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THE IMPACT OF EL NINO AND LA NINA TOWARDS THE PRICES OF CABBAGE AND SHALLOT IN INDONESIA

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Abstract: This study examines the impact of El Nino and La Nina on cabbage and shallot prices by applying the spatial correlation analysis method with 34 provinces from 2010 to 2020 to classify affected areas. The next method is a spatial panel with the main variables: rainfall as an indicator of El Nino and La Nina, commodity prices, spatial effects, and other supporting variables such as income, productivity, wages, and COVID-19 dummy. To get the output model, it is necessary to analyze the selection of the best model between the Structural Equation Model and the Spatial Autoregressive. The results of the study provide findings: (1) there are 16 provinces affected by El Nino and La Nina in Indonesia; (2) the best spatial panel model used is Spatial Autoregressive with the resulting La Nina has a large effect on increasing of cabbage and shallots prices because excess soil water content will cause crops and bulbs to rot easily. The spatial aspect has a significant influence, meaning that the price of cabbage and shallots in one area will affect the prices of the two commodities in other areas through distribution patterns. Policy implications of the impact of El Nino and La Nina in this study are classified into managerial, mitigation, and adaptation strategies including the policy of the Regional Inflation Control Team in the form of inter-regional cooperation.

Keywords: cabbage, el nino, la nina, shallot, spatial

***Abstrak**: Penelitian ini mengkaji dampak El Nino dan La Nina terhadap harga kubis dan bawang merah dengan menerapkan metode analisis korelasi spasial dengan 34 provinsi dari tahun 2010 hingga 2020 untuk mengklasifikasikan daerah terdampak. Metode selanjutnya adalah panel spasial dengan variabel utama curah hujan sebagai indikator El Nino dan La Nina, harga komoditas, efek spasial, dan variabel pendukung lainnya seperti pendapatan, produktivitas, upah, dan dummy COVID-19. Untuk mendapatkan output model, perlu dilakukan analisis pemilihan model terbaik antara Structural Equation Model dan Spatial Autoregressive. Hasil penelitian memberikan temuan: (1) terdapat 16 provinsi terdampak El Nino dan La Nina di Indonesia; (2) model panel spasial terbaik yang digunakan adalah Spatial Autoregressive dengan output yang dihasilkan yaitu La Nina berpengaruh besar terhadap kenaikan harga dari kubis dan bawang merah karena kandungan air tanah yang berlebih akan menyebabkan umbi dan krop mudah busuk. Aspek spasial memiliki pengaruh yang signifikan, artinya harga kubis dan bawang merah di suatu daerah akan mempengaruhi harga kedua komoditas tersebut di daerah lain melalui pola distribusi. Implikasi kebijakan akibat dampak El Nino dan La Nina dalam penelitian ini diklasifikasikan menjadi strategi manajerial, mitigasi, dan adaptasi termasuk kebijakan Tim Pengendali Inflasi Daerah dalam bentuk kerjasama antar daerah.*

***Kata kunci**: bawang merah, el nino, kubis, la nina, spasial*

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INTRODUCTION

Over the last century, a significant surge in global surface temperature has led to changes in climatic conditions in various regions of the world. One form of climate change is the El Nino Southern Oscillation (ENSO) which consists of El Nino and La Nina. El Nino (La Nina) causes a decrease (increase) in rainfall from normal measurements and has an impact on significant fluctuation in precipitation. Athoillah et al. (2017) stated that the El Nino event has an impact on decreasing air humidity and encouraging a decrease in rainfall in dry months and vice versa. The extent of ENSO effects can be measured by using the Oceanic Nino Index (ONI) indicator (Figure 1).

Precipitation in each area in Indonesia differs in response to El Nino and La Nina. For instance, in 2019, there were several provinces that actually experienced an increase in rainfall during El Nino (Figure 2). There are other factors that influence the variability of precipitation aside from ONI, so ENSO only causes fluctuations of rainfall in the affected area.

Climate change is highly influential on the agricultural sector because the growth of this sector is closely related to climatic and environmental conditions (Esperanza et al. 2018). The El Nino and La Nina have a major impact on the agricultural sector which directly affects the availability of water, thereby it inhibit agricultural yields and plant growth (Lobell et al. 2012). One of the agricultural commodities affected by ENSO is vegetables (Sarvina and Sari, 2017). In 2020 La Nina pushed down vegetable productivity by an average of 12,5% (Direktorat Jenderal Hortikultura, 2022). This is in line with research from Fadairo et al. (2020) which states that changes in climate promotes pathogenic contamination of vegetables and water availability. The vegetables affected are cabbage and shallots, which are the five largest vegetables produced in Indonesia. Moreover, shallots have a fairly high share of inflation, which is 0,04%-0,08% every month (Badan Pusat Statistik 2021). Cabbage and shallot planting is prone to different risks between seasons; high precipitation leads to high decay rates, while low precipitation inhibits the growth of the vegetable. Direktorat Jenderal Hortikultura (2022) stated that fluctuations in rainfall lead to pests' increase and disrupted water availability, so that the success of planting shallot seeds only reached 85,47% of the set target. Production instability due to climate change will induce shocks on the supply side, thus affecting the increase in the prices of affected commodities.

Juhro and Iyke (2019) stated that prices of agricultural raw materials and consumption expenditures are important predictors of inflation. High commodity price volatility during the last decade should have substantially influenced economic activities in these economies (Rizvi and Sahminan 2020). The agricultural sector is the most vulnerable sector if it is affected by climate change, and 56% of MSMEs in Indonesia are engaged in the agricultural sector such as food, beverages, rubber, and other agricultural products. MSMEs provide a fairly large share of GDP, therefore when agricultural MSMEs are disrupted due to climate change, it will impact on GDP (Siregar et al. 2020). In response to this, one of the ways to minimize the production gap due to climate change is played by Central Inflation Control Team /Tim Pengendali Inflasi Pusat (TPIP) and Regional Inflation Control Team /Tim Pengendali Inflasi Daerah (TPID). In 2019-2021, for example, TPID has succeeded in developing a business model of inter-regional cooperation/Kerjasama Antar Daerah (KAD) so it can distribute agricultural products from surplus areas to deficit areas.

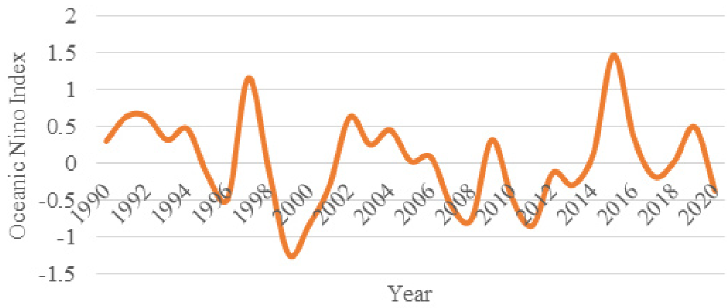

Figure 1. Oceanic Nino Index fluctuations (ONI) 1990-2020 (Climate Prediction Centre, 2021)

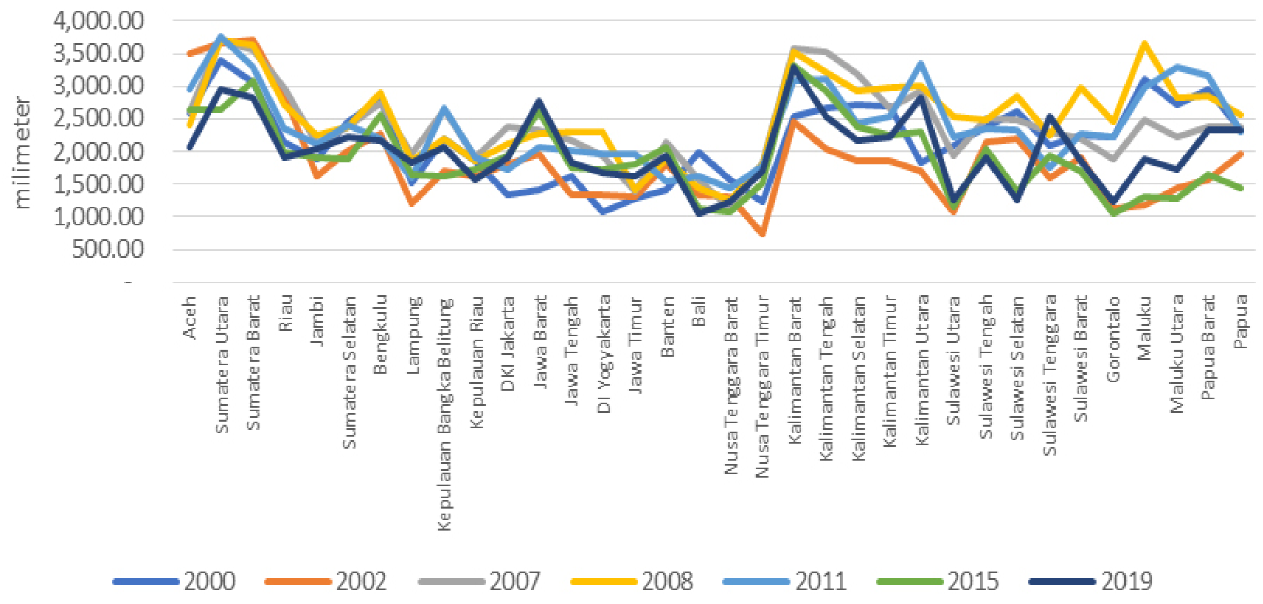

Figure 2. Precipitation in 34 provinces in Indonesia (when strong El Nino and La Nina occurred during 2000-2020 period)(NASA Langley Research Centre, 2021)

Research on the impact of ENSO on prices of agricultural products has been carried out previously in Indonesia. However, the majority of research focus on food crops, while research on horticulture, especially vegetables is still limited (Servina, 2019). Furthermore, the majority of research only uses the static panel method and does not include aspects of spatial interaction between regions, even though spatial interaction is a very important component to be considered in order to avoid biased estimation outputs (LeSage, 2009). Spatial aspects are often found in panel data due to differences in the characteristics of each region. This is usually caused by the flow of goods/services from one area to another so that inter-regional dependencies are created. Therefore, fluctuations in the price and production of commodities in one area have the potential to affect fluctuations in the price and production of these commodities in neighboring areas.

The formation of the price of a commodity is not only influenced by fluctuations in production which is part of the supply side but is also influenced by demand side and access to distribution (Ariani et al. 2020). Increasing the quantity and quality of connectivity will maintain easy distribution and reduce price gaps between regions in order to sustain the stability of prices. The distribution of goods experienced some problems during the 2020 period due to the COVID-19 pandemic. The constraints in commodity distribution due to mobility restriction regulations during COVID-19 pandemic caused wide price disparity between regions, resulting in a decline of supply in deficit areas and an increase of supply in surplus areas. Therefore, this study is keen to categorize provinces affected by ENSO in Indonesia during 2010-2020 period and analyze the impact of ENSO on cabbage and shallots prices with spatial interactions in affected areas using supporting variables from both the demand and supply sides. This study aims to: (1) classify provinces affected and not affected by ENSO in Indonesia in 2010-2020; (2) examine ENSO impact on the price of cabbage and shallots with spatial interactions in El Nino and La Nina affected areas.

METHODS

This study applies a data panel, with a combination of cross sections in the form of provinces affected by El Nino and La Nina and are cabbage and shallot producing areas. Time series data in the form of the 2010-2020 quarter period. Sources of data used in this study include ONI data from the National Oceanic and Atmospheric Administration (NOAA) and rainfall report from NASA Langley Research Center. Data on commodity prices, commodity productivity, Gross Regional Domestic Product (GRDP), and wages for the horticulture sub-sector are sourced from Badan Pusat Statistik (BPS).

Spatial Correlation Analysis

This method was used to determine the areas affected by El Nino and La Nina by using the ONI variable and precipitation for each province. This method aims to identify the degree of linear relationship between one variable and another (Isaac and Chikweru, 2018). The next step is to test the significance using t-statistical testing with the research hypothesis as follows:

$H_0 : \rho=0$
$H_1 : \rho \neq 0$

Significance of the correlation test:

$$t = \rho \sqrt{\frac{n-2}{1-\rho^2}}$$

Note: ρ (Correlation coefficient); n (Observation amount)

Spatial Panel Analysis

This method was used to analyze the impact of climate change represented by indicators of rainfall on the price of cabbage and shallots. Spatial panels are closely related to spatial interactions, where interactions between adjacent areas have the potential for economic movements such as trade and commodity flows. Spatial panel models can be divided into two types, Spatial Autoregressive (SAR) model that contains spatial autoregression information.

The formulation of the model refers to the research of Fajri et al. (2019) entitled the impact of El Nino and La Nina on food prices in affected areas by adding several additional variables according to the research context and differences in the commodities studied. This research includes an update in the form of an element of spatial interaction which refers to the research of Ahmad et al. (2019). The equation model in this study are as follow:

$$LnHK_{it} = \alpha + u_i + \rho\Sigma^N_{i=i} w_{ij}HK_{jt} + \beta_1 LnCH_{it} + \beta_2 LnPrdtvK_{it} + \beta_3 LnPDRB_{it} + \beta_4 LnUpah_{it} + \beta_5 DummyCOVID_{it} \ldots\ldots(1)$$

$$LnHBM_{it} = \gamma + u_i + \rho\Sigma^N_{i=i} w_{ij}HBM_{jt} + \varphi_1 LnCH_{it} + \varphi_2 LnPrdtvBM_{it} + \varphi_3 LnPDRB_{it} + \varphi_4 LnUpah_{it} + \varphi_5 DummyCOVID_{it} \ldots\ldots(2)$$

Note: $LnHK_{it}$ (Natural logarithm of cabbage price in province i in year t); $LnHBM_{it}$ (Natural logarithm of shallot prices in province i in year t); $\rho\Sigma^N_{i=i} w_{ij}HK_{jt}$ (Spatial lag of cabbage prices in province i to province j in year t); $\rho\Sigma^N_{i=i} w_{ij}HBM_{jt}$ (Spatial lag of shallot prices in province i against province j in year t); $LnCH_{it}$ (Natural logarithm of rainfall in province i in year t); $LnPrdtvK_{it}$ (Natural logarithm of cabbage and shallot productivity in province i in year t); $LnPrdtvBM_{it}$ (Natural logarithm of shallot productivity in province i in year t); $LnPDRB_{it}$ (Natural logarithm of gross regional domestic product in province i in year t); $LnUpah_{it}$ (Natural logarithm of wages for farm laborers in the horticulture sub-sector in province i in year t); $DummyCOVID_{it}$(Dummy COVID, value 0 for period before COVID-19 and 1 for period after COVID-19).

RESULTS

Determining the affected areas of El Nino and La Nina: Spatial Correlation Analysis

The volume and intensity of precipitation varies greatly according to place and time, based on geographical location, topography, and circulation or upper air flow. These factors along with El Nino and La Nina further elevate the unpredictability of rainfall between regions and over time. Therefore, determining the number of the affected areas in Indonesia can be done through correlation analysis between the Oceanic Nino Index (ONI) variable and precipitation in every province of Indonesia (Figure 3).

Based on the results of the correlation analysis between ONI and precipitation rate, all correlation values are negative, which means that the higher the ONI, the lower the rainfall (El Nino) and vice versa (La Nina). The higher the correlation value, the stronger the relationship between the two variables. The next step is to determine the significant correlation results through the t-statistical test with a significance level of 10 percent.

The output from the t-statistical test shows that there are 24 provinces affected by El Nino and La Nina in Indonesia, but not all of them are cabbage and shallots-producing provinces (Table 1). Therefore, it is necessary to filter and produce research objects of 16 affected provinces and cabbage and shallot producers, including Aceh, North Sumatra, West Sumatra, Jambi, South Sumatra, Central Java, Bali, West Nusa Tenggara, East Nusa Tenggara, East Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, West Sulawesi, Gorontalo, and North Maluku.

Analysis on the impact of El Nino and La Nina towards the prices of cabbage and shallot

The next analysis is to determine the impact of El Nino and La Nina on cabbage and shallot prices (Table 2). This analysis starts with selecting the best model between PLS, FEM, or REM which produces the FEM model. The next stage of the classical assumption test begins with the multicollinearity test, in which the result is the VIF value of all variables in the model is less than 5. Therefore, there is no multicollinearity problem in the model. The next assumption test is the heteroscedasticity test that shows the p-value <0,05, rejects H0. Thus, there is no heteroscedasticity in the residuals.

The next stage of analysis is the LM and CD Pesaran test which results in the conclusion that there is a spatial dependence between provinces. The next step is determining the best spatial panel model between the SAR, SEM, and GSM by comparing the R-square, AIC, and RMSE values of each model. Based on this comparison, the SAR model has the largest R-square value and the smallest AIC and RMSE values, therefore the best spatial panel model in this study is SAR.

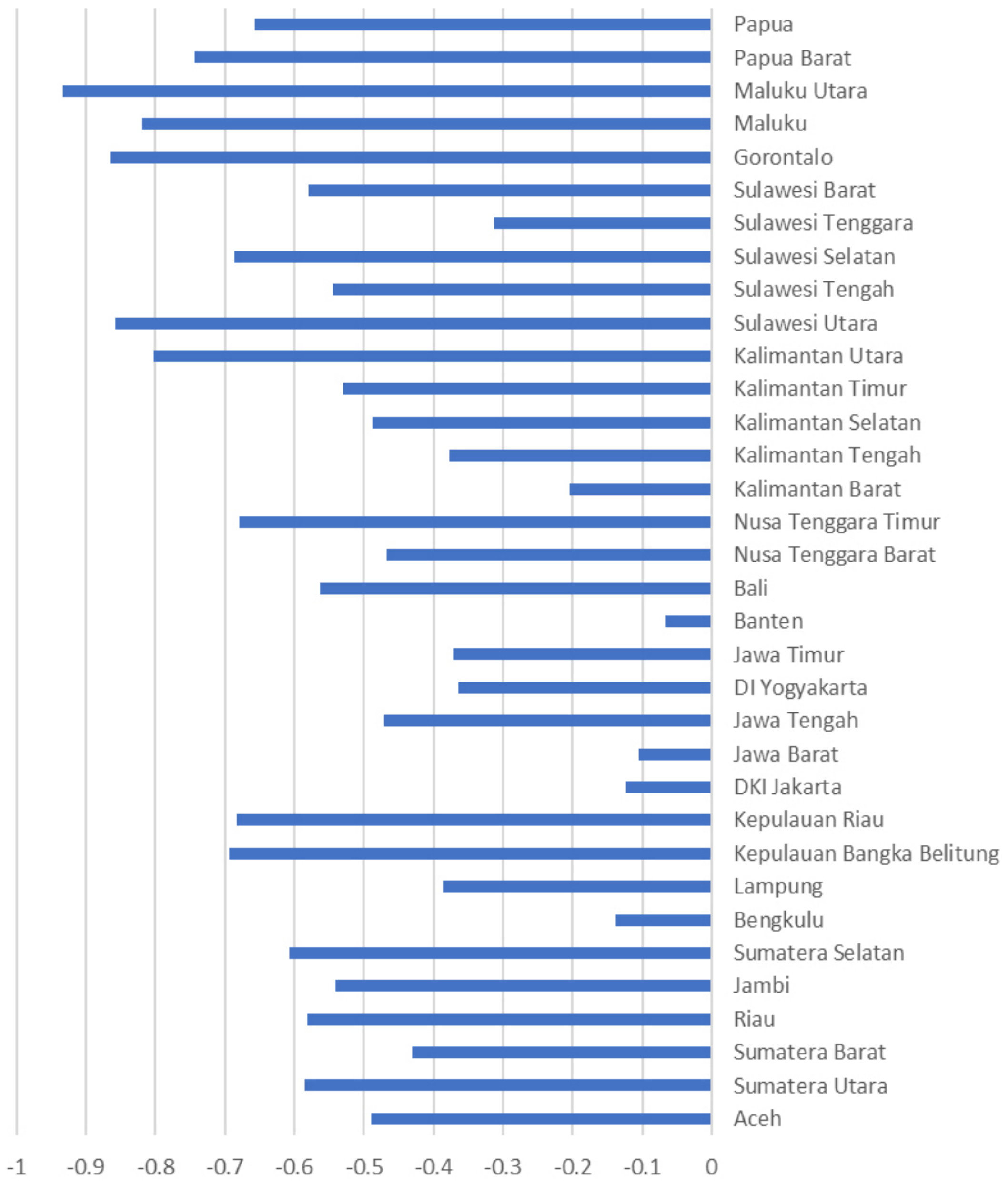

Figure 3. Results of the correlation analysis between ONI and precipitation rate in Indonesia

Table 1. The results of the t-test

Province	t-test	Province	t-test
Maluku Utara	-7.76*	Jambi	-1.93*
Gorontalo	-5.18*	Kalimantan Timur	-1.87*
Sulawesi Utara	-4.99*	Aceh	-1.68*
Maluku	-4.28*	Kalimantan Selatan	-1.68*
Kalimantan Utara	-4.04*	Jawa Tengah	-1.60*
Papua Barat	-3.34*	Nusa Tenggara Barat	-1.59*
Kepulauan Bangka Belitung	-2.90*	Sumatera Barat	-1.43*
Sulawesi Selatan	-2.84*	Lampung	-1.26
Kepulauan Riau	-2.80*	Kalimantan Tengah	-1.23
Nusa Tenggara Timur	-2.78*	Jawa Timur	-1.20
Papua	-2.61*	DI Yogyakarta	-1.17
Sumatera Selatan	-2.30*	Sulawesi Tenggara	-0.99
Sumatera Utara	-2.16*	Kalimantan Barat	-0.63
Riau	-2.14*	Bengkulu	-0.42
Sulawesi Barat	-2.13*	DKI Jakarta	-0.37
Bali	-2.05*	Jawa Barat	-0.32
Sulawesi Tengah	-1.95*	Banten	-0.20

*) |t-count| > 1,282

Table 2. Output of the analysis of the impact of El Nino and La Nina on the price of cabbage and shallots in the province affected (SAR Model)

Variabel	Cabbage Prices		Shallot Prices	
	Coefficient	Probability	Coefficient	Probability
Lag spasial	0.409***	0.000	0.549***	0.000
LnCH	0.026**	0.016	0.056***	0.000
LnPRDTV	-0.183***	0.000	-0.169***	0.000
LnPDRB	0.328***	0.000	0.207***	0.001
LnUpah	0.219***	0.000	0.415***	0.000
Dummy COVID-19	-0.130***	0.000	-0.001	0.974
R-Square	0.829		0.885	

Notes: * (Significant variable at the level of significance 0.1 (10%)); **(Significant variable at the level of significance 0.05 (1%)); *** (Significant variable at the level of significance 0.01 (1%)).

Based on the output of the analysis, the spatial interaction indicated by the spatial lag variable (lambda) has a positive and significant effect in the study of the impact of ENSO on cabbage and shallot prices in 16 affected provinces (Figure 4). This illustrates that the price of both commodities in an area/province is also influenced by the price of cabbage and shallots from other affected provinces which are close to each other. The lambda value in the output is 0.409 and 0.549, of which 40.9% and 54.9% the formation of cabbage and shallot prices is influenced by other nearby provinces.

Dependencies between regions are closely related in the aspect of formation prices. Boundaries between regions can affect the relationship between price formation or inflation rate between a bordering region. Spatial autocorrelation analysis with Moran's Index also shows that the p-value for both commodities is 0.000. In other words, there is a spatial autocorrelation to the prices of cabbage and shallots in locations close to each other. In addition, the Moran Index value shows a positive value so that spatial autocorrelation to cabbage and shallot prices has similarities in adjacent locations. Between provinces that are close to each other tend to have the same colour.

The precipitation variable which is an indicator of ENSO climate change in this study has a positive and significant effect on the price of cabbage and shallots with a coefficient value of 0.026 and 0.056, which means that if the rainfall increases by 1%, it will increase the price of cabbage by 0.026% and shallots by 0.056%

(ceteris paribus). The estimation results support the research conducted by Rovi'ati et al. (2019), that if the cabbage family is planted when the rainfall is high, the cabbage buds and cabbage flowers produced will be small in number and rot easily. The estimation results also support the research of Pradana et al. (2022) which explains that shallot plants are very susceptible to high precipitation which causes the products to be submerged in water and rotting so that the quality of shallots decreases. Therefore, the La Nina phenomenon has an impact on decreasing the quantity and quality of shallots and has the potential to increase the selling price in the market.

Productivity is one indicator on both commodities production that gives a significant effect on cabbage and shallot prices with a coefficient value of -0.183 and -0.169. The estimation results support the research of Manna et al. (2020) which states that the decline in the productivity of shallots that occurred in India over the last 10 years has led to an increase in the price of shallots in that time span by more than 500%. The success of shallot cultivation is highly dependent on a climate that is dynamic and difficult to control (Sholikin and Haryono, 2019).

The next factor that contributes to the change in cabbage and shallots price is GRDP which represents the demand side. Based on the results of the analysis, GRDP has a positive and significant effect on the price of shallots with a coefficient value of 0.328 and 0.207. This illustrates that every 1% increase in GRDP will lead to an increase in the price of cabbage by 0.328% and shallots by 0.207% (ceteris paribus). This is in accordance with the market equilibrium theory, that GRDP or income is an indicator that represents the demand side and if income increases, it will cause an equilibrium price to be formed at a price that higher (Ozmen et al. 2019).

The wages of farm laborers in the horticulture sub-sector also have a positive effect on the price of both commodities. This output is in line with Jacoby (2013) research that changes in rural wages in India also affect the formation of food prices and subsequently affect people's welfare. The situation involving COVID-19 pandemic has also negatively affected the price of cabbage and shallots, although not significantly on the price of shallots. The decline in the price during the pandemic was also caused by the delay in the distribution process from producing areas to deficit areas. This phenomenon is supported by research from Djafar (2020) that the presence of COVID-19 caused a lockdown at the border Kalimantan area, causing a surplus of agricultural production to be difficult distributed to other areas and causes prices to decrease. This is also in line with the World Food Program (2020) report, which in 2020 stated that COVID-19 did not significantly affect the price changes of 10 strategic food commodities except garlic and sugar. Another study conducted by Katsushi et al. (2020) also shows that the COVID-19 pandemic has not significantly affected (the value is close to the 10% significance level) the shallot price gap in India.

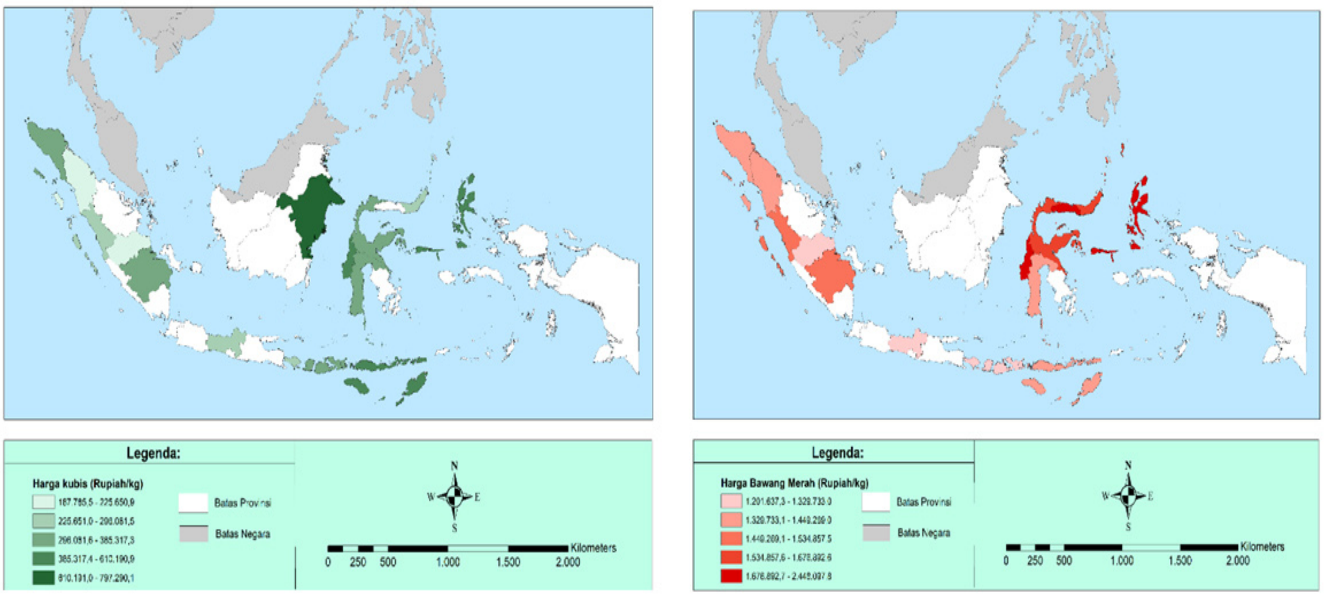

Figure 4. Spatial influence on the formation of cabbage and shallot prices in the region affected

Manajerial Implication

The result show that there are problems in the form of inter-regional dependencies (spatial lag) in price establishment, as well as additional other factors that are also related to price formation, such as distribution barriers during COVID-19, and factors from the demand side in the form of GRDP, TPID can strengthen the formation of KAD which is vital for the handling of affairs involving cross-regional impacts, one of which is the movement of commodity prices between regions (Tulus et al. 2020). KAD will be able to increase efficiency and effectiveness of commodity distribution so that each region can fulfill its commodity needs and minimize the potential for depleting supply due to increased demand, decreased supply, and distribution constraints.

The results show that commodity productivity is disrupted and tends to decline due to ENSO. Therefore, a response in the form of adaptive efforts such as *kalender tanam* (KATAM) or planting calendar is launched in an attempt to improve the dynamic and integrated climate information technology development program aimed at supporting the climate information understanding program (Perdinan et al. 2018). Another solution that can be done as a form of adaptive response is to use Early Warning System (EWS) The Hopers Development. Early warning system built as a preventive measure to minimize the harmful effects of climate change such as potential floods, droughts and pest attacks by utilizing information on rainfall forecasts for the next 3 to 6 months. The access of integrated counselling and education are also examples of the attempts to increase the knowledge and skills of farmers in adapting to climate change that disrupts the agricultural sector to maintain price stability through productivity, including holding a climate field school for horticultural commodities.

ENSO will generally attack plant resistance in adapting to environmental conditions such as water stress, humidity, and air temperature. Therefore, it is necessary to develop superior seeds or seeds (variety development) so that commodities can grow and adapt to various climatic and environmental conditions. The first adaptive strategy to sustain the stability of cabbage and shallot production is through the development of high-yielding varieties that are able to adapt to any climatic conditions. One of the superior varieties of cabbage is Cabbage F1 Green Nova which has a high level of adaptation in highland areas and is resistant to pests and diseases.

In line with the development of varieties, there are attempts to maintain production stability in the midst of climate change, one of which is through the implementation of technology. For instance, screen houses that are able to reduce pests on horticultural crops by 12-28.5% and increase production up to 927.5% (Moekasam and Prabaningrum, 2012). Another example of the use of superior cultivation technology is True Shallot Seed/TSS (shallot botanical seeds) which are durable and free from pathogens so that plants are healthier.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

El Nino and La Nina affect the Indonesian region around the equator and located close to the Pacific Ocean. In 2010-2020, there were 24 provinces affected with 16 provinces of which were producers of the two research object commodities. El Nino and La Nina have an impact on the prices of both commodities, but La Nina has a larger role in price and production fluctuations. This is because soil that contains too much water will encourage the rotting of shallot bulbs and cabbage crops, for example caused by pests and bacteria. Therefore, the impact of El Nino and La Nina is to decrease production and increase prices. The formation of commodity prices in a region is also influenced by price fluctuations from other regions. Fluctuations in production and commodity prices based on the analysis results also affect other regions through distribution patterns and distribution of goods between regions.

Recommendations

Suggestions for further research is the use of additional variables relevant to related research so it can explain diversity influencing factors in determining the price of cabbage and shallots. Variables from the supply side have an influence in price formation, for example through changes in the amount of supply which can also be caused by international trade activities in the form of exports and imports. Further research is also recommended to include aspects of lag/price period previously on the commodities studied. This matter is of urgency because price movements in the previous period will affect the decision producers in the process of selecting commodities to be planted in the current period and in the future.

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