8.913***
TEMP	At level	-10.458***	At level	-7.998***
IMP	At level	-20.390***	At level	-11.886***
AVA	At level	-8.089***	1st difference	-8.546***
FCPI	At level	-10.330***	At level	-8.429***
POP	At level	-8.737***	At level	-4.884***
HCI	At level	-7.119***	At level	-4.604***
IGI	At level	-11.865***	At level	-8.907***

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Source: Authors computation, 2024

Table 2: ADF unit root test.

Variable	Developing countries		Developed countries	
	Coeff.	Std. Error	Coeff.	Std. Error
Dependent variable: GPI				
NIT	0.000002*** (3.2540)	0.0000007	-0.000009*** (-6.9571)	0.000001
MAN	-0.00002*** (-6.1569)	0.000004	0.000006 (1.8768)	0.000003
PES	0.00008*** (5.5184)	0.00001	0.0003*** (7.3947)	0.00004
EMP	-0.0001*** (-3.8108)	0.00004	-0.0063*** (-5.6950)	0.0011
MAC	4.2834*** (5.9397)	0.7212	0.7873*** (4.3374)	0.1815
IRRI	0.0006*** (4.2886)	0.0001	-0.0012** (-2.6462)	0.0005
TEMP	0.8927 (-0.7363)	1.2124	0.8486 (1.2807)	0.6626
Cons.	66.0374*** (59.7929)	1.1044	93.5784*** (89.8068)	1.042
Adj R^2		0.2066		0.1228
F test		56.7627		16.554
Overidentification test		6.8752		12.8604
Weak identification test		8.7293		21.0952
Endogeneity test		4.9017		5.8949
Dependent variable: PPI				
GPI	0.9381*** (3.3854)	0.2771	0.8426*** (5.8533)	0.1439
IMP	0.3319*** (3.9423)	0.0842	0.2088*** (5.6229)	0.0371
AVA	0.00002* -2.352	0.000009	-0.00002 (-0.7809)	0.00002
FCPI	0.0093 (-1.3811)	0.0067	-0.0663*** (-5.4595)	0.0121
POP	1.8582. (1.9679)	0.9443	-4.6078*** (-6.0843)	0.7573
HCI	9.3717*** (3.8963)	2.4053	13.0113*** (5.4584)	2.3837
IGI	0.3369* (2.3595)	0.1428	0.2225* (2.193)	0.1015
Cons.	-33.5000** (-2.4336)	13.7654	-62.6327*** (-3.3961)	18.4425
Adj R^2		0.4865		0.3210
F test		327.2783		120.9312
Overidentification test		6.3312		9.7267
Weak identification test		8.8872		14.4309
Endogeneity test		4.1870		8.3691

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Source: Authors computation, 2024

Table 3: Determinant factors of agricultural production and producer price in developing and developed countries

value added (AVA), population growth (POP), human capital (HCI), and information globalization (IGI) rose. PPI increased by 0.9381, 0.3319, 0.00002, 1.8582, 9.3717, and 0.3369, respectively, due to increases in GPI, IMP, AVA, POP, HCI, and IGI. Another explanatory variable, food consumer price inflation (FCPI), has no influence on PPI in developing countries. The phenomenon in developed countries shows that PPI will rise by 0.8426, 0.2088, 13.0113 and 0.2225 due to increases in GPI, IMP, HCI and IGI. Meanwhile, increases in FCPI and POP reduced PPI by -0.0663 and -4.6078. The only explanatory variable that has no effect on PPI in developed countries is AVA.

Based on the findings, there are several explanatory variables that support and do not support the hypothesis of this study (Table 4).

Hypotheses	Developing countries	Developed countries
Hypothesis 1: The use of nitrogen fertilizer will increase agricultural production.	Supported	Unsupported
Hypothesis 2: The use of manure will increase agricultural production.	Unsupported	Supported
Hypothesis 3: The use of pesticides will increase agricultural production.	Supported	Supported
Hypothesis 4: The use of labor will increase agricultural production.	Unsupported	Unsupported
Hypothesis 5: The use of machines will increase agricultural production.	Supported	Supported
Hypothesis 6: The use of irrigation will increase agricultural production.	Supported	Unsupported
Hypothesis 7: The increasing temperature will disrupt agricultural production.	Unsupported	Unsupported
Hypothesis 8: the increase in agricultural production will reduce producer prices.	Unsupported	Unsupported
Hypothesis 9: the increase in agricultural value-added will increase producer prices.	Supported	Unsupported
Hypothesis 10: the increase in food price inflation will increase producer prices.	Unsupported	Unsupported
Hypothesis 11: the increase in agricultural imports will reduce producer prices.	Unsupported	Unsupported
Hypothesis 12: the increase in population growth will increase producer prices.	Supported	Unsupported
Hypothesis 13: the increase in human capital will increase producer prices.	Supported	Supported
Hypothesis 14: the increase in information globalization will increase producer prices.	Supported	Supported

Source: Authors identification, 2024

Table 4: Supported or unsupported the hypothesis of this study.

Determinant factors of agricultural production in developing and developed countries

The use of NIT has a U-shaped relationship. When used appropriately, NIT has a positive effect on GPI, but it will have the opposite effect when NIT is used excessively (Qiu et al., 2022). NIT helps the process of forming chlorophyll and plant photosynthesis, resulting in increasing GPI in developing countries (Gholizadeh et al., 2017). The opposite condition occurs in developed countries where excessive NIT has increased environmental damage, soil acidity, biodiversity loss, and reduced its use efficiency, causing a decrease in GPI (Ding et al., 2022). In addition, developed countries have low NIT efficiency, or agricultural sectors utilize excessive fertilizer to achieve the same amount of output (Rudinskaya and Náglová, 2021). Hence, many developed countries have long switched to utilizing manure (MAN), which has been shown to boost GPI.

The addition of MAN improves soil organic matter, nutrient absorption, and water retention capacity. The positive influence of MAN on crop productivity is especially noticeable during dry seasons with low rainfall. The change in orientation of the use of NIT to MAN in developed countries is also due to a growing awareness of increasing sustainable agriculture, curbing soil nitrogen depletion, lowering GHG emissions, maintaining plant yield, and improving human and soil health (Gholkar et al., 2022). This action was also taken by developing countries, although it resulted in a drop in GPI. This is very typical because utilizing MAN initially lowers the GPI and gradually raises it.

The use of the next production factor, pesticides (PES), has proven effective in both developed and developing countries in reducing crop yield loss and quality decline by controlling insect pests, weeds, and diseases. Hence, PES use rose 56% and 38% in the United States (US) and Australia, respectively, between 2009 and 2016. Developing countries have used PES since the Green Revolution and continue to play an important part in current food, vegetable, and fruit production (Maino et al., 2023).

Total employment (EMP) has a negative correlation with GPI in both developing and developed countries. There are numerous child laborers and precarious labors in agriculture, which reduces the agricultural system's efficiency due to low skills (Behrendt et al., 2021). This makes agriculture unattractive since it cannot provide a decent income for labors. As a result, EMP is shifting from agriculture to industry and services as well as mobilization from villages to cities. The remaining agricultural labor has a limited ability to absorb knowledge and innovation spillovers (Usman et al., 2021). This suggests that agriculture does not require more EMP, but rather specialized EMP and mechanization to increase GPI.

The use of agricultural machinery (MAC) has been shown to increase GPI in both developing and developed countries. Each region's governance is vigorously supporting the use of MAC and artificial intelligence to alleviate labor shortages, save labor costs, boost production efficiency, and improve agricultural production speed. Furthermore, this process increases the agricultural added value of each worker as well as the profits of production factors, promotes economic complexity, and strengthens economic ties between agriculture and the industrial sector (Liu and Wang, 2022). Even during the Covid-19 pandemic and lockdown, the decline in agricultural production can be reduced because of the use of agricultural mechanization (Zhang et al., 2020). Based on that, the government even provided MAC assistance and subsidies to make this program successful (Zaman et al., 2022).

Aside from production factors, increasing GPI can be accomplished through the provision of infrastructure, particularly irrigation (IRRI). IRRI in developing countries has much increased productivity and land values. (Phu, 2023; Usman et al., 2021). The use of advanced irrigation technologies such as drip irrigation is also an effective way to reduce soil salinity in the root zone and increase crop yields (Du et al., 2023). Hence, many developing countries prioritize policies for developing irrigation networks. For example, the Vietnamese government has built a vast irrigation infrastructure and waived irrigation fees for farmers to reduce rural poverty and improve the public image of the government (Phu, 2023). Meanwhile, developed countries use more wastewater that has been reprocessed utilizing artificial wetlands, waste stabilization ponds, membrane bioreactors, vermi-biofiltration, and land treatment technologies for the elimination of chemical and biological contaminants (Biswas et al., 2021). Hence, IRRI causes a decline in GPI in developed countries.

Temperature (TEMP) is the only explanatory variable that does not affect GPI. Although it differs from many other research, this can be explained for a variety of reasons, the most important of which are mitigation and adaptation to climate change. Recent discoveries have made researchers aware of multiple methods for mitigating the effects of drought disasters. The methods are based on forecasting future drought features several months or even seasons in advance. The outcomes of this method are used to make decisions in water resource management (Wang et al., 2023). In practice, climate change mitigation methods such as boosting the resilience of agricultural production practices, increasing human adaptation, and building project-based early warning systems for weather reports are being implemented (Omotoso et al., 2023). Farmers also implement climate change adaptations such as crop rotation, boosting agricultural inputs, modifying crop sowing dates, engaging in off-farm activities, expanding cropland areas, and raising more livestock to preserve GPI stability (He et al., 2023).

Determinant factors of agricultural producer price in developing and developed countries

Increased GPI benefits both developed and developing countries' producer prices (PPI). The GPI is not only used to meet domestic needs but also international demand. Many countries are now able to participate in the global agricultural food chain. This integration encourages each country to diversify its exports (Yakovenko et al., 2018). Many countries are also trying to enhance the commodity structure of agricultural exports and boost the export share of high value-added processed and food products (Pohlová et al., 2018). This is what raises PPI and provides many benefits for agricultural business participants and the food industry's sustainable growth (Yakovenko et al., 2018).

Another factor that influences PPI is agricultural imports (IMP). PPI was increased by IMP in this study. This is contrary to trade theory, which holds that imports cause a fall in the price of domestic products and keep producer prices to a minimum. The difference in results is caused by the fact that many countries pay subsidies to producers while importing products. Subsidies are widely used because they are thought to safeguard producers' ability to reach decent prices, boost production efficiency, and modernize agriculture (Rudinskaya and Náglová, 2018). In addition, economic openness has boosted product competitiveness, resulting in higher product quality (Shao et al., 2022). This can also be seen from the fact that agricultural value-added (AVA), which is a representation of product quality, has a positive relationship with PPI, especially in developing countries. AVA is critical for increasing the farmers' prices and export diversification in developing countries (Sanida et al., 2016). For example, boosting AVA in Brazil was critical for rising PPI (Hagel et al., 2019). Logically, increasing AVA will improve product quality and provide farmers with a decent price.

The relationship between food prices (FCPI) and PPI in this study is asymmetric. This means that the increase in FCPI is not transmitted to producers, resulting in a drop in PPI. The strong influence of consumer prices on PPI formation occurs in many developed countries. In Lithuania, for example, consumer prices have a greater short- and medium-run impact on producer prices than vice versa (Živkov et al., 2023). This occurs frequently in agriculture because many business participants conceal price information and in imperfect pure market conditions (Nugroho, 2021). Furthermore, when the FCPI rises quickly or is on an upward trend, the government will emphasize it by limiting the PPI. The government should also postpone moderate monetary policy easing until the FCPI cycle has stabilized or is in a decreasing phase (Shaoping and Xiaotao, 2014).

Population growth in developing countries raises the demand for food products. In these circumstances, producers have the opportunity to increase prices to meet market demand (Pindyck and Rubinfeld, 2013). In contrast, population growth in developed countries lowers PPI. Meanwhile, Behrendt et al. (2021) show that the role of skill and education development can be relied upon in increasing the efficiency of production and marketing systems. Increasing human capital helps agricultural participants to think rationally, resulting in higher producer prices, more efficient product creation, and better response to market demand. Producers can also quickly comprehend and utilize new agricultural technologies (Effendy et al., 2022).

Impacts of information globalization on agricultural producer price in developing and developed countries

Information globalization (IGI) can increase PPI in developed and developing countries The massive spread of IGI has resulted in increased access and transfer of agricultural knowledge. IGI has a significant positive influence on rural household income. IGI also lowers information costs and incentivizes farmers to engage in product markets (Leng, 2022). Information to identify pests and diseases, pesticide use, and appropriate production techniques is now delivered more quickly as IGI develops. Because of this, farmers can raise their selling prices since they can communicate directly with customers and create product compatibility with consumer needs (quality, health, and safety standards) (Krone et al., 2014). Farmers can also reduce the possibility of asymmetric information in the agricultural market, shorten the marketing chain to reduce marketing costs, enhance pricing transparency, boost farmers' bargaining power, and reduce crop losses as perishable products are sold more quickly (Nugroho, 2021).

The development of IGI also enables the agricultural industry to examine the extent and distribution of drought, as well as vegetation cover and soil temperature trends, and the impact of climate change. This allows them to devise measures to mitigate climate change, maintain agricultural output stability, and raise producer prices (Alimbekova and Walker, 2022).

Despite its promising impact, IGI development still faces several challenges. First, there is a lack of literacy and skills among farmers using IGI technology, especially in developing countries. Only young, educated and high-income farmers are familiar with modern information technology (Subejo et al., 2019). Second, there is a lack of information infrastructure. This is evident in underdeveloped technologies, low levels of internet adoption, and disparities in urban and rural growth. This issue stems from a limitation of infrastructure development funds (Leng, 2022).

Conclusion

This study uses two-stage least squares to determine the impact of information globalization on agricultural producer prices in developing and developed countries. The first stage of analysis shows that pesticides and farm machinery increase agricultural production in developing and developed countries, while employment in agriculture, forestry and fishing has the opposite effect. Meanwhile, nutrient nitrogen, manure, and irrigation have differing effects on agricultural production in the two areas. The second stage of analysis shows that agricultural producer prices in developing and developed countries will rise when agricultural production, agricultural import, and human capital increase. Agricultural value added, food consumer price inflation, and population growth have varying impacts on agricultural producer prices. Meanwhile, the main variable investigated in this study, information globalization, has been proven to increase agricultural producer prices in both developing and developed countries.

This study contributes to the application of innovation adoption theory in agriculture. The application of globalization information in agriculture provides benefits for increasing agricultural prices. According to the findings of this study, several steps are required to increase agricultural producer prices, including 1. increasing public access to the internet (information globalization) by providing infrastructure and valid information; 2. increasing agricultural market participant's ability to use modern tools and process information; 3. increasing agricultural production by increasing quantity and efficiency of agricultural inputs use, especially pesticides and agricultural machinery; and 4. creating a more open agricultural business environment, especially the entry of imported products to increase the efficiency of agricultural businesses.

The main limitation of this study is that it looks at information globalization progress at a macro level. Meanwhile, many barriers to information technology adoption and innovation in the micro sector, make information globalization difficult to implement. Based on this, we recommend that future studies examine farmers' adoption of information technology in a broad geographic area, rather than just one country. Another limitation is that it does not account for subsidies. Even though subsidies have a considerable impact on agricultural producer prices. As a result, we recommend that future studies include subsidies as a variable influencing agricultural producer prices.

Corresponding author:
Agus Dwi Nugroho
Faculty of Agriculture, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia
Phone: +62274516656, Email: agus.dwi.n@mail.ugm.ac.id

References

[1] Alimbekova, N. A. and Walker, N. (2022) "Kyrgyz Open Data Cube of Satellite Images and Environmental Products as a Tool for Pasture Monitoring", *International Journal of Geoinformatics*, Vol. 18, No. 1, pp. 81-85. ISSN 2673-0014. DOI 10.52939/ijg.v18i1.2113.

[2] Amiri, H., Sayadi, M. and Mamipour, S. (2021) "Oil price shocks and macroeconomic outcomes; Fresh evidences from a scenario-based NK-DSGE analysis for oil-exporting countries", *Resources Policy*, Vol. 74, No. July, p. 102262. ISSN 1873-7641. DOI 10.1016/j.resourpol.2021.102262.

[3] Bassett, T. J., Koné, M. and Pavlovic, N. R. (2018) "Power relations and upgrading in the cashew value chain of Côte d'Ivoire", *Development and Change*, Vol. 49, No. 5, pp. 1223-1247. ISSN 1467-7660. DOI 10.1111/dech.12400.

[4] Batmunkh, A., Nugroho, A. D., Fekete-Farkas, M. and Lakner, Z. (2022) "Global challenges and responses: Agriculture, economic globalization, and environmental sustainability in Central Asia", *Sustainability (Switzerland)*, Vol. 14, No. 4. ISSN 2071-1050. DOI 10.3390/su14042455.

[5] Behrendt, L., Estruch, E., Sauer, J., Ayenew, H. Y., Abate-Kassa, G. and Wobst, P. (2021) "Decent rural employment in a specialised and a diversified production system in Tanzania", *Development Southern Africa*, Vol. 38, No. 6, pp. 1017-1030. ISSN 0376-835X. DOI 10.1080/0376835X.2021.1948389.

[6] Biswas, A., Mailapalli, D. R. and Raghuwanshi, N. S. (2021) "Treated municipal wastewater to fulfil crop water footprints and irrigation demand – A review", *Water Science and Technology*, Vol. 21, No. 4, pp. 1398-1409. ISSN 1996-9732. DOI 10.2166/WS.2021.031.

[7] Chandio, A. A., Gokmenoglu, K. K., Khan, I., Ahmad, F. and Jiang, Y. (2023) "Does internet technology usage improve food production? Recent evidence from major rice-producing provinces of China", *Computers and Electronics in Agriculture*, Vol. 211, No. March, p. 108053. ISSN 1872-7107. DOI 10.1016/j.compag.2023.108053.

[8] Dait, J. M. G. (2022) "Impact of climate change and economic activity on Philippine agriculture: A cointegration and causality analysis", *Universal Journal of Agricultural Research*, Vol. 10, No. 4, pp. 405-416. ISSN 2332-2284. DOI 10.13189/ujar.2022.100410.

[9] Deichmann, U., Goyal, A. and Mishra, D. (2016) "Will digital technologies transform agriculture in developing countries?", A*gricultural Economics (United Kingdom)*, Vol. 47, pp. 21-33. ISSN 0169-5150. DOI 10.1111/agec.12300.

[10] Ping, D., Jing-han, L., Jia-huan, L., Wei-feng, Z. and Xiang-ping, J. (2022) "ICT-based agricultural advisory services and nitrogen management practices: A case study of wheat production in China", *Journal of Integrative Agriculture*, Vol. 21, No. 6, pp. 1799-1811. ISSN 2352-3425. DOI 10.1016/S2095-3119(21)63859-5.

[11] Du, Y., Liu, X., Zhang, L. and Zhou, W. (2023) "Drip irrigation in agricultural saline-alkali land controls soil salinity and improves crop yield: Evidence from a global meta-analysis", Science of the Total Environment, Vol. 880, No. April, p. 163226. ISSN 1879-1026. DOI 10.1016/j.scitotenv.2023.163226.

[12] Effendy, Antara, M., Muhardi, Pellokila, M. R. and Mulyo, J. H. (2022) "Effect of socio-economic on farmers' decisions in using lowland rice production inputs in Indonesia", *International Journal of Sustainable Development and Planning*, Vol. 17, No. 1, pp. 235-242. ISSN 1743-761X. DOI 10.18280/ijsdp.170123.

[13] Gholizadeh, A., Saberioon, M., Borůvka, L., Wayayok, A. and Mohd Soom, M.A. (2017) "Leaf chlorophyll and nitrogen dynamics and their relationship to lowland rice yield for site-specific paddy management", *Information Processing in Agriculture*, Vol. 4, No. 4, pp. 259-268. ISSN 2214-3173. DOI 10.1016/j.inpa.2017.08.002.

[14] Gholkar, M., Thombare, P., Koli, U. and Kumbhar, N. (2022) "Techno-economic assessment of agricultural land remediation measures through nutrient management practices to achieve sustainable agricultural production", *Environmental Challenges*, Vol. 7, No. February, p. 100492. ISSN 2667-0100. DOI 10.1016/j.envc.2022.100492.

[15] Gourevitch, J. D., Keeler, B. L. and Ricketts, T. H. (2018) "Determining socially optimal rates of nitrogen fertilizer application", *Agriculture, Ecosystems and Environment*, Vol. 254, No. January, pp. 292-299. ISSN 1873-2305. DOI 10.1016/j.agee.2017.12.002.

[16] Greene, W. H. (2003) "*Econometric analysis*", 5th ed., New Jersey, Prentice Hall. ISBN 0-13-066189-9.

[17] Gygli, S., Haelg, F., Potrafke, N. and Sturm, J. E. (2019) "The KOF globalisation index – revisited", *Review of International Organizations*, Vol. 14, No. 3, pp. 543-574. ISSN 1559-7431. DOI 10.1007/s11558-019-09344-2.

[18] Hagel, H., Hoffmann, C., Irmão, J.F. and Doluschitz, R. (2019) "Socio-economic aspects of irrigation agriculture as livelihood for rural families in Brazil's semi-arid northeast", *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, Vol. 120, No. 2, pp. 157-169. ISSN 2363-6033. DOI 10.17170/kobra-20191127814.

[19] He, X., Huang, A., Yan, J., Zhou, H., Wu, Y., Yang, L. E. and Paudel, B. (2023) "Smallholders' climate change adaptation strategies on the eastern Tibetan Plateau", Natural Hazards, Vol. 118, No. 1, pp. 641-667. ISSN 0921-030X. DOI 10.1007/s11069-023-06022-w.

[20] Jararweh, Y., Fatima, S., Jarrah, M. and AlZu'bi, S. (2023) "Smart and sustainable agriculture: Fundamentals, enabling technologies, and future directions", *Computers and Electrical Engineering*, Vol. 110, No. May, p. 108799. ISSN 1879-0755. DOI 10.1016/j.compeleceng.2023.108799.

[21] Jeder, H. (2023) "Total agricultural productivity in the Mediterranean region using the Malmquist index approach", *New Medit,* Vol. 2023, No. 2, pp. 51-61. ISSN 1594-5685. DOI 10.30682/nm2302d.

[22] Krone, M., Schumacher, K. P. and Dannenberg, P. (2014) "The impact of mobile phones on knowledge access and transfer of small-scale horticultural farmers in Tanzania", *Erde*, Vol. 145, No. 3, pp. 158-161. ISSN 0013-9998. DOI 10.12854/erde-145-14.

[23] Krugman, P. R. and Obstfeld, M. (2003) "*International economics theory and policy*", 6th ed., Boston, Pearson Education. ISBN 0-321-11639-9.

[24] Leng, X. (2022) "Digital revolution and rural family income: Evidence from China", *Journal of Rural Studies*, Vol. 94, No. December 2020, pp. 336-343. ISSN 1873-1392. DOI 10.1016/j.jrurstud.2022.07.004.

[25] Levin, A., Lin, C.F. and Chu, C.S.J. (2002) "Unit root tests in panel data: Asymptotic and finite-sample properties", *Journal of Econometrics*, Vol. 108, No. 1, pp. 1-24. ISSN 1872-6895. DOI 10.1016/S0304-4076(01)00098-7.

[26] Levin, J. and Vimefall, E. (2015) "Welfare impact of higher maize prices when allowing for heterogeneous price increases", *Food Policy*, Vol. 57, pp. 1-12. ISSN 1873-5657. DOI 10.1016/j.foodpol.2015.08.004.

[27] Liu, S. and Wang, B. (2022) "The decline in agricultural share and agricultural industrialization—some stylized facts and theoretical explanations", *China Agricultural Economic Review*, Vol. 14, No. 3, pp. 469-493. ISSN 1756-137X. DOI 10.1108/CAER-12-2021-0254.

[28] Maino, J. L., Thia, J., Hoffmann, A. A. and Umina, P. A. (2023) "Estimating rates of pesticide usage from trends in herbicide, insecticide, and fungicide product registrations", *Crop Protection*, Vol. 163, No. October 2022, p. 106125. ISSN 1873-6904. DOI 10.1016/j.cropro.2022.106125.

[29] Marinoudi, V., Sørensen, C. G., Pearson, S. and Bochtis, D. (2019) "Robotics and labour in agriculture. A context consideration", *Biosystems Engineering*, Vol. 184, pp. 111-121. ISSN 1537-5129. DOI 10.1016/j.biosystemseng.2019.06.013.

[30] Nugroho, A. D. (2021) "Agricultural market information in developing countries: A literature review", *Agricultural Economics (Czech Republic)*, Vol. 67, No. 11, pp. 468-477. ISSN 1805-929. DOI 10.17221/129/2021-AGRICECON.

[31] Oliveira, P. and Turčínková, J. (2019) "Human capital, innovation and internationalization of micro and small enterprises in rural territory – A case study", *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, Vol. 67, No. 2, pp. 545-563. ISSN 2464-8310. DOI 10.11118/actaun201967020545.

[32] Omotoso, A. B., Letsoalo, S., Olagunju, K. O., Tshwene, C. S. and Omotayo, A. O. (2023) "Climate change and variability in sub-Saharan Africa: A systematic review of trends and impacts on agriculture", *Journal of Cleaner Production*, Vol. 414, No. May, p. 137487. ISSN 1879-1786. DOI 10.1016/j.jclepro.2023.137487.

[33] Phu, L. V. (2023) "Water value, irrigation policy, and implementation hazards in Vietnam's rural economy", *Water Resources and Economics*, Vol. 43, No. June, p. 100229. ISSN 2212-4284. DOI 10.1016/j.wre.2023.100229.

[34] Pindyck, R. S. and Rubinfeld, D. L. (2013) "*Microeconomics*", 8th ed., New York, Pearson Education. ISBN 978-0-13-285712-3.

[35] Pohlová, K., Smutka, L., Laputková, A. and Svatoš, M. (2018) "Czech agrarian foreign trade according to the degree of processing", *Agris On-Line Papers in Economics and Informatics*, Vol. 10, No. 3, pp. 103-118. ISSN 1804-1930. DOI 10.7160/aol.2018.100309.

[36] Qiu, T., Choy, S. T. B. and Luo, B. (2022) "Is small beautiful? Links between agricultural mechanization services and the productivity of different-sized farms", *Applied Economics*, Vol. 54, No. 4, pp. 430-442. ISSN 1466-4283. DOI 10.1080/00036846.2021.1963411.

[37] Rogers, E. M. (2003) "*Diffusion of innovations, achieving cultural change in networked libraries*", 5th ed., New York, Free Press. ISBN 0-02-926650-5.

[38] Rudinskaya, T. and Náglová, Z. (2018) "Impact of subsidies on technical efficiency of meat processing companies", *Agris On-Line Papers in Economics and Informatics*, Vol. 10, No. 1, pp. 61-70. ISSN 1804-1930. DOI 10.7160/aol.2018.100106.

[39] Rudinskaya, T. and Náglová, Z. (2021) "Analysis of consumption of nitrogen fertilisers and environmental efficiency in crop production of EU countries", *Sustainability (Switzerland)*, Vol. 13, No. 16, pp. 1-13. ISSN 2071-1050. DOI 10.3390/su13168720.

[40] Saboori, B., Alhattali, N. A. and Gibreel, T. (2023) "Agricultural products diversification-food security nexus in the GCC countries; introducing a new index", *Journal of Agriculture and Food Research*, Vol. 12, No. December 2022, p. 100592. ISSN 2666-1543. DOI 10.1016/j.jafr.2023.100592.

[41] Sanida, O., Asafu-Adjaye, J. and Mahadevan, R. (2016) "Challenges for agricultural development in a resource-rich developing country: a case study of Papua New Guinea", *Journal of the Asia Pacific Economy*, Vol. 21, No. 2, pp. 235-256. ISSN 1469-9648. DOI 10.1080/13547860.2016.1145789.

[42] Shao, A., Ning, J., Wu, T. Y., Li, H. and Wu, J. M. T. (2022) "Designing the novel imported pork producer declaration price index using Chinese customs import declarations", *Wireless Communications and Mobile Computing*, Vol. 2022, No. 5654482, pp. 1-15. ISSN 1530-8669. DOI 10.1155/2022/5654482.

[43] Shaoping, W. and Xiaotao, S. (2014) "Codependent cycles of Chinese inflation", *Social Sciences in China*, Vol. 35, No. 4, pp. 31-45. ISSN 0252-9203. DOI 10.1080/02529203.2014.968343.

[44] Singh, S., Rawat, M., Malyan, S. K., Singh, R., Tyagi, V. K., Singh, K., Kashyap, S., Kumar, S., Sharma, M., Panday, B. K. and Pandey, R. P. (2023) "Global distribution of pesticides in freshwater resources and their remediation approaches", *Environmental Research*, Vol. 225, No. February, p. 115605. ISSN 1096-0953. DOI 10.1016/j.envres.2023.115605.

[45] de Souza, C. M., Massi, K. G. and Rodgher, S. (2023) "Meta-analysis reveals negative responses of freshwater organisms to the interactive effects of pesticides and warming", *Biologia*, Vol. 78, No. 8, pp. 2119-2130. ISSN 1336-9563. DOI 10.1007/s11756-023-01334-5.

[46] Subejo, Untari, D. W., Wati, R. I. and Mewasdinta, G. (2019) "Modernization of agriculture and use of information and communication technologies by farmers in coastal Yogyakarta", *Indonesian Journal of Geography*, Vol. 51, No. 3, pp. 332-345. ISSN 2354-9114. DOI 10.22146/ijg.41706.

[47] Sun, C., Xu, S. and Xu, M. (2023) "What causes green efficiency losses in Chinese agriculture? A perspective based on input redundancy", *Technological Forecasting and Social Change*, Vol. 197, No. March, p. 122907. ISSN 1873-5509. DOI 10.1016/j.techfore.2023.122907.

[48] Usman, M., Hameed, G., Saboor, A. and Almas, L. K. (2021) "Research and development spillover, irrigation water use and agricultural production in pakistan", *WSEAS Transactions on Environment and Development*, Vol. 17, pp. 840-858. ISSN 2224-3496. DOI 10.37394/232015.2021.17.79.

[49] Wang, T., Tu, X., Singh, V. P., Chen, X., Lin, K. and Zhou, Z. (2023) "Drought prediction: Insights from the fusion of LSTM and multi-source factors", *Science of the Total Environment*, Vol. 902, No. June, p. 166361. ISSN 1879-1026. DOI 10.1016/j.scitotenv.2023.166361.

[50] Yakovenko, N. A., Rodionova, I. A., Ivanenko, I. S., Kireeva, N. A. and Sukhorukova, A. M. (2018) "Export potential as the competitiveness indicator of the agri-food complex", *International Journal of Engineering and Technology (UAE)*, Vol. 7, No. 4, pp. 654-658. ISSN 1793-8236. DOI 10.14419/ijet.v7i4.38.24640.

[51] Zaman, S., uz Zaman, Q., Zhang, L., Wang, Z. and Jehan, N. (2022) "Interaction between agricultural production, female employment, renewable energy, and environmental quality: Policy directions in context of developing economies", *Renewable Energy,* Vol. 186, pp. 288-298. ISSN 1879-0682. DOI 10.1016/j.renene.2021.12.131.

[52] Zhang, S., Wang, S. and Yuan, L. (2020) "The impact of epidemics on agricultural production and forecast of COVID-19 epidemics", *China Agricultural Economic Review*, Vol. 12, No. 3, pp. 409-425. ISSN 1756-137X. DOI 10.1108/CAER-04-2020-0055.

[53] Živkov, D., Đurašković, J. and Ljubenović, S. (2023) "Multiscale interdependence between consumer and producer prices in emerging Eastern European countries", *Politická ekonomie*, Vol. 71, No. 3, pp. 319-341. ISSN 2336-8225. DOI 10.18267/j.polek.1390.

Appendix

Developing Countries			Developed Countries	
1. Argentina	24. Honduras	47. Paraguay	1. Australia	24. Switzerland
2. Bangladesh	25. Hungary	48. Peru	2. Austria	25. United Kingdom
3. Belize	26. India	49. Philippines	3. Canada	26. United States of America
4. Benin	27. Indonesia	50. Poland	4. Cyprus	
5. Bolivia	28. Iran	51. Qatar	5. Czech Republic	
6. Botswana	29. Iraq	52. Romania	6. Denmark	
7. Brazil	30. Jamaica	53. Russia	7. Finland	
8. Burkina Faso	31. Jordan	54. Saudi Arabia	8. France	
9. Cambodia	32. Kenya	55. Senegal	9. Germany	
10. Cameroon	33. Lao PDR	56. South Africa	10. Greece	
11. Chile	34. Madagascar	57. Sri Lanka	11. Israel	
12. China	35. Malaysia	58. Tanzania	12. Italy	
13. Colombia	36. Mali	59. Thailand	13. Japan	
14. Democratic Republic of the Congo	37. Mauritius	60. Togo	14. Republic of Korea	
15. Costa Rica	38. Mexico	61. Trinidad and Tobago	15. Latvia	
16. Dominican Republic	39. Mozambique	62. Tunisia	16. Lithuania	
17. Ecuador	40. Myanmar	63. Turkiye	17. Malta	
18. Egypt	41. Nepal	64. Uruguay	18. Netherlands	
19. El Salvador	42. Nicaragua	65. Vietnam	19. New Zealand	
20. Ethiopia	43. Niger	66. Zimbabwe	20. Norway	
21. Fiji	44. Nigeria	65. Vietnam	21. Portugal	
22. Gambia	45. Pakistan	66. Zimbabwe	22. Spain	
23. Ghana	46. Panama		23. Sweden	

Source: Authors identification, 2024

Table A1: List of developing and developed countries.