An Examination on the Structure and Behaviour of Global Agricultural Productivity: a Markov-Switching Regression

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Abstract

This study investigates the behaviour of agricultural productivity and its determinants using nonlinear Markov-switching regression. The objective is to investigate how agricultural productivity reacts to global factors and if the regression function varies due to threshold breaks. The study focuses on three agricultural sectors (crop, food, and livestock) from 1961 to 2021. The results are compared. The results show that the world uncertainty index has negative effects on the production of crops and food, but not on livestock. Besides, other global factors, namely GDP, inflation, energy, and non-energy commodity prices, have limited or no direct impact on agricultural production growth, but these factors may affect agricultural production indirectly. Furthermore, all agricultural production categories tend to grow at a decreasing rate. Additionally, agricultural production growth for all categories is expected to remain in a high production state with a higher probability. The findings might provide useful information to policymakers to improve the production and development of agricultural sectors.

Keywords	***DOI***	***JEL code***
Agriculture, commodity price, inflation, macroeconomic factors, nonlinear Markov-switching regression, uncertainty	*https://doi.org/10.54694/stat.2024.47*	*C24, Q10*

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INTRODUCTION

Agriculture is widely used to describe the various ways that domestic animals and crop plants support the human population by supplying food and other goods. In other words, agricultural production refers to the process of landscape-scale food production (Harris and Fuller, 2014). Nowadays, agriculture is still a vital sector of many economies, particularly in developing countries. Increasing agricultural productivity can make the country's economy grow and reduce poverty. Changes in agricultural productivity will also affect farm incomes, employment opportunities, and rural development. Additionally, agriculture is a global industry, and agricultural productivity plays an important role in the global market. However, fluctuations in macroeconomic indicators, such as inflation, can affect the cost and profitability of agricultural sectors. Thus, recognising key factors that affect agricultural productivity is crucial in targeting resource allocations. This is to ensure that resources can be utilised efficiently and effectively, leading to maximum productivity gains, besides developing risk management strategies.

Agricultural productivity, or its production growth, is not a new topic. Many studies have been conducted, and they mainly focus on environmental factors, such as temperature, weather, and land conditions. However, the outbreak of the COVID-19 pandemic and the global influences/crises have been evident in the increasing role and influence of global factors in changing and affecting socio-economics, politics, and living standards. Agriculture is a part of commodities where the quantities and prices are highly volatile and determined by global market conditions or global factors. Hence, uncertainties caused by sudden shocks, unpredictable crises, and pandemics may affect the demand and supply of agricultural products and decisions on investment and economic stability. Thus, these global factors might be essential factors in influencing the productivity of agriculture. Yet, the examination of their influences on agricultural productivity is not yet well explored.

Moreover, most past studies applied conventional approaches, which assume a linear or constant relationship in modelling agricultural productivity. Nonetheless, economic relationships always vary in real-world situations. The change in economic structures, policy decisions, crises, or shocks may trigger changes in the relationship examined. Besides, the data series may contain structural breaks or trends triggered by economic events. It implies that the outcomes of the study nexus might vary accordingly. The use of linear approaches in this situation is inappropriate since nonlinear or structural changes could not be uncovered by linear techniques employed in the literature. Consequently, linear models may lead to misleading conclusions and faulty policy decisions if they ignore the changes in the nexus. Furthermore, different categories of agriculture, namely crop, food, and livestock, may exhibit dissimilar behaviours or reactions in responding to the impacts of global factors. However, past studies that focused on and compared different agricultural sectors are lacking. Most researchers investigated the determinants of total agricultural productivity instead of different categories of agricultural productivity.

In filling the research gaps mentioned, this study aims to investigate global agricultural productivity using Markov-switching (MS) regression, i.e., Markov-switching autoregressive (MS-AR) and Markov-switching dynamic regression (MS-DR) from 1961 to 2021. The objectives of this study are (i) to examine the behaviour and structural change in global agricultural productivity (crop, food, and livestock) using nonlinear Markov-switching regression, (ii) to reveal the main determinants of global agricultural productivity, and (iii) to compare the results across agriculture categories of crop, food, and livestock. Therefore, this study contributes to the agricultural productivity research in the multivariate time-series framework with macroeconomic factors as determinants. The analysis of this study applies four different model specifications for each equation of agricultural productivity (crop, food, livestock, and total agricultural productivity) with MS-AR and MS-DR approaches. The Markov-switching model is a nonlinear technique that could capture the structural change in global agricultural productivity. Hence, this study could provide better representations of real situations, thus delivering more accurate estimates.

The remainder of this study is organised as follows. Section 1 provides the literature review on agricultural productivity. Section 2 describes the data and methodology employed. Section 3 reports the model selection, estimation results of MS regressions, probability of transition across regimes, and expected durations of each regime. Last sections are Discussion and Conclusion.

1 LITERATURE REVIEW

There are a few production functions and theories that explain the changes in agricultural productivity. The production function consists of linear homogeneous production function, Cobb-Douglas production function, constant elasticity of substitution production function, and variable elasticity substitution production function. These production functions primarily describe how labour and capital inputs contribute to the total output. Besides, the Malthus theory and the Boserup theory can be linked to agriculture. These two theories have some differences. According to Malthus theory, the pace of agricultural productivity will always underperform population growth, forcing the excess population to die off. The view of agricultural production as relatively inelastic, with output increasing principally by putting more land under tillage, has performed poorly in subsequent comparative agricultural research. By contrast, the Boserup theory asserts that agricultural innovation can be driven by population growth. This theory contradicted Malthus' postulation that agricultural systems yielded at the greatest scale possible given available technologies. Instead, the land was discovered to be utilised rarely, with an immense dependence on fire to clear fields and then to restore fertility in the commonly practiced slash-and-burn farming (Boserup, 1965).

Many studies have examined the behaviour and structural change in global agricultural productivity. It was found that global agricultural productivity is affected by several determinants, including gross domestic product (GDP), inflation rate, and commodity price. Jayne (2021) reported a relationship between GDP and agricultural productivity. The result of the study conveyed that productivity growth is more important to maintain Africa's agricultural development in sub-Saharan Africa. Chandio et al. (2022) also found that per capita income (a proxy of GDP per capita) has a positive and significant influence on agricultural production in China in both the long and short runs. Besides, some studies discovered that agricultural productivity had positive effects on GDP. Among the studies are Anwar et al. (2015), Rehman et al. (2017), and Gero and Egbendewe (2020).

Regarding the nexus between inflation and agriculture, there is no agreement on whether inflation will affect agricultural productivity or no relationship between the two variables. Some studies, such as Ansari et al. (2022), and Ngong et al. (2023), revealed that the inflation rate hinders agricultural productivity. On the contrary, the inflation rate was found to have an insignificant result on agricultural productivity, as reported by Kadir and Tunggal (2015), and Oluwatoyese et al. (2016). For commodity prices as a factor of agricultural productivity, Dorward (2013) has proven that low food prices are important for raising the food productivity of agriculture. On the other hand, some researchers, such as Binuomote and Odeniyi (2013), and Taghizadeh-Hesary et al. (2019), showed that oil prices affected agricultural productivity.

Some studies reported that the temperature change is one of the factors that affect agricultural productivity. Among them are Abebe (2017), Ahmad et al. (2020), and Syed et al. (2022). Climate shocks also impacted the productivity of agriculture (Praveen and Sharma, 2020; Gurgel et al., 2021; Dhifaoui et al., 2023). Gurgel et al. (2021) claimed that climate change had a direct influence on crops and livestock commodities in many developing countries. Other factors, such as air quality, may also influence agricultural productivity. Dong and Wang (2023) reported that air pollution is one of the critical factors affecting global agricultural productivity. Moreover, Eshete et al. (2020) and Chopra et al. (2022) found that carbon dioxide (CO_2) emissions had negatively affected agricultural productivity. By contrast, the findings by Alhassan (2021) demonstrated a U-shaped relationship between agricultural productivity and CO_2 emissions. On the other hand, Alajeeli et al. (2023) exposed that agricultural productivity was impeded by the present value of CO_2 emissions but stimulated by the lagged value of CO_2 emissions. Contrarily, renewable energy consumption enhanced the agricultural sector (Chopra et al, 2022) and the short-run food security (Rehman et al., 2024).

Furthermore, Seven and Tumen (2020), and Rehman et al. (2024) found that the availability of credit had a positive impact on agricultural productivity and food security, respectively. Gender differences in agricultural productivity were analysed by Tufa et al. (2022) and showed that female-managed plots were less productive than male-managed plots. Other determinants of agricultural productivity include land size (Abman and Carney, 2020; Britos et al., 2022; Chandio et al., 2022; Alajeeli et al., 2023), population growth (Njegovan and Simin, 2020), rainfall (Amare et al., 2018; Vema et al., 2022; Alajeeli et al., 2023), technology (Sarma, 2021; Amuakwa-Mensah and Surry, 2022), and fertiliser constituents (Djoumessi, 2021). Also, the world is more integrated or globalised due to the advancement of communication technology, transportation, and networking through trade. Hence, external factors such as the world uncertainty index, commodity prices, and global demand and supply may have increasing influences on agriculture.

In terms of approaches and methodologies used, ordinary least squares (OLS) regression is the most common technique used in studying agricultural markets. Among these studies are Anwar et al. (2015), Urgessa (2015), Rehman et al. (2017), Abman and Carney (2020), Alhassan (2021), Djoumessi (2021), Amuakwa-Mensah and Surry (2022), Alajeeli et al. (2023), and Dong and Wang (2023). Particularly, Alhassan (2021) and Amuakwa-Mensah and Surry (2022) applied the fully modified OLS (FMOLS) technique in their model estimations. Also, Djoumessi (2021) and Dong and Wang (2023) used two-way fixed effects panel regression models to explore agricultural productivity for 22 Sub-Saharan African countries and 146 countries (global evidence), respectively. These OLS-type approaches are linear regressions. Apart from OLS techniques, various linear methods were adopted by past studies, e.g., instrumental-variable methods were utilised by Seven and Tumen (2020), the linear autoregressive distributed lag (ARDL) model was used by Ahmad et al. (2020) and Ansari et al. (2022), the panel ARDL model was applied by Ngong et al. (2023), the panel vector autoregression (VAR) model was used by Taghizadeh-Hesary et al. (2019), the cross-sectionally augmented ARDL (CS-ARDL) approach was utilised by Ali et al. (2021), and Heckman's two-stage model was adopted by Sarma (2021). Only a few researchers employed nonlinear methods in exploring agricultural productivity. For example, Zhou et al. (2022) applied nonlinear ARDL models to study the role of the agriculture sector in CO_2 emissions in China. By using an exogenous switching regression (ESR) model, Tufa et al. (2022) showed that gender is one of the determinants of agricultural productivity.

2 DATA AND METHODOLOGY

2.1 Data

This study focuses on the behaviour of the global growth rate of agriculture for food, livestock, crop, and total agriculture. The determinants of the global growth rate of agriculture considered in this study are the consumer price inflation (CPI) inflation rate, gross domestic product (GDP) per capita growth, changes in the world uncertainty index (WUI), inflation rate of Energy Commodity Price Index (NRG), and inflation rate of Non-Energy Commodity Price Index (NNRG). The data frequency for all the variables used is annually from 1961 to 2021, which has a total of 61 observations. The datasets are collected from multiple sources. The indexes of food, livestock, and crop are obtained from the Food and Agriculture Organisation of the United Nations. The GDP, INF, NRG, and NNRG are gathered from the World Bank, whereas WUI is from the Federal Reserve Bank of St. Louis. The variables used in this study are summarised in Table 1.

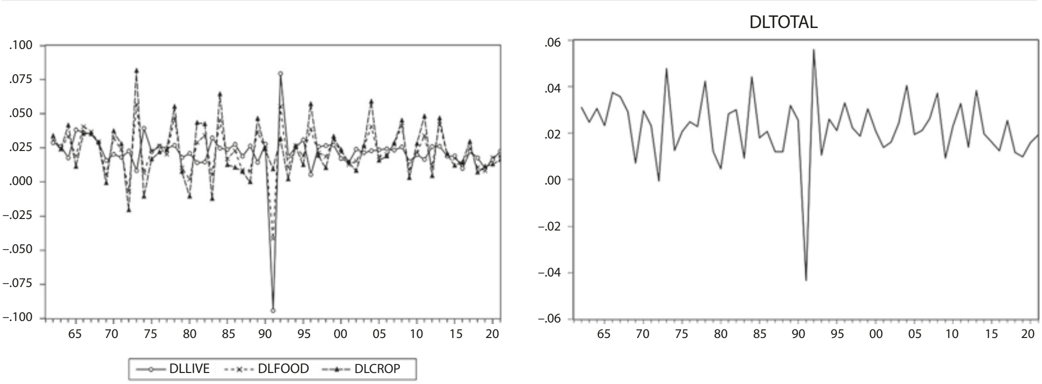
Table 1 The list of variables

Variable	Description	Unit of measurement
DLCROP	CROP = global crop production index DLCROP = growth rate of CROP	Annual % change in CROP
DLFOOD	FOOD = global food production index DLFOOD = growth rate of FOOD	Annual % change in FOOD
DLLIVE	LIVE=global livestock production index DLLIVE = growth rate of LIVE	Annual % change in LIVE
DLTOTAL	TOTAL = total agriculture index (average of three indices) DLTOTAL = growth rate of total agriculture	Annual % change in TOTAL
GDP	GDP per capita growth	Annual %
INF	CPI inflation rate	Annual % change in CPI
DLWUI	WUI = world uncertainty index DLWUI = changes in WUI	Annual % change in WUI
DLNRG	NRG = energy commodity price index DLNRG = inflation rate of NRG	Annual % change in NRG
DLNNRG	NNRG = non-energy commodity price index DLNNRG = inflation rate of NNRG	Annual % change in NNRG

Source: Own construction

The CROP, FOOD, LIVE, TOTAL, WUI, NRG, and NNRG are transformed into percentage form using the log difference. They are interpreted as the growth rate or changes in price indexes, i.e., DLCROP, DLFOOD, DLLIVE, DLTOTAL, DLWUI, DLNRG, and DLNNRG, respectively. For instance, DLCROP is obtained as the log of CROP or LCROP at the current year (t) minus the previous term (t – 1), i.e., DLCROP = $LCROP_t$ – $LCROP_{t-1}$. Referring to Figure 1, the series of DLLIVE, DLFOOD, DLCROP, and DLTOTAL show fluctuating above and below the imaginary horizontal line throughout the period from the year 1961 to 2021. Therefore, the series of all variables might be stationary. DLLIVE, DLFOOD, and DLTOTAL had negative global growth rates in 1991 due to the early 1990s recession. The early 1990s recession was the period of economic downturn affecting much of the Western world in the early 1990s.

Figure 1 Time-series plots of DLLIVE, DLFOOD, DLCROP, and DLTOTAL



Source: Own constructions

2.2 Methodology

The analysis involves several steps. After data collection, the datasets in index form are transformed into percentage form using the log difference. Next, preliminary tests (unit root tests and the breakpoint unit root test) are conducted to verify the characteristics of the variables used in this study. This step is to make sure that all variables used are stationary. The variables that are not stationary are transformed into stationary series by first differencing using statistical software, i.e., EViews 10. After studying the variables and verifying the characteristics exhibited by the variables, the study proceeds to model estimations using Markov-switching (MS) models. The results are also obtained from EViews 10. Lastly, interpretations and comparisons are made based on the results obtained.

The Markov-switching models incorporate multiple structures/regimes to characterise the variation and switching behaviours of time series across different regimes; hence, they can capture more complex dynamic patterns in time series variables. According to Kuan (2002), Markov switching models can be distinguished from the models of structural changes, as the models with structural changes allow for frequent changes at random time points, while Markov switching models only have occasional and exogenous changes in modelling data with distinct dynamic patterns under different regimes of periods. Markov-switching models are employed if a series is expected to transition over a finite number of unobserved states. The process is allowed to develop uniquely in each state. Several global crises, such as oil price shocks, financial crises, and the COVID-19 pandemic, might affect agricultural productivity. Thus, structural breaks might present during unexpected events. Accordingly, this study applies Markov-switching regressions to examine the relationship that might demonstrate structural breaks or regime changes. This study only considers one structural break or a two-regime model for better interpretation (low versus high inflation regimes). The transitions across regimes follow a Markov process, which is stochastic or random. This study applies two types of MS models, which are Markov-switching autoregressive (MS-AR) and Markov-switching dynamic regression (MS-DR). MS-AR models involve a gradual adjustment after the process changes state. In state *s* and time *t* of a process, the MS-AR model AR(1) with two state-dependent AR terms is:

$$y_t = \mu_{s_t} + \phi_1\left(y_{t-1} - \mu_{s_{t-1}}\right) + \alpha x_t + \varepsilon_{s_t}, \tag{1}$$

where y_t represents the dependent variable, μ_{st} indicates the state-dependent intercept, in which s_t indicates regime ($s_t = 1, 2$), x_t are covariates with state-invariant coefficients α, ε_{St} is the independent and identically distributed (i.i.d.) normal error with mean zero and state-dependent variance, $\varepsilon_{s_t} \sim N\left(0, \sigma^2_{s_t}\right)$.

In this study, Model (b) for each equation is conducted with regime switching, while Model (a) is conducted without regime switching. Formula (1) is with regime switching. If without switching, the equation becomes Formula (2) as follows:

$$y_t = \mu_{s_t} + \phi_1\left(y_{t-1} - \mu_{s_{t-1}}\right) + \alpha x_t + \varepsilon, \tag{2}$$

where ε is the i.i.d. normal error with mean 0 and variance σ^2, which is non-switching.

By contrast, MS-DR models involve a rapid adjustment after the process changes state. Generally, the MS-DR model specification is:

$$y_t = \mu_{s_t} + \alpha x_t + z_t \beta_{s_t} + \varepsilon_{s_t}, \tag{3}$$

where z_t denotes exogenous variables with state-dependent coefficients β_{St}. x_t and z_t may contain lags of y_t.

In this study, the MS models take the following form:

State 1: $y_t = \mu_1 + \phi y_{t-1} + \alpha x_t + \varepsilon_t$, (4)

State 2: $y_t = \mu_2 + \phi y_{t-1} + \alpha x_t + \varepsilon_t$, (5)

where μ_1 and μ_2 are the intercept terms in State 1 and State 2, respectively, ϕ is the DR parameter, and ε_t is a white noise error with variance σ^2. This is specified with Model (d), with switching of mean and variance of error term. In the case of interest, s_t is not observed. MS regression models specify that the unobserved s_t follows a Markov chain. In the simplest case, the model can be expressed as a state-dependent intercept term for k states:

$$y_t = \mu_{s_t} + \phi y_{t-1} + \alpha x_t + \varepsilon_{s_t}, \tag{6}$$

where $\mu_{S_t} = \mu_1$ when $s_t = 1$, $\mu_{St} = \mu_2$ when $s_t = 2$, ..., and $\mu_{S_t} = \mu_k$ when $s_t = k$. The conditional density of y_t is assumed to be dependent only on the realisation of the current state s_t and is given by $f\left(y_t | s_t = i, y_{t-1}; \theta\right)$, where θ is a vector of parameters. There are k conditional densities for k states, and estimation of θ is performed by updating the conditional likelihood using a nonlinear filter. On the other hand, Model (c) is specified as the same as Model (d), but the error term is not regime-switching (StataCorp, 2023).

This study examines four models as follows:

Model 1: DLCROP = F(GDP, INF, DLWUI, DLNRG, DLNNRG),
Model 2: DLFOOD = F(GDP, INF, DLWUI, DLNRG, DLNNRG),
Model 3: DLLIVESTOCK = F(GDP, INF, DLWUI, DLNRG, DLNNRG),
Model 4: DLTOTAL = F(GDP, INF, DLWUI, DLNRG, DLNNRG).

Each equation is estimated using two types of MS models, i.e., MS-AR and MS-DR models. Besides that, each type of MS model has two types of switching variables: (i) mean included only, and (ii) mean and variance included. Therefore, one dependent variable has four different types of equations, and a total of sixteen equations are analysed in this study. The MS-AR and MS-DR lag-one models are applied. The AR or DR terms (lag 1 of the dependent variable) are added as a regressor accordingly under different model specifications, as shown in Table 2. Model (a) and Model (b) refer to MS-AR with constant and varying variance, respectively, whereas Model (c) and Model (d) are MS-DR with constant and varying variance, respectively. In particular, Models (a) and (c) specify the mean variable as a switching variable with other variables as non-switching variables. Models (b) and (d) specify mean and variance as switching variables with other variables as non-switching variables.

Table 2 Model specifications

Model	Dependent variable (y)	Non-switching variable (x)	Switching variable	Types
1(a)	DLCROP	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean	MS-AR
1(b)	DLCROP	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean, variance	MS-AR
1(c)	DLCROP	GDP, INF, DLWUI, DLNRG, DLNNRG, DLCROP(-1)	Mean	MS-DR
1(d)	DLCROP	GDP, INF, DLWUI, DLNRG, DLNNRG, DLCROP (-1)	Mean, variance	MS-DR

Table 2 (continuation)

Model	Dependent variable (y)	Non-switching variable (x)	Switching variable	Types
2(a)	DLFOOD	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean	MS-AR
2(b)	DLFOOD	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean, variance	MS-AR
2(c)	DLFOOD	GDP, INF, DLWUI, DLNRG, DLNNRG, DLFOOD(-1)	Mean	MS-DR
2(d)	DLFOOD	GDP, INF, DLWUI, DLNRG, DLNNRG, DLFOOD(-1)	Mean, variance	MS-DR
3(a)	DLLIVESTOCK	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean	MS-AR
3(b)	DLLIVESTOCK	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean, variance	MS-AR
3(c)	DLLIVESTOCK	GDP, INF, DLWUI, DLNRG, DLNNRG, DLLIVESTOCK(-1)	Mean	MS-DR
3(d)	DLLIVESTOCK	GDP, INF, DLWUI, DLNRG, DLNNRG, DLLIVESTOCK(-1)	Mean, variance	MS-DR
4(a)	DLTOTAL	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean	MS-AR
4(b)	DLTOTAL	GDP, INF, DLWUI, DLNRG, DLNNRG, AR(1)	Mean, variance	MS-AR
4(c)	DLTOTAL	GDP, INF, DLWUI, DLNRG, DLNNRG, DLTOTAL(-1)	Mean	MS-DR
4(d)	DLTOTAL	GDP, INF, DLWUI, DLNRG, DLNNRG, DLTOTAL(-1)	Mean, variance	MS-DR

Source: Own constructions

3 RESULTS

Before running the estimations, unit root tests are performed to check the stationarity of each variable. The results of Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and breakpoint unit root test are summarised in Table 3. The null hypothesis for ADF and breakpoint unit root tests is that the series is not stationary, and rejecting the null hypothesis indicates a stationary series. By contrast, the null hypothesis for KPSS is that the series is stationary, which is the opposite. From the results of unit root tests, all variables show stationarity at level. Only GDP and INF show a contradiction between ADF and KPSS test results. Hence, breakpoint unit root test results serve as references for GDP and INF. Therefore, the variables in level form are used in the analysis. After the preliminary tests, the models are estimated using MS approaches. The results can be divided into three parts, which are model selection, MS estimation, and transition probability and expected duration.

Table 3 The results of unit root tests

Variable	Test statistics (level variable)		
	ADF	KPSS	Breakpoint
DLCROP	–8.8621***	0.0269	–12.1434***
DLFOOD	–11.4947***	0.0359	–14.2241***
DLLIVE	–11.4811***	0.1099	–11.7045***
DLTOTAL	–11.2122***	0.0401	–14.8083***
GDP	–6.7206***	0.1410*	–7.8125***

Table 3 (continuation)

Variable	Test statistics (level variable)		
	ADF	**KPSS**	**Breakpoint**
INF	−3.5736**	0.1298*	−7.4086***
DLWUI	−11.5393***	0.0716	−11.9592***
DLNRG	−6.6376***	0.0631	−7.9251***
DLNNRG	−6.1473***	0.0476	−6.5874***

Note: ***, **, and * indicates significance at 1%, 5%, and 10% levels, respectively.
Source: Own constructions

3.1 Model selection

The MS-AR and MS-DR models are applied with different specifications, as indicated in Table 2. The performance of models is evaluated by model-fitting indicators (SC, AIC, and log-likelihood) and forecast performances (RMSE, MAE, and MAPE). Table 4 summarises the results of Schwarz info criterion (SC), Akaike info criterion (AIC), log-likelihood, root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) for all models. The best model should minimise the SC, AIC, RMSE, MAE, and MAPE, but it should maximise the log-likelihood value. Accordingly, Models 1(b), 2(c), 3(b), and 4(c) are selected as the best models. Thus, this study focuses more on the results of these four models, and other models are used as references.

Table 4 Model selection

Model	SC	AIC	Log likelihood	RMSE	MAE	MAPE	Preferred model
1(a)	−4.7258	−5.1132	161.8389	0.0194	0.0147	210.1643	**Model 1(b)**
1(b)	**−4.8251**	**−5.2477**	**166.8071**	**0.0192**	0.0147	291.8070	
1(c)	−4.6821	−5.0694	160.5479	0.0199	0.0148	226.4907	
1(d)	−4.6597	−5.0823	161.9273	0.0197	**0.0141**	**152.2665**	
2(a)	−5.1699	−5.5572	174.9378	**0.0151**	0.0106	**76.9625**	**Model 2(c)**
2(b)	−5.2831	−5.7056	**180.3162**	0.0153	**0.0105**	83.0563	
2(c)	**−5.3387**	**−5.7260**	179.9168	0.0155	0.0108	77.3872	
2(d)	−5.2745	−5.6971	180.0642	0.0155	0.0108	77.8173	
3(a)	−5.4437	−5.8310	183.0146	0.0179	0.0084	34.5207	**Model 3(b)**
3(b)	−5.9241	**−6.3467**	**199.2276**	0.0179	**0.0081**	33.4715	
3(c)	**−5.9499**	−6.3372	197.9488	0.0179	0.0083	34.2633	
3(d)	−5.9229	−6.3454	199.1901	0.0179	**0.0081**	**33.4267**	
4(a)	−5.4392	−5.8265	182.8832	**0.0136**	**0.0091**	115.0295	**Model 4(c)**
4(b)	−5.5669	−5.9895	**188.6901**	0.0140	**0.0091**	131.2411	
4(c)	**−5.6036**	**−5.9909**	187.7314	0.0137	0.0092	**112.8415**	
4(d)	−5.5455	−5.9680	188.0568	0.0139	0.0093	119.4857	

Source: Own constructions

3.2 Markov-switching (MS) regression

Table 5 reports the estimated mean of the agricultural production growth rate. Regime 1 denotes a period with a downward trend and is interpreted as a low regime. Contrarily, Regime 2 indicates a period with an upward trend and is interpreted as a high regime. The regimes refer to agricultural production to move between high and low states in the models. Most models show a significant mean of agricultural production growth. In certain cases, the value of the mean is negative in the low regime, which indicates the decline rate. All estimated means are positive in the high regime, signifying an increasing growth rate. In the low regime, the model of the total agricultural production rate has the most significant values. In the high regime, coefficients are significant for most models. Among the three agriculture categories, the crop production rate is relatively higher, whereas the livestock production rate is relatively lower in both regimes. However, different specifications may provide slightly different estimates of the mean value.

Table 5 The estimated mean of agricultural production growth rate

Dependent variable	Model	Regime 1 (low)	Regime 2 (high)
DLCROP	1(a)	0.0042	0.0444***
	1(b)	0.0067	0.0232***
	1(c)	–0.0151	0.0303***
	1(d)	0.0329***	0.0339
DLFOOD	2(a)	–0.0298**	0.0226***
	2(b)	0.0082	0.0207***
	2(c)	–0.0198**	0.0321***
	2(d)	–0.0186	0.0322***
DLLIVESTOCK	3(a)	–0.0861***	0.0232***
	3(b)	–0.0032	0.0210***
	3(c)	–0.0834***	0.0289***
	3(d)	–0.0046	0.0218***
DLTOTAL	4(a)	–0.0321***	0.0220***
	4(b)	0.0214***	0.0701
	4(c)	–0.0326***	0.0311***
	4(d)	–0.0087	0.0306***

Note: *** and ** indicates significance at 1% and 5% levels, respectively.
Source: Own constructions

The estimated coefficients of control variables are shown in Table 6. From the table, the impacts of global factors on agricultural production growth vary across agricultural categories, i.e., crop (Model 1), food (Model 2), livestock (Model 3), and total agriculture (Model 4). The log(sigma) refers to the log of the standard deviation of error terms. As observed, Models (a) and (c) report a constant value in both regimes, whereas Models (b) and (d) show varying variances between Regime 1 (R1) and Regime 2 (R2). The log(sigma) values are negative in all cases, indicating a low standard deviation, which is less than one. In MS-AR models (i.e., Models (a) and (b)), the AR(1) term indicates the deviation of the dependent variable from its mean at one past period. In MS-DR models (i.e., Models (c) and (d)), the DR(1) term refers to the lag one of the dependent variable. Both AR(1) and DR(1) coefficients capture the gradual adjustment in the dependent variable, which is the agricultural production growth over time. The negative coefficients indicate a declining growth rate.

Table 6 The estimated coefficients of control variables

Variable	Model 1(a)	Model 1(b)	Model 1(c)	Model 1(d)
GDP	0.0011	0.0023**	0.0023	0.0021
INF	–0.0009*	–0.0002	9.55e-05	–0.0014
DLWUI	–0.0097***	–0.0100***	–0.0076***	–0.0069***
DLNRG	0.0280***	0.0119	0.0183	0.0279**
DLNNRG	–0.0104	0.0109	–0.0240	–0.0556**
DLCROP(–1)			–0.4636***	–0.3975***
AR(1)	–0.7960***	–0.7165***		
Log(sigma)	–4.4445***	–3.6683***(R1)	–4.2872***	–4.3157***(R1)
		–4.9025***(R2)		–3.2037***(R2)
Variable	**Model 2(a)**	**Model 2(b)**	**Model 2(c)**	**Model 2(d)**
GDP	0.0010	0.0193**	0.0018*	0.0017
INF	–0.0004	0.0003	–0.0006	–0.0005
DLWUI	–0.0041	–0.0056***	–0.0044**	–0.0043**
DLNRG	0.0065	0.0025	0.0124	0.0120
DLNNRG	–0.0091	–0.0038	–0.0231	–0.0224
DLFOOD(–1)			–0.4161***	–0.4152***
AR(1)	–0.4152***	–0.5020***		
Log(sigma)	–4.4693***	–3.7706***(R1)	–4.6122***	–4.2870***(R1)
		–4.8723***(R2)		–4.6247***(R2)
Variable	**Model 3(a)**	**Model 3(b)**	**Model 3(c)**	**Model 3(d)**
GDP	0.0002	0.0006	0.0009	0.0006
INF	–0.0001	–1.16e-05	7.56e-05	–8.30e-06
DLWUI	0.0017	0.0009	0.0014	0.0009
DLNRG	0.0020	0.0017	0.0007	0.0018
DLNNRG	1.24e-05	0.0002	–0.0049	–3.87e-05
DLLIVE(–1)			–0.3534***	–0.0343
AR(1)	–0.0942	–0.0342		
Log(sigma)	–4.6066***	–2.5238***(R1)	–4.8596***	–2.5310***(R1)
		–4.9882***(R2)		–4.9877***(R2)
Variable	**Model 4(a)**	**Model 4(b)**	**Model 4(c)**	**Model 4(d)**
GDP	0.0011	0.0014*	0.0012	0.0016*
INF	–0.0003	–0.0003	–0.0005	–0.0004
DLWUI	–0.0030	–0.0043***	–0.0023	–0.0033**
DLNRG	0.0059	0.0078	0.0109	0.0100
DLNNRG	–0.0068	–0.0162	–0.0164	–0.0174
DLTOTAL			–0.3868***	–0.3833***
AR(1)	–0.3525**	–0.2924**		
Log(sigma)	–4.6044***	–4.8484***(R1)	–4.6863***	–3.8113***(R1)
		–2.3523***(R2)		–4.7758***(R2)

Note: ***, **, and * indicates significance at 1%, 5%, and 10% levels, respectively.
Source: Own construction

From the results of the preferred model in Model 1, i.e., Model 1(b), GDP significantly affects crop productivity with a positive impact. Besides, changes in WUI (DLWUI) show a significant negative impact on crop productivity. Inflation and commodity price index do not significantly affect crop productivity in Model 1(b). DLWUI is the only variable that significantly affects crop production for all four models in Model 1. In short, the changes in GDP and the WUI index affect crop production growth. Next, Model 2(c), the preferred model among Model 2, is the MS-DR model that takes the mean variable as a switching variable. This model shows some similar features to Model 1. Both GDP and DLWUI significantly affect food productivity. The change in GDP has a positive impact on food productivity, whereas the change in the WUI index has a negative impact on food productivity. Other models in Model 2 show that all models give a similar view of the results.

Among the three areas of agricultural productivity (crop, food, and livestock), only livestock productivity, Model 3(b), shows that all control variables are insignificant. By comparing all four models in Model 3, all control variables show the same features, which are insignificant. It implies that no variable significantly affects livestock production growth. For the total agricultural productivity model (Model 4), the results of Model 4(c) (the preferred model) show that all control variables are insignificant. Therefore, other models in Model 4 are taken as references. From the model that takes both mean and variance as switching variables (Models 4(b) and 4(d)), GDP and DLWUI significantly affect the total agricultural productivity. Changes in GDP have positive impacts on total agricultural productivity, while changes in the WUI index have negative impacts on total agricultural productivity.

3.3 Transition probability and expected duration

The trend and behaviour of agricultural productivity can be studied from the transition probability and expected duration results in Table 7. Transition probabilities P11 and P22 indicate the transition of probability to remain in Regime 1 (low regime) and Regime 2 (high regime), whereas P12 and P21 are defined as the transitions of the probabilities between both regimes. The transition probabilities of Model 1 are rather dissimilar, where Models 1(a) and 1(d) show a higher probability of remaining in the low regime, whereas Models 1(b) and 1(c) show a higher probability of remaining in the high regime. Nevertheless, the preferred model, Model 1(b), shows that crop production growth has a higher probability of staying in the high production growth (Regime 2). Particularly, there is a 57.69% chance of remaining in the high regime compared to almost 0% (8.89e-10) of remaining in the low regime. The corresponding expected durations of crop production growth to remain in the low regime (Regime 1) and high regime (Regime 2) are 1 year and 2.36 years, respectively. The predicted transition probability (in percentage) from Regime 2 to Regime 1 is 42.31%. However, it is more likely that there will be almost 100% certainty that crop production growth may shift from the low regime to the high regime.

Table 7 Transition probability and expected duration for Models 1, 2, 3, and 4

Variable	Model 1(a)	Model 1(b)	Model 1(c)	Model 1(d)
Transition probability				
P11	0.1669	8.89e-10	8.75e-06	0.9656
P12	0.8331	1.0000	1.0000	0.0344
P21	0.9568	0.4231	0.0491	0.4773
P22	0.0432	0.5769	0.9509	0.5227
Expected duration				
I	1.2004	1.0000	1.0000	29.0600
II	1.0452	2.3634	20.3579	2.0953

Table 7 (continuation)

Variable	Model 2(a)	Model 2(b)	Model 2(c)	Model 2(d)
Transition probability				
P11	7.30e-11	1.20e-11	8.18e-06	3.02e-09
P12	1.0000	1.0000	1.0000	1.0000
P21	0.0172	0.2515	0.0349	0.0362
P22	0.9828	0.7485	0.9651	0.9638
Expected duration				
I	1.0000	1.0000	1.0000	1.0000
II	58.2456	3.9758	28.6611	27.5961
Variable	**Model 3(a)**	**Model 3(b)**	**Model 3(c)**	**Model 3(d)**
Transition probability				
P11	8.23e-07	0.4910	5.56e-09	0.4899
P12	1.0000	0.5090	1.0000	0.5101
P21	0.0171	0.0195	0.0173	0.0197
P22	0.9629	0.9805	0.9827	0.9803
Expected duration				
I	1.0000	1.9647	1.0000	1.9606
II	58.5238	51.1540	57.9661	50.6726
Variable	**Model 4(a)**	**Model 4(b)**	**Model 4(c)**	**Model 4(d)**
Transition probability				
P11	4.31e-09	0.9610	7.20e-09	4.09e-09
P12	1.0000	0.0390	1.0000	1.0000
P21	0.0170	1.0000	0.0173	0.0464
P22	0.9830	0.0000	0.9827	0.9536
Expected duration				
I	1.0000	25.6706	1.0000	1.0000
II	58.8106	1.0000	57.8339	21.5341

Source: Own construction

Similar characteristics are displayed among all specifications in Model 2 (food production growth). All models show a higher probability of remaining in the high regime. The best model, which is Model 2(c), shows a 96.51% chance that food production growth may be maintained in the high regime compared to almost 0% (8.18e-06) for it to be maintained in the low regime. There is a 3.49% chance of moving from Regime 2 to Regime 1 and an almost 100% chance of moving from Regime 1 to Regime 2. The expected durations are 1 year and 28.66 years for the low and high regimes, respectively. The results of all specifications in Model 3 report that livestock production growth has a higher probability of remaining in the high regime. The best model, which is Model 3(b), shows that there is a 49.10% chance for the livestock to remain in the low regime, while 98.05% for it to remain in the high regime. It also shows that there is only a 1.95% chance to move from the high regime to the low regime and a 50.90% chance to move from the low regime to the high regime. The expected durations are 1 year and 51.15 years for the low and high regimes, respectively.

For total agricultural productivity (Model 4), most models show similar characteristics, which demonstrate a higher probability of remaining in the high regime, except for Model 4(b), which shows an inverse result, i.e., a higher probability of remaining in the low regime. However, the best model, Model 4(c), shows a 98.27% chance that total agricultural productivity will remain in the high regime compared to almost 0% (7.20e-09) of staying in the low regime. The corresponding expected durations are 1 year and 57.83 years for the low and high regimes, respectively. It can be found that there is a 1.73% chance for total agricultural productivity to move from Regime 2 to Regime 1, but it is most likely that the total agricultural productivity may shift out of Regime 1 with an almost 100% chance.

4 DISCUSSION

The change in WUI shows a significant negative effect on the total agricultural productivity. This finding is consistent with existing studies, such as Gregorioa and Ancog (2020) and Lusk and Chandra (2021). It is caused by a reduction in agricultural farm labour (Gregorioa and Ancog, 2020; Lusk and Chandra, 2021). Community lockdowns imposed during the pandemic had restricted the movement of all residents, including farm labourers, causing decreased agricultural output. The limited access of farmers to farm inputs and markets can also cause reduced agricultural productivity, which then leads to financial losses and farm product wastage. Subsequently, long-term income loss and economic recession might reduce the demand, especially among farmers and their families without any protection systems (Gregorioa and Ancog, 2020). The change in WUI also hinders the production growth of crops and food, but not livestock production growth. During the pandemic, most household incomes were reduced, and rising retail prices have triggered serious threats to food security. Consumers are forced to limit both the quantity and quality of food consumed. Thus, the crop (such as grain, vegetable, or fruit) and food production are considerably reduced. Contrarily, our findings suggest that livestock productivity is more resilient to the pandemic.

By comparing the impacts of global factors across agricultural categories, the results show that the GDP increases the crop, food, and total agricultural productivity. This finding on agricultural productivity is consistent with several studies, such as Jayne (2021), and Chandio et al. (2022). It is possible that when the GDP of a country rises, the purchasing power of farmers will increase. This raises the opportunities for adopting superior quality seedlings and enhanced planting technologies. Ultimately, the production of agriculture increases. The GDP may also stimulate higher agricultural productivity through an indirect channel, which is the environmental concern. Past studies, such as Eshete et al. (2020), and Chopra et al. (2022), reported that environmental degradation proxied by CO_2 emissions reduced agricultural productivity. Ample researchers, such as Zubair et al. (2020), Pejović et al. (2021), Mohsin et al. (2022), and Park et al. (2023), also found that a rise in GDP reduced CO_2 emissions. Accordingly, an increase in GDP improves the environmental quality (reduced CO_2 emissions), which then accelerates agricultural productivity. Moreover, Park et al. (2023) claimed that GDP per capita reduced global future fire carbon emissions, enabling enhanced fire management and capitalised agriculture. It confirms our results that show higher GDP causes greater crop and food agricultural productivity. Farmers routinely have land-burning activities after harvesting. It is an economical way to dispose leftover crops.

The inflation rate has a negative but insignificant effect on all agricultural categories. This result is supported by Kadir and Tunggal (2015), and Oluwatoyese et al. (2016). The possible explanation is that agricultural products, such as grains, wheat, and dairy products, are basic needs in human lives to survive. Accordingly, the elevated level of inflation will not impede the demands on agriculture. Thus, agricultural productivity is not severely affected. However, the poor may be challenged by the high inflation rate, which affects their income levels or the ease with which they may obtain food, resulting in a greater risk of mortality due to malnutrition or starvation. Yet, the empirical finding of this study reveals the insignificant effect of inflation on agricultural productivity.

Besides, the commodity price inflations (energy and non-energy commodities) only have limited effects on the crop productivity growth and not on other agricultural productivity areas. The limited impact of commodity price inflation is similar to the phenomenon narrated previously. Agricultural productivity is not influenced by the increased commodity price due to the continuous demand for agricultural products. Additionally, Model 3 is the only model with insignificant control variables in all four models, even for the best-fitted model. This suggests that livestock productivity growth is not significantly affected by the determinants employed in this study. It might be influenced by other factors. In general, global factors have limited impacts on agricultural production growth.

In terms of production growth behaviour, the results of the best-fitted models for all four equations disclose that the agricultural production of most models has a higher probability of moving from the low regime to the high regime. It implies that all production indices have a structural change as an increasing trend over time. Moreover, all agricultural production categories tend to exhibit gradual or partial adjustment with decreasing scale in the growth rate, i.e., production grows at a lower or decreasing rate. Furthermore, the agricultural production growth of all categories is expected to remain in the high production state and linger with a higher probability. Livestock production tends to show a much longer duration to remain in the high production state. By comparing the results across the three areas of agricultural productivity growth (crop, food, and livestock), the crop production model (Model 1) is sensitive to model specifications under the MS-DR model. The results of the four models from crop production show rather different results on the transition probability. In general, all production categories exhibit quite similar characteristics. The world uncertainty index has a significant impact on crop and food production growth, but not on livestock production growth.

CONCLUSION

This study applies the Markov-switching autoregressive (MS-AR) and Markov-switching dynamic regression (MS-DR) models to examine the influences of global factors on global agricultural production growth (crop, food, livestock, and total agriculture) from 1961 to 2021. The results of the models correspond to two regimes. Regime 1 shows a period with a downward trend and implies a low regime, whereas Regime 2 shows a period with an upward trend and implies a high regime. The results report that the estimated mean value of agricultural production growth is significant in the high regime for most models. Besides, the change in the world uncertainty index shows a significant negative impact on most agricultural productivity, except for livestock productivity. Notwithstanding, its negative impact is the highest on crop productivity. The other global factors, namely global GDP, inflation, and commodity price inflation (energy and non-energy sectors), either have limited or insignificant effects on agricultural production growth of all categories. The results reveal that global factors may not have direct impacts on agricultural production growth, but this does not mean that they may not influence agricultural production growth. They may affect agricultural production growth indirectly by changing the global market trend or structure, the change of policy planning and decision, and investment flows. Environmental factors, such as temperature, soil, and land conditions, might have more direct impacts on the production of agriculture.

This study is unique and original. This study differs from past studies by investigating the three sectors of agricultural productivity using nonlinear Markov-switching regression. Previous studies mainly concentrated on the total agricultural production instead of disaggregated outcomes. By focusing on different sectors of agricultural productivity, the results report that crop and food production are affected by the GDP and the world uncertainty index. Therefore, governments should encourage diversification in crop and food production to mitigate the impact. Increasing the types and variety of crops and food production may reduce the vulnerability to economic shocks. Governments can increase investments in crops and food, such as improving farming techniques, and lead the development of resilient crop varieties and sustainable agricultural practices. Moreover, governments should facilitate the accessibility of farming equipment with adequate incentives to mitigate the manpower shortage on farms.

From the results of this study, livestock production is unaffected by all macroeconomic variables. This suggests that livestock production is more likely to be affected by other factors, perhaps climate change or environmental issues. Nonetheless, our empirical finding of livestock production also reveals a longer duration lingering in the high production state. In other words, the duration of staying in the high production state for other sectors, i.e., crop and food production, is relatively shorter. In maintaining high crop or food production, farmers should take proactive actions in dealing with any unexpected circumstances or natural disasters. Farmers are advised to prepare a few backup plans for sustainable agricultural development. In further maintaining high livestock production, governments can invest in capacity-building programmes to educate farmers regarding the building information, besides providing the necessary techniques for their farming experiences. Accordingly, the probability of livestock surviving from negative externalities will increase.

This study also discloses that most macroeconomic factors do not significantly impact agricultural productivity. Governments should pay more attention to other aspects to improve agricultural productivity. One of the approaches is increasing the investment in agricultural research and development (Deng et al., 2021). Governments can provide resources that support universities and research institutions that explore agricultural areas. This funding can support their research, such as crop improvement, soil health, and disease management. If improved or hybrid technologies can be gained from the research, agricultural productivity can be increased. Also, governments can facilitate access to affordable credit (Seven and Tumen, 2020; Rehman et al., 2024) and risk management tools for farmers (Cariappa et al., 2021). It can be achieved by providing agricultural financing schemes, insurance programmes, and risk-sharing mechanisms. Additionally, governments should emphasise agricultural education to build high education levels of workforce in agricultural sectors (Deng et al., 2021). Some examples include providing educational opportunities in agricultural sciences, management training, and training in farming skills. This enables farmers to obtain entrepreneurship skills and discover modern techniques in agriculture. Accordingly, farmers will have more efficient ways to maintain their agricultural products.

From the perspective of farmers/producers, they should be aware that the production and prices of agriculture are highly affected by many factors. Despite the direct factors, such as climate change, land or soil conditions, changes in seasons, weather, natural disasters, and external or global factors, are increasingly affecting agricultural prices. The global demand, the pandemic outbreak, the world commodity crisis, and other global factors may affect the economy, including the agricultural prices of each country at different levels. The impact could be large and persistent, especially the sudden shocks such as the commodity price crisis and the pandemic. While the impacts of shocks could be unavoidable, farmers/producers can reduce the negative impacts if they take some earlier get-ready actions and adaptations. They should not rely on the traditional farming method but should adapt to the new technologies or skills by participating in training programmes provided by the local government. They should try to find alternatives or plant multiple types of crops, not focus on one single crop alone. They should be concerned about the current news or trends, such as climate change, pandemics, etc., to stay updated with the current situation or the change in the global market. Farmers and producers should not be satisfied or remain in the same working conditions. They should take the initiative to learn new technology, voice up their needs, and adapt to the change in the market.

In general, agricultural prices fluctuate and are determined by many factors. As natural disasters, weather, climate change, land or soil factors, etc., are examined and evidenced in many studies, this study is focused on several global and external influences, which are quite lacking in the literature. As the world is getting globalised, the impacts of external factors are expected to increase over time. Hence, this direction in examining the impact of globalisation could provide new insights for policy planning and international economic analysis. This study utilises the regime-switching models to capture the transition of agricultural price changes between low and high regimes and contribute to the role of globalisation in examining the behaviour of three agricultural prices: food, livestock, and crop in the global economy.

However, this study is constrained by data availability. Due to this constraint, this study only tested several macro variables. Also, the agricultural price data is not available for many countries/regions. Hence, the examination is not permitted to compare the results across countries or regions. In the future, the study can be extended by applying other advanced econometric methods or optimisation models such as agent-based models, which permit simulations and forecasting under different economic scenarios by emphasising the role of globalisation and external shocks.

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