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Agricultural production index: International comparison

İbrahim Bozkurt[1], *M. Veysel Kaya*[2]*

[1]*Department of Finance and Banking, Faculty of Economics and Administrative Sciences, Cankiri Karatekin University, Cankiri, Turkey*
[2]*Department of Economics, Faculty of Economics and Administrative Sciences, Kirikkale University, Kirikkale, Turkey*

**Corresponding author: mveyselkaya@yahoo.com*

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Abstract: This paper investigates the influences of macroeconomic policies on agricultural production and other factors affecting it, based on panel data in a global sample for the period 2010–2017. Because spatial interactions in the agricultural production levels of countries are determined, spatial panel models are employed in the analyses. According to the analysis results, countries' financial, fiscal and monetary policies have an important effect on agricultural production. Besides, other important determinants of agricultural production are climatic conditions, land use and modern input use in agriculture. Our findings have important implications, especially for countries with low agricultural production.

Keywords: crop output index; macroeconomic policies; spatial interactions

For many years, agricultural production has been one of the focal points of policymakers in many countries because of its favourable effects on social and economic issues such as *i*) economic growth (Singariya and Naval 2016; Mohammed 2020), *ii*) employment (Mellor 1995), *iii*) poverty (Machethe 2004; Dhahri and Omri 2020), *iv*) food security (Bishwajit et al. 2014; Asim and Akbar 2019; Dhahri and Omri 2020), *v*) immigration (Cristea and Noja 2019), *vi*) civil conflict (Crost et al. 2018), and *vii*) malnutrition (Gulati et al. 2012; Rao and Pingali 2018). Agriculture, which accounted for thereabout 25% of the gross domestic product of some developing countries (4% of the global economy) in 2018, is vital to economic growth (World Bank 2020a). Also, agricultural growth is about four times more efficient in increasing incomes among the poorest than in the other sectors (World Bank 2020a). Agricultural production (or sector) has also raised the importance of countries' agenda due to today's problems such as global warming and the Covid-19 outbreak.

In the light of the information above, the determinants of agricultural production have become important for scholars and decision-makers. They have been delved empirically to help discover the drivers of the development in agriculture (and consequently countries). The empirical studies examining the factors affecting the improvement in agricultural production (or sector) can be mainly discussed in several groups. Studies focusing on the impacts of climatic conditions on agriculture may form the first group (Deschênes and Greenstone 2007; Maddison et al. 2007; Wang et al. 2009; Brown et al. 2010; Akram 2012; Mishra et al. 2016). Among these studies, Akram (2012) evinced the positive (negative) effects of the increase in precipitation (temperature) on the agriculture sector.

On the other hand, Crost et al. (2018) found that the increase in precipitation during the wet season decreased agricultural production while the increase in dry season rainfall raised the crops. In another group, studies examining the effects of land use on agriculture can be included. From these studies, Yan et al. (2009) stated that a net increase in cropland area resulted in a slight increase in agricultural productivity, while Mungai and Boitt (2016) did not find a strong

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relationship between the cropland and agricultural production. Studies focused on the modern input uses, such as the study of Sun et al. (2019), which demonstrated that fertiliser use increases rice production, and the work of Vinogradov et al. (2020) revealing the effects of fertilisers, plant growth regulators and herbicides on oat productivity, can be considered as studies in the third group. Studies scrutinising the effects of agricultural mechanisation can also be treated in the fourth group. Barman et al. (2019) detected the positive impact of the tractor and power tiller on cropping intensity (and ultimately agricultural production). Another study found that the use of tractors and pump-sets made a major contribution to agricultural commercialisation through crop production increment (Nepal and Thapa 2009). Apart from factors such as climatic, land use, modern inputs, and agricultural mechanisation, financial, fiscal, and monetary policies (or macroeconomic variables used as a proxy of these policies) can also affect agriculture. Wagan et al. (2018) concluded that monetary tightening reduces agricultural production. Akbar and Jamil (2012) showed that correct fiscal and monetary policies are important for improving agricultural GDP. Koç et al. (2019) revealed that agricultural credits positively affect the agricultural sector. Similar studies make important contributions to the literature, have focused on either a certain country or a group of countries instead of worldwide (Townsend and Thirtle 1998; Kargbo 2005; Emmanuel et al. 2015; Bidisha et al. 2018; Salim 2019). Therefore, in this paper, we want to assist policymakers by providing recent global evidence of whether these policies are important for countries' agricultural production. The main objective of this paper is to investigate the impacts of financial, fiscal, and monetary policies on agricultural production levels of countries in the globe during 2010–2017 by using spatial regression models.

This paper has several contributions to the literature. Firstly, we have used the latest data available for many countries around the world. Secondly, we have employed spatial econometric models. Although some studies are using spatial regression models in the relevant literature (Cho et al. 2010; Yuandong et al. 2013; Koç et al. 2019), as far as we know, this paper is the first study examining the impacts of macroeconomic policies on agriculture using spatial methods with a global sample. Finally, we have shown a maximum effort to use many variables in the empirical literature to make the results robust. In this study, uncommon climate data (evaporation rates and frost days) are also used in addition to the other accessible variables used widely in the literature.

MATERIAL AND METHODS

Agricultural production index and its spatial pattern. In this paper, we use per capita agricultural production index (API) data of 213 countries during 2010–2017 obtained from the Food and Agriculture Organization (FAO) of the United Nations database as a proxy of the countries' agricultural production level (FAO 2020a). The per capita API is obtained by dividing the value of the API by the population. The API calculated according to the Laspeyres formula shows the relative level of the aggregate volume of agricultural production for each year compared to the base period 2004–2006 (FAO 2020b). Since 2018 data for other variables are not available, the analyses are limited to 2017.

According to the 2010–2017 averages of API scores, which are not tabled here because of space limitations, nine of 20 countries with the highest API are African countries (Djibouti, Botswana, Gambia, Zimbabwe, Somalia, Mozambique, Sierra Leone, Rwanda, and Madagascar), seven are Asian (Iraq, Syrian Arab Republic, Maldives, Lebanon, Saudi Arabia, Oman, and Qatar), two are South American [Falkland Islands (Malvinas) and Trinidad and Tobago] and the other two are Oceanian (the Marshall Islands and Fiji). Falkland Islands (Malvinas) has the highest average API level with a value of 130, while Lao People's Democratic Republic is the country with the lowest API with 87 points.

Quantile maps in Figure 1, where the countries are divided into three groups according to API scores, depicture the geographical distribution of the API levels of the countries. In reference to Figure 1, countries with similar API scores generally tend to cluster geographically. This clustering observed in Figure 1 betokens the presence of spatial interaction (i.e. spatial dependency and spatial heterogeneity) in agricultural production levels of countries, and Global Moran statistics (Moran 1950; Cliff and Ord 1981) in Table 1 also prove the existence of this statistically.

The Moran's I statistics, which are positive and statistically significant at 1%, 5%, or 10% significance level for each year, reveal that there is generally a positive spatial dependency in API data (Table 1). The positive spatial dependency (or autocorrelation) here alludes that the agricultural production levels of neighbouring countries are similar. Accordingly, the agricultural production level of a country is affected by the agricultural production levels of other contiguous countries due to the spillover effect.

Although positive Z-scores in Table 1 reveal that spatial heterogeneity (aggregation) in agricultural produc-

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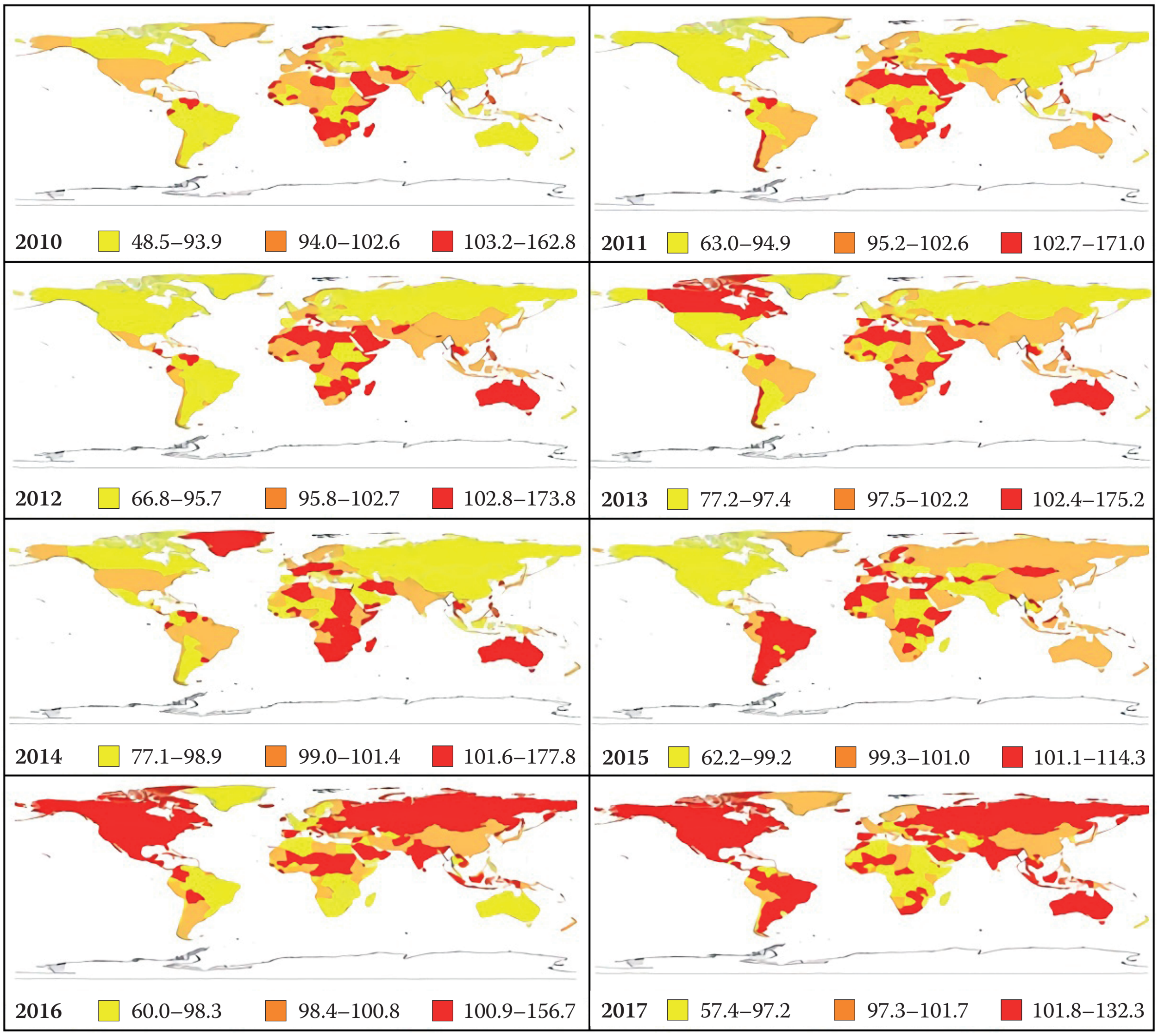

Figure 1. Geographic distributions of per capita agricultural production index (API) scores

Source: Authors' calculations based on data from FAO (2020a)

Table 1. Global Moran statistics for API scores

Year	*I* statistic	SD	*P*-value	*Z*-score
2010	0.42	0.08	0.00	5.33
2011	0.30	0.07	0.00	3.98
2012	0.40	0.08	0.00	5.15
2013	0.30	0.07	0.00	3.99
2014	0.13	0.07	0.02	1.84
2015	0.12	0.07	0.06	1.51
2016	0.18	0.07	0.01	2.29
2017	0.12	0.08	0.07	1.45

API– per capita agricultural production index

H_0 for Moran's *I* test is that there is no spatial autocorrelation in the agricultural production levels

Source: Authors' calculations based on data from FAO (2020a)

tion exists for each year, it does not indicate the exact location of the clustering. Therefore, we also used the Local Indicators of Spatial Association (LISA) cluster maps proposed by Anselin (1995). LISA cluster maps in Figure 2 depicture in detail the local clustering structure of API scores and confirm spatial heterogeneity at the 1% significance level.

According to Figure 2, until 2015, North Asian countries belong to low clustered areas (LL) while South African countries belong to the high clustered areas (HH). LL is predominantly in Eastern Europe, while HH is in North Asia and South America in 2015. In 2016 and 2017, in general, countries in Eastern Europe are the members of HH, and South African countries are the members of LL.

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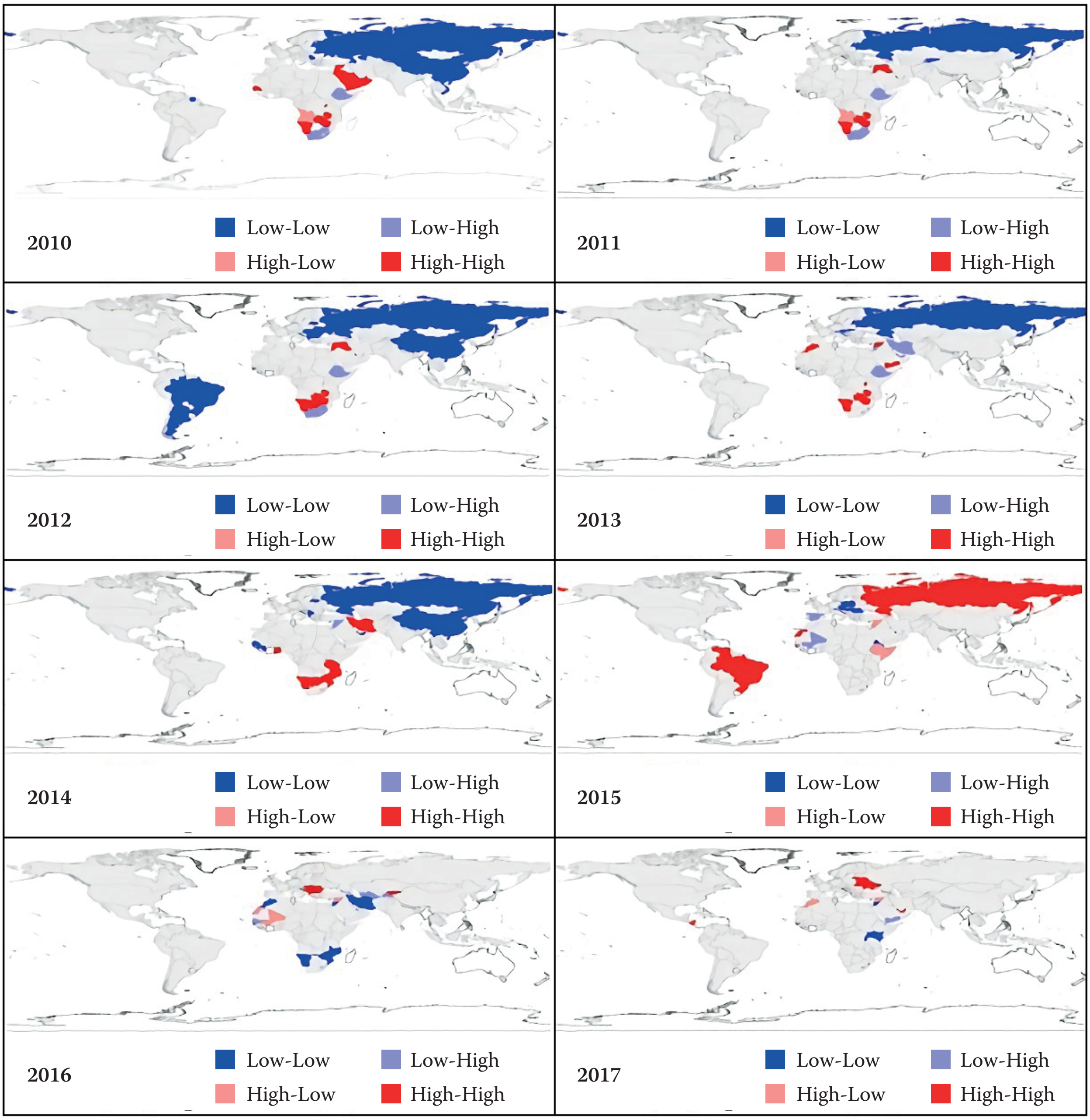

Figure 2. LISA cluster maps of API scores

LISA – local indicators of spatial association; API – per capita agricultural production index

Low-Low refers to the areas where countries have a low per capita agricultural production together with their neighbours; High-High is clustered areas where countries have a high per capita agricultural production along with their contiguous countries; Low-High or High-Low are areas where countries with high (low) API are adjacent to the countries with low (high) API

Source: Authors' calculations based on data from FAO (2020a)

Econometrics models. Since spatial autocorrelation and heterogeneity in the agricultural production levels of countries were detected, we employed the best fit from among the spatial panel regression models formulated by Equations (1–4). If the spatial interaction is detected in the observations of the dependent variable, spatial regression methods provide more consistent results than classical regressions by controlling spatial interactions.

Spatial lagged model (SLM)

$$\log(API_{it}) = \rho \sum_{j=1}^{n} W_{ij} \log(API_{jt}) + \sum_{k=1}^{K} \beta_k X_{kit} + \varepsilon_{it} \qquad (1)$$

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Spatial error model (SEM)

$$\log(API_{it}) = \sum_{k=1}^{K}\beta_k X_{kit} + \lambda\sum_{j=1}^{n}W_{ij}\upsilon_{it} + \varepsilon_{it} \quad (2)$$

Spatial Durbin model (SDM)

$$\log(API_{it}) = \rho\sum_{j=1}^{n}W_{ij}\log(API_{jt}) + \sum_{k=1}^{K}\beta_k X_{kit} + \sum_{j=1}^{n}\sum_{k=1}^{K}\theta_k W_{ij}X_{kjt} + \varepsilon_{it} \quad (3)$$

Spatial autoregressive with spatially autocorrelated errors model (SAC)

$$\log(API_{it}) = \rho\sum_{j=1}^{n}W_{ij}\log(API_{jt}) + \sum_{k=1}^{K}\beta_k X_{kit} + \lambda\sum_{j=1}^{n}W_{ij}\upsilon_{it} + \varepsilon_{it} \quad (4)$$

where: *API* – per capita agricultural production index; log(*API*) – logarithm of API scores; *i*, *j* – countries; *t* – period from 2010 to 2017; *X* – set of independent variables; ε – error term; *W* – spatial weight matrix which shows the proximity relationship between countries *i* and *j*; *k* – number of explanatory variables; *ρ* – spatial spillover across API levels of countries (parameter); λ – spatial spread among the unobserved territorial characteristics that may influence API (parameter); θ – effect of weighted average values of independent variables belonging to neighbouring countries (parameter).

Spatially lagged API (*W*log(*API*)), the spatially lagged independent variable (*WX*) and spatially autocorrelated error term (*W*υ) exist to provide robust results by controlling the spatial interactions in *i*) the API scores, *ii*) the explanatory variables, and *iii*) the error terms.

Explanatory variables. The core explanatory variables of this paper are *AgriExp* representing fiscal policies of countries, *AgriCredit* representing financial policies and *FoodInf*, *Exchange* and *RealInt* as the proxies of monetary policies (Table 2).

Public expenditures for activities such as implementing agricultural training and research, delivering technical assistance in agricultural activities, improving infrastructure, and the payment of input subsidies can improve agricultural productivity and, consequently, production. Therefore, public agricultural expenditures have been accepted as one of the main variables of this study. Another main variable is agricultural sector credits. Agricultural loans can increase agricultural productivity and production by allowing access to the capital required for agricultural modernisation. In addition, the exchange rate and food price inflation, which influence the cost of products and their selling prices (or agricultural import and export), and interest rates that impact access to agricultural credits may also affect agricultural activities and production. Increases in real interest rates can also divert producers from agricultural activities by directing them to earn interest. In line with these explanations, the variables have been selected as potential macroeconomic factors that may affect agricultural production.

In addition to these core variables, we also adopt other variables, which are frequently used in the literature and are accessible to us, to elicit the effects of main factors accurately. The descriptions and data sources of all explanatory variables are given in Table 2.

Table 2. Explanatory variables

Variable	Description	Source
AgriExp	log of the share of agricultural public expenditures in total	FAO
AgriCredit	log of the ratio of the agricultural sector credits to total loans	FAO
FoodInf	log of annual food price inflation (%)	FAO
Exchange	log of annual average exchange rate (local currency per USD)	FAO
RealInt	log of annual real interest rate (%)	World Bank
Land	log of the share of the cultivated land in the total agricultural area	FAO
Fertiliser	log of fertiliser used per area of cropland (kg/ha)	FAO
Pesticide	log of pesticide used per area of cropland (kg/ha)	FAO
Eva	annual average daily evaporation (mm)	BADC
Frost	annual average number of frost days per month (days)	BADC
Temp	annual average of daily mean temperature (°C)	BADC
Pre	annual average monthly precipitation (mm)	BADC

Source: Authors' own representation based on data from FAO (2020a), World Bank (2020b) and BADC (2020)

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RESULTS AND DISCUSSION

Selection of the best-fit model. The effects of macroeconomic policy proxies adopted in this paper on agricultural production are analysed separately due to the possible high intercorrelations among the fiscal, financial, and monetary policies. Following studies like Anselin et al. (2008) and Bozkurt and Karakuş (2020), we make a selection of the most appropriate spatial model for each separate analysis, using Lagrange multiplier (LM) tests based on ordinary least squares (OLS) model. The results of Table 3 reveal that all LM values are statistically significant (i.e. all null hypotheses are rejected), and the most suitable spatial panel model for the regression equation involving *AgriCredit* is the SDM while the best-fit model for the other core explanatory variables is SAC.

Analysis results and discussion. According to the parameter estimates of core variables (ɰ) in Table 4, macroeconomic policies have an important role in determining the API scores.

The direct effect coefficient (0.0118) for the variable of *AgriExp* is positive and statistically significant at 1%; *videlicet*, the API has come a long way with an increase in agricultural public expenditures. This outcome aligns with previous studies (Huffman and Evenson 2006; Yuandong et al. 2013). The indirect impact of *AgriExp* is also positive (0.0055), indicating that a country's API has improved due to the rise of public agricultural expenditures in its neighbours. This result may be due to strong spatial relationships between countries. For each analysis result in Table 4, ρ, which is positive and statistically significant at 1% level, exhibits that average API level of neighbouring countries affects the local API. In other words, a factor (here, public expenditures) that improves (or decreases) the agricultural production of neighbours affects that country in the same direction through a strong spillover effect in API. However, statistically significant but negative λ indicates that the shocks affecting a country exhibit negative spread effects on its neighbours.

As for the effects of *AgriCredit*, its direct and indirect effect coefficient is statistically significant but negative (–0.02 and –0.03). Agricultural sector credits (or financial policies) are expected to increase agricultural output by providing more agricultural mechanisation or expanding the use of modern inputs. Our contrary findings may have resulted from the fact that the credits in the analysis period were used to meet the working capital need (or personal needs of farmers) instead of increasing agricultural production.

The general level of prices increasing within reasonable limits contributes to the revival of all economic activities, including agriculture. Lamb (2000) has demonstrated that agricultural production reacts positively to the raises in food prices. According to findings on the variable of *FoodInf*, a rise in food price inflation in a country or its neighbours influences that country' API level positively (its direct and indirect effect

Table 3. Specification test results

	A	B	C	D	E
LM test results for SEM					
LM	84.7*	39.3*	145.1*	140.6*	79.6*
LM robust	70.5*	772.7*	188.3*	26 300.0*	11 900.0*
LM test results for SLM					
LM	84.4*	45.3*	155.4*	147.8*	89.5*
LM robust	70.3*	778.6*	198.6*	26 300.0*	11 900.0*
Selected model	SAC	SDM	SAC	SAC	SAC
AIC for SDM	–2 633.3	–2 385.2	–4 288.5	–3 772.8	–2 835.9
AIC for SAC	–2 644.5	–2 364.7	–4 289.7	–4 449.5	–2 863.7

*States statistical significance at 1% level; LM – Lagrange multiplier; SEM – spatial error model; SLM – spatial lagged model; AIC – Akaike information criterion; SDM – spatial Durbin model; SAC – spatial autoregressive with spatially autocorrelated errors model

The findings related to the *AgriExp* are presented in the column named A, *AgriCredit* in column B, *FoodInf* in column C, *Exchange* in column D and *RealInt* in column E; for LM and LM robust tests in SEM, H_0: Error terms are not spatially autocorrelated ($\lambda = 0$); for LM and LM robust tests in SLM, H_0: Dependent variable is not spatially autocorrelated ($\rho = 0$); if both hypotheses are not accepted, the choice is made between SAC and SDM according to AIC; the model with the smallest AIC is the best-fit; chi-squared test results based on SDM, which are not included herein due to the space limitation, are also the same as LM test results

Source: Authors' calculations in Stata program/IC 15.0 based on data from FAO (2020a), World Bank (2020b) and BADC (2020)

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Table 4. Empirical results

	A (ɥ: *AgriExp*)		B (ɥ: *AgriCredit*)		C (ɥ: *FoodInf*)		D (ɥ: *Exchange*)		E (ɥ: *RealInt*)	
Direct effects										
ɥ	0.0118*	(0.0043)	−0.0250*	(0.0084)	0.0371*	(0.0069)	−0.0182*	(0.0050)	−0.0139	(0.0287)
Land	0.0682	(0.0703)	0.1723***	(0.0891)	0.0640**	(0.0300)	0.0642	(0.0431)	0.1241*	(0.0470)
Fertilizer	0.0176*	(0.0030)	0.0140	(0.0161)	0.0150*	(0.0020)	0.0149*	(0.0021)	0.0040	(0.0125)
Pesticide	0.0405*	(0.0094)	0.0133	(0.0180)	0.0036	(0.0048)	0.0068	(0.0056)	0.0066	(0.0217)
Eva	−0.0610*	(0.0173)	−0.0569*	(0.0145)	−0.0596*	(0.0099)	−0.0753*	(0.0105)	−0.0554**	(0.0220)
Frost	−0.0046***	(0.0024)	−0.0066	(0.0127)	−0.0011	(0.0016)	−0.0011	(0.0027)	0.0000	(0.0030)
Temp	0.0117*	(0.0032)	0.0031	(0.0180)	0.0198*	(0.0021)	0.0104*	(0.0022)	0.0223*	(0.0079)
Temp^2	−0.0003*	(0.0001)	–	–	−0.0005*	(0.0001)	–	–	−0.0006**	(0.0003)
Pre	−0.0002*	(0.0001)	−0.0005	(0.0137)	−0.0002*	(0.0000)	−0.0001*	(0.0000)	−0.0001	(0.0001)
Indirect effects										
ɥ	0.0055***	(0.0035)	−0.0318**	(0.0160)	0.0290*	(0.0073)	−0.0146*	(0.0047)	−0.0163	(0.0315)
Land	0.0409	(0.0541)	0.0381	(0.1087)	0.0509***	(0.0265)	0.0528	(0.0381)	0.1120**	(0.0443)
Fertilizer	0.0079**	(0.0033)	−0.0165	(0.0296)	0.0115*	(0.0009)	0.0117*	(0.0010)	0.0040	(0.0123)
Pesticide	0.0185**	(0.0089)	0.0008	(0.0275)	0.0028	(0.0037)	0.0055	(0.0047)	0.0061	(0.0213)
Eva	−0.0251*	(0.0061)	−0.0610*	(0.0167)	−0.0458*	(0.0070)	−0.0599*	(0.0106)	−0.0526***	(0.0273)
Frost	−0.0018***	(0.0010)	0.0041	(0.0166)	−0.0010	(0.0013)	−0.0011	(0.0023)	0.0000	(0.0030)
Temp	0.0060	(0.0044)	0.0066	(0.0313)	0.0153*	(0.0021)	0.0082*	(0.0014)	0.0205**	(0.0083)
Temp^2	−0.0002	(0.0001)	–	–	−0.0004*	(0.0001)	–	–	−0.0005***	(0.0003)
Pre	−0.0001*	(0.0000)	0.0003	(0.0072)	−0.0001*	(0.0000)	−0.0001*	(0.0000)	−0.0001	(0.0001)
Spatial parameters										
ρ	0.3615*	(0.1205)	0.1692*	(0.0147)	0.5011*	(0.0272)	0.5100*	(0.0341)	0.5514*	(0.0710)
λ	−0.0569***	(0.1467)	–	–	−0.2216*	(0.0347)	−0.2430*	(0.0282)	−0.3665*	(0.1027)
Countries	74		71		125		130		85	
Model	SAC with country and time FE		SDM with country FE		SAC with country FE		SAC with country FE		SAC with country FE	
LR_1 test	8.45*		8.17*		31.23*		29.85*		17.42*	
LR_2 test	18.65*		0.40		0.60		0.73		0.44	
Hausman test	54.52*		94.65*		85.59*		76.36*		75.06*	
R^2	0.18		0.15		0.15		0.18		0.09	

*, **, ***Statistical significance at 1%, 5%, and 10% levels, respectively; ɥ – variable: *AgriExp* in column A, *AgriCredit* in column B, *FoodInf* in column C, *Exchange* in column D, *RealInt* in column E; SAC – spatial autoregressive with spatially autocorrelated errors model; SDM – spatial Durbin model; FE – fixed effect; LR – likelihood ratio

The explanations of all explanatory variables are given in Table 2; because the observations on some variables are not available for some countries, the number of countries included in the analyses varies; the values in round bracket are the Driscoll-Kraay errors that overcome the potential heteroscedasticity, autocorrelation and cross-sectional correlation problems (i.e. results are robust); for LR_1 test (LR_2 test), H_0: Errors of individual (time) effects are equal to zero $\sigma_i = 0$ ($\sigma_t = 0$); according to the results of *LR* tests, while there is an individual effect in each model, only the model with *AgriExp* has time effect; also, FE models are the best fit for all spatial analysis with reference to Hausman test results; finally, low R^2 values are, as here, plausible for the large-scale data

Source: Authors' research in Stata program/IC 15.0 based on data from FAO (2020a), World Bank (2020b) and BADC (2020)

coefficients are shown in Table 4). As stated before, the reason for the positive indirect effect of *FoodInf* is the spillover effect between the API scores of countries indicated by the ρ parameter.

The direct impact coefficient of *Exchange* is statistically significantly negative. An increase of 10% in the annual average value of the dollar causes a fall of approximately 0.2% in the API score of that country. This outcome may have resulted from the countries whose agriculture depends on imports because the cost increases in these countries due to the increases in exchange rates may cause the renunciation of agricultural

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activities with the expectation that profitability will decrease. The indirect effect of *Exchange* is also expectedly negative because of the spillover effect in API.

When inflation and exchange rate results are evaluated together, it can be thought that the level of agricultural production is closely related to the profitability expectations of the producers. Accordingly, *ceteris paribus*, a decrease in costs due to a fall in exchange rates or an increase in sales prices will expedite the growth in agricultural production with the expectation of an increase in profitability.

Finally, the negative coefficients for variable *RealInt* are consistent with the literature but statistically insignificant.

Apart from core variables, the outcomes of the control variables are also illuminating.

One of the causes of drought that negatively affects agricultural production and human life quality is water loss due to evaporation. For all models in Table 4, the effect of evaporation on agricultural production is negative, as expected. Another factor that causes drought is generally low rainfall. But even in countries where the amount of rainfall increases, drought (consequently decreases in agricultural production) can be observed due to heavy rainfalls and precipitations that do not coincide with the crop growth period. This may be an explanation of the results in Table 4 in columns A, C, and D, indicating that precipitation decreases agricultural production. High temperatures are also expected to reduce production. The results regarding the *Temp* variable in columns A, C, and E reveal that temperature affects API in parabolic form. API ascends up to an annual average of the daily mean temperature of about 18.5–20 °C and falls after this temperature level. *Eva* variable is significantly negative for only the regression equation with *AgriExp*. In addition to climate variables, the effect of *Land* (in column B, C, and E), *Fertiliser* (in column A, C, and D) and *Pesticide* (in only column A) variables on agricultural production are statistically significant and positive. The indirect effects of all variables except *Land* in column B and *Temp* in column A are the same as their direct effects. The reason is both the existence of a strong spatial autocorrelation detected in the API levels of the countries (i.e. positive ρ) and the similarity in their climatic conditions.

CONCLUSION

The principal purpose of this paper is to analyse the impacts of macroeconomic policies on agricultural production based on the global sample for the period of 2010–2017. In the preliminary analyses using Global Morans' *I* and LISA techniques, spatial interactions in the agricultural production levels of the countries are determined. Therefore, analyses are carried out with the best-fit spatial models that control spatial connections in both error terms in the model and variables. Besides, control variables are included in the analyses.

As a result of the analyses, the effects of *AgriExp* representing fiscal policies, *AgriCredit* representing financial policies and *FoodInf* and *Exchange* representing monetary policies on API, positively or negatively, are found to be statistically significant. In addition, *Fertiliser*, *Land*, *Pesticide*, *Eva*, *Frost*, *Temp* and *Pre* – control variables have also affected agricultural production.

In line with our findings, we can advise countries, especially ones with low API, on how to enhance agricultural production. Countries can boom their API levels by increasing public agricultural expenditures and allowing food price inflation to rise to tolerable levels. Here, public expenditures, which enhance the incomes of producers and productivity, may be more effective. For example, increasing input subsidies and training activities for farmers can ameliorate agricultural production *i*) by generalising optimum input use, *ii*) by improving production methods thanks to the presence of trained farmers, *iii*) thus by obtaining higher yields per unit area, and *iv*) by motivating the producers to cultivate due to low costs (high incomes) based on subsidies. Also, countries with low API and whose agriculture or industry depends on imports should reduce the dollar to the levels that will reduce costs and increase agricultural activities. Ensuring that agricultural loans are directed to investments that will provide agricultural development can also be a good policy to convert the negative effect of agricultural credits on API into positive. Apart from these, all countries should focus expeditiously on agricultural water management against drought hazards. Lastly, the spatial spillover effect detected in API levels of countries makes an inference that as far as possible, cooperation among the countries is crucial for increasing agricultural production.

The main limitation of this paper is that other control variables, which may affect agricultural production according to the literature, are not taken into account in this study due to the lack of available data for sufficient numbers of countries. Therefore, by working with a smaller sample, diligent researchers can examine the effect of macroeconomic factors by also considering other factors shaping agricultural production.

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