Journal of Agricultural Science; Vol. 14, No. 6; 2022
ISSN 1916-9752 E-ISSN 1916-9760
Published by Canadian Center of Science and Education

Improving Maize Production and Farmers' Income Using System Dynamics Model

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Received: March 10, 2022 Accepted: April 15, 2022 Online Published: May 15, 2022

doi:10.5539/jas.v14n6p68 URL: https://doi.org/10.5539/jas.v14n6p68

The research is financed by Institut Teknologi Sepuluh Nopember, under project scheme of the Publication Writing and IPR Incentive Program (PPHKI).

Abstract

Maize demand for feed, industry, and consumption is increasing in line with the increase in population and industry, while the supply of maize does not meet the demand. Therefore, it is necessary to identify the significant variables that affect maize cultivation and scenarios to increase maize production and farmers' income using simulation model. As a method to develop the models, a system dynamics simulation model is used to accommodate internal and external variables that affect the production and farmers' income which can be done using organic fertilizer, the integration between land expansion and organic fertilizer, and the implementation of precision agriculture. The simulation results show that land area, use of fertilizers, and technology adoption affect the production and income of maize farmers. The scenarios developed include organic fertilizer scenario, expansion and organic fertilizer scenario, and precision agriculture scenario. The resulting scenario can be used as a recommendation for the government and stakeholders in developing strategies and policies related to a sustainable maize farming system that can help increase the production and income of maize farmers.

Keywords: sustainable agricultural, economic development, model, representative decision making, simulation, system dynamics

1. Introduction

The Maize is one of the important cereal crops in Indonesia, as a staple food crop to replace rice and as animal feed (Ikayanti, 2018). The demand for maize increases from year to year is in line with the increasing number of population and industry, resulting in the increase of maize demand (Purwanto, 2007). Demand for maize comes from feed, industry, and consumption. The maize production absorbed by feed mills is insufficient and the quality of maize is less uniform (Kariyasa et al., 2018). The growth of maize production in East Java relies more on the increase of harvested area (Kariyasa et al., 2018). Agricultural production is changing due to shifts in consumer demand, input costs, food safety concerns, and environmental impacts (Walters et al., 2016). Changes in weather and climate are indicated to be one of the causes of crop failure and low productivity (Lewi et al., 2019). The food sovereignty program focuses on food security as a community's right to determine the community's food and agriculture system with limited corporate intervention (Lin, 2017). Dynamic farming systems model can be used as a tool to generate valuable data in assessing the productivity and environmental effects of cropping systems on agricultural land (Khaembah et al., 2021). Furthermore, climate change conditions can increase or decrease in frequency and intensity, leading to the losses even greater in the future (Aqil et al., 2013). The continuous use of inorganic chemical fertilizers has degraded agricultural land, thereby reducing the agricultural production (Simanjuntak et al., 2013). Appropriate management practices can improve soil quality and efficient use of Nitrogen (N) fertilizers to increase maize production (Qiao et al., 2021). A better appreciation of the community of soil balancing practice can enhance collaboration with scientists in soil health (Brock et al., 2021). The vertically integrated leaf N content under different field experiments can be accurately estimated by the optimized

red-edge absorption area (OREA) index (Wen et al., 2021). Long-term fertilization causes a decrease in soil quality, crop yields, and hampers agriculture (Wang & Wei, 2019). The integrated use of compost, human waste organic fertilizer and livestock manure is an approach that involves a series of strategic decisions by farmers to increase the use of organic fertilizers (Daadi & Latacz-Lohmann, 2021). Soil balancing is an approach to manage soil fertility that focuses on several elements such as Ca, Mg, and K to achieve a desired base cation saturation ratio (Brock et al., 2021).

In reaction to concerns over agricultural biotechnology, environmentalists strongly advocate organic farming (Azadi & Ho, 2010). Organic farms use more renewable energy and have less of an impact on natural ecosystems (Smith et al., 2014). Membership in agricultural cooperatives, organic fertilizer subsidies, and farm size play a positive role in influencing farmers' choices of using organic fertilizers (Wang et al., 2018). Fertilization using organic fertilizers rich in Zn and ZnO can increase food production and quality (Dimkpa et al., 2020). The addition of organic fertilizers has a positive effect on soil organic balance and farmers' incomes (Flores-Sanchez et al., 2014).

The need for precision agricultural technology in agricultural operations is a current trend (Kostic et al., 2018). This technology was developed for agricultural management, for example seeding, fertilizer, irrigation, harvesting and planting, and precision agriculture technologies such as GNSS tractors and UAVs (Li et al., 2020). The development of mechanical kernel harvesting maize varieties offsets the effects of climate change to provide sustainable maize development in a particular area (Liu et al., 2021). The reduction in water availability has a limited effect on the allometry of plant mass allocation (Ciampitti et al., 2021). Precision agriculture equipment has great potential to contribute to agricultural production, as well as environmental protection and food safety (Gebbers & Adamchuk, 2010). Variables of perceived need for technology needs, perceived benefits, and facilitation conditions (knowledge and training) have a significant impact in increasing farmers' willingness to adopt precision agricultural technology (Li et al., 2020). Technological knowledge develops following a life cycle, therefore there are sectoral evolutionary differences according to the knowledge base (Krafft et al., 2014). So far, the methodology used in solving agricultural cultivation problems has only focused on operations such as field experiments and surveys. Effective conservation strategies in maize cultivation are required to ensure that genetic resources are available in the future (McLean-Rodríguez et al., 2019). With reference to the research background, several research questions that arise include:

(1) How to increase maize production by considering several production factors such as the use of organic fertilizers, land expansion, and the use of precision agriculture technology?

(1) How to increase the income of maize farmers by considering the cost of maize cultivation?

To overcome this problem, we developed a system dynamics (SD) simulation model to accommodate the non-linear relationship between model variables that affect maize production and farmer's income (Cavana, 1999). SD facilitates the development of several scenarios modelling to increase the maize production and farmers' income including: (1) scenarios of applying organic fertilizer; (2) land expansion scenario and the application of organic fertilizer; and (3) precision agriculture scenario. The data and information used in this study were obtained from BPS (Central Bureau of Statistics), the Ministry of Agriculture of the Republic of Indonesia (Kementan), and the Ministry of National Development Planning (BAPPENAS). The resulting models and scenarios can be used by the government and other stakeholders in developing strategies and policies related to cultivation systems that can help increase maize production and farmers' income. To increase maize productivity, agricultural planning and policy implementation in the form of the right combination of fertilizers and yield estimates need to be prioritized (Otieno et al., 2020).

By referring to the research problem, research questions, and research outputs, we define our research contributions as follows: (1) the development of simulation models to demonstrate the dynamics and interactions of various factors that affect productivity, production, and income of maize farmers; (2) the development of model scenarios to increase production and income of maize farmers by considering internal and external variables such as the use of organic fertilizers, integration of Land Expansion and Organic Fertilizer, and the use of technology to support precision agriculture; (3) the results of the model scenario can be used as input in formulating policies related to the maize cultivation system that can increase the production and income of maize farmers.

This paper is organized as follows. Section 1 presents the introduction. Section 2 presents a literature review covering maize productivity and production, farm income, and system dynamics. Section 3 describes the model development consisting of the development of a causal loop diagram (CLD) and the development of stock and flow diagram (SFD). Section 4 presents model validation. Section 5 describes the scenario development. Finally, Section 6 presents conclusions and future research.

2. Literature Review

This section describes the literature review used in the research covering maize productivity and production, farm income, and system dynamics.

2.1 Maize Productivity and Production

Productivity is the ability of the soil to produce crop production under certain conditions and tillage (Nurmala, 2012). Several factors that affect maize productivity include harvested area (BPS Surabaya, 2020), seeds of superior varieties (Food Security Agency, 2009), fertilization (Ambarita & Kartika, 2015), irrigation (Sirappa & Razak, 2010), climate and weather (Prado Tanure et al., 2020), and labor (Hafidh, 2009). Productivity is used to compare the output with input in a production process. The output is the result of production, while the input is the area of land. Productivity is the result of rice production per unit area of land. The land productivity formulation can be seen in Equation (1).

$$Productivity\ (\text{tons/ha}) = \frac{Production\ (\text{tons})}{Land\ Area\ (\text{ha})} \tag{1}$$

The largest contribution to national maize production comes from East Java Province, *i.e.*, 25.60% (Kariyasa et al., 2018). Production is determined by land area and productivity. Production is obtained from the product of the multiplication of land area and productivity per hectare (Kariyasa et al., 2018) as shown in Equation (2).

$$Production\ (\text{tons}) = Land\ Area\ (\text{ha}) \times Productivity\ (\text{tons/ha}) \tag{2}$$

2.2 Farm Income

Agricultural development aims to improve the welfare of the community in the agricultural sector (Rahim & Hastuti, 2008). Farm income will encourage farmers to be able to allocate these funds for various needs such as production costs for the next period, savings, and other expenses to meet family needs (Soekartawi, 1996). Farmers need to implement farm management practices and business skills to increase their income (Chilemba & Ragasa, 2020). Increasing inputs and technical facilities can increase yields and improve quality to increase farmers' income (Reardon et al., 2009). Agricultural economics can increase its impact through better collaboration with other disciplines, stakeholder engagement, adopting a more systematic approach to major challenges, and innovation (Fresco et al., 2021). Appropriate and well-informed government support can significantly improve national innovation systems (Rong et al., 2021). Farmers with low incomes do not benefit significantly from participation in the market, this indicates the need to prioritize farmers' incomes to ensure that they are not left behind (Nguyen et al., 2021). When the elasticity of price transmission decreases, the variability of domestic prices decreases, and the variability of world prices increases (Wang & Wei, 2019). The higher the price, the more efficient the labor force, and the tighter the credit limits on smallholders, the greater the income gain from supplying inputs to large farms rather than operating small farms (Ma & Sexton, 2021).

2.3 System Dynamics

System dynamics is a method used to study the behavior of complex systems (Sterman, 2000). System dynamics can model non-linear behavior and dynamic interactions (feedback) between interrelated factors by performing scenarios on the existing systems (Walters et al., 2016). System dynamics (SD) is a method used to study and analyze complex systems (Sterman, 2000). It combines mathematics and computer simulation to explore the behavior of real-world systems and relationships over time (Neuwirth et al., 2015). System dynamics can be used as a tool in decision making, which can represent problems and facilitate stakeholders with various inputs needed in decision analysis (Bérard et al., 2017). System dynamics (SD) is a model-based decision support system that considers uncertainty as well as predicts dynamic and complex project behavior (Khatun et al., 2022). The evolution of the complexity of the processes of agricultural modernization, specialization, and differentiation, emphasizes the responsiveness of economic and legal institutions to various social and environmental problems of agriculture (de Olde & Valentinov, 2019).

Several software that can be used to support SD modeling includes Dynamo, Powersim, Vensim, I-think, and so on. (Paut et al., 2021) have used dynamic bio-economic models to simulate management strategies for mixed farming and assess their impact on the long-term study. SD can model the interaction between individual behavior, personal factors, and environmental challenges (Lo Schiavo et al., 2019). The dynamic model can be used to determine the optimal rate, frequency, and method of lime application for a wheat monoculture system (Shoghi Kalkhoran et al., 2021). Furthermore, SD emphasizes the feedback interaction and the non-linear character of the feedback system. Some SD variables can be seen in Table 1 (Sterman, 2000).

Table 1. System Dynamics Variables (Sterman, 2002)

Variable	Symbol	Description
Stock (Level)	▭	A quantity that accumulates over time. It changes its value through integrating rates.
Flow (Rate)	⧗	Changes the values of the stock variable.
Auxiliary	○	The formulation that involves one or more calculations.

3. Model Development

This section describes the model development covering causal loop diagrams (CLD) and stock and flow diagrams (SFD). Model development aims to analyze and forecast future business prospects (Frenzel & Grupp, 2009).

3.1 Causal Loop Diagram (CLD) Development

CLD is used to describe the relationship between several variables that affect the maize production and farmers' income as well as several alternative strategies to increase the maize production and farmers' income as shown in Figure 1. Understanding causal relationships between complex and dynamic systems is a major challenge (Pahl et al., 2008). This CLD is the initial hypothesis in developing a dynamic system model, which will later be converted into stock and flow diagram model (SFD) and validated to check whether the hypothesis is valid or not.

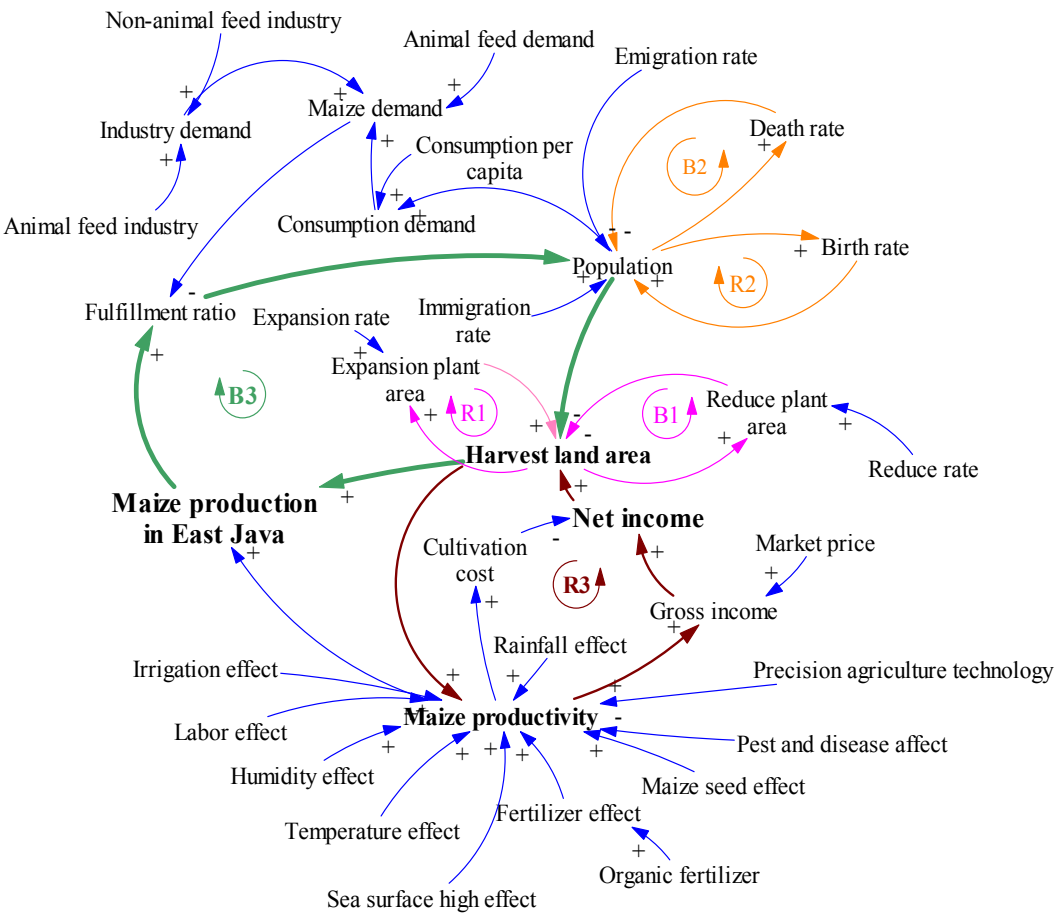


Figure 1. CLD of maize production and farmers' income

The increasing consumption per capita and the population shows a positive polarity (+) will increases the demand for maize. Harvested area is influenced by land expansion (R1), land conversion (B1), population, and net income of farmers. Land conversion is influenced by population, in which the greater the land conversion, the fewer the land availability. Land conversion is affected by the conversion of land use into housing, industry, and other public facilities. Harvest land area data were taken from East Java in 2007-2020. The minimum harvest area is

1,153,496 ha and maximum 1,295,070 ha, the average harvest area is 1,237,938 ha and the standard deviation is 40.520 ha (Ministry of Agriculture & Central Bureau of Statistics, 2017). Harvested area affects the total amount of maize production. Maize production data is taken from maize production in East Java in 2007-2020. The minimum production is 4,252,182 tons and the maximum is 7,239,433 tons, the average production is 5,923,477 tons and the standard deviation is 788,710 tons (Ministry of Agriculture & Central Bureau of Statistics, 2017).

Maize demand is influenced by consumption needs, animal feed industry, non-animal feed, and independent animal feed (Suwandi et al., 2016). The fulfillment ratio is influenced by production and the maize demand. Maize demand for consumption is influenced by maize consumption per capita and population. The population is influenced by several factors such as the number of immigrations, the number of emigrations, fulfillment ratio, the birth rate (R2), and the death rate (B2). Population data were taken from East Java in 2007-2020. The minimum population is 36,506.003 people and the maximum is 39,768,554 people, the average population is 38,408,289 people and the standard deviation is 1,042,447 people (Central Bureau of Statistics, 2019; Ministry of National Development Planning & Central Bureau of Statistics, 2018; Ministry of National Development Planning et al., 2013). Fulfillment ratio of food commodities including maize is closely related to population growth (Khairati & Syahni, 2016). The fulfillment ratio will increase the number of populations which can reduce the amount of harvest land area (B3).

There are several factors that affect the maize productivity, namely: (1) the use of seed varieties, (2) the use of fertilizers, (3) the irrigation channels, (4) the labor, (5) the changes in climate and weather, including temperature, humidity, soil height above sea level and rainfall, (6) harvested area, and (7) pest attacks. Maize productivity data is taken from the average productivity of East Java in 2007-2020. The minimum productivity is 3.69 tons/ha and the maximum is 5.56 tons/ha, the average productivity is 4.77 tons/ha and the standard deviation is 0.54 ton/ha (Ministry of Agriculture & Central Bureau of Statistics, 2017). The net income of farmers is influenced by gross income and maize cultivation costs. Farmers' gross income per hectare is influenced by the price of maize at the farm level and the productivity. While the cost of cultivation is influenced by the overall input costs required for maize cultivation.

3.2 Stock and Flow Diagram (SFD) Development

The conceptual model that has been described through the CLD is then converted into a system dynamics model described through the SFD which contains levels, rates, auxiliary, source, and sinks (Sterman, 2000). Based on the CLD in Figure 1, several SFDs were developed covering the area of harvested land, maize productivity and production, population, and demand for maize, as well as farmers' income.

3.2.1 Harvest Land Area Submodel

Harvested area is the area of plants that are collected after the plants are old enough (BPS Surabaya, 2020). The land conversion rate in 2007-2012 was around 3.71% per year, it decreased to 2.75% in 2013, and it was around 0.82% per year starting 2014 (Ministry of Agriculture & Central Bureau of Statistics, 2017). The SFD of the harvest land area submodel can be seen in Figure 2.

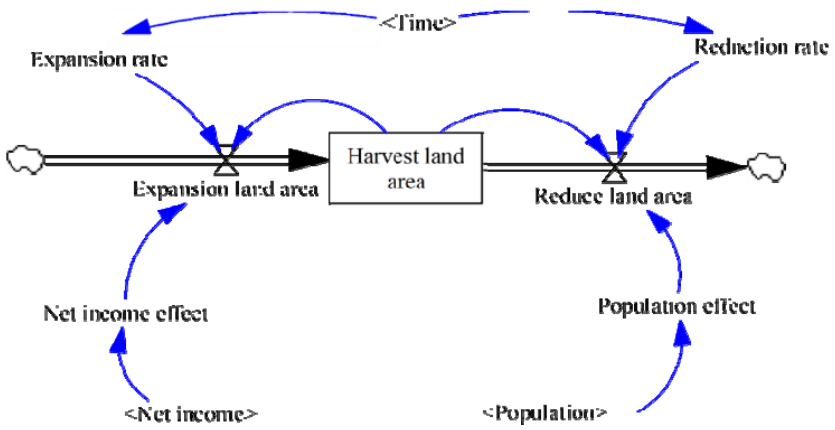


Figure 2. Submodel of harvest land area

The formulation of the harvest land area submodel can be seen in Equation (3):

$$Harvest\ land\ area\ (t+1) = Initial\ harvest\ land\ area\ (t0) + \int_{t0}^{t} [Expansion\ land\ area\ (t) - Reduce\ land\ area\ (t)]\mathrm{dt} \quad (3)$$

The simulation result of the harvest area submodel is shown in Figure 3. The harvested area fluctuated during the period 2007 to 2020 with an average increase of 0.92% per year. The average harvested area in the period 2007 to 2020 was around 1,251,946 ha. Harvest land area fluctuated in the period 2007-2020 because it was influenced by land expansion and land conversion as illustrated in Figure 2. Harvest land area reached its peak in 2010 because the rate of land expansion in 2007-2009 was around 5.97% per year which had an impact on harvest land area in 2010. Meanwhile, starting in 2014, the rate of land expansion was only 2.06% (Ministry of Agriculture & Central Bureau of Statistics, 2017).

3.2.2 Maize Productivity and Production Submodel

Several factors that affect maize productivity include:

(1) The use of seed varieties (Ardiani, 2009; Food Security Agency, 2009; Guo et al., 2017; Kariyasa et al., 2018).

(2) The use of fertilizers to meet nutrient deficiencies in the soil (Li et al., 2020).

(3) Irrigation channels that function to support irrigation in maize cultivation (Kariyasa et al., 2018; Li et al., 2020).

(4) Labor in the cultivation process covering almost the entire production process (Hafidh, 2009; Suryani et al., 2019; Mohammadi & Tavakolan 2019).

(5) Climate and weather changes (Prado Tanure et al., 2020).

(6) Harvested area (BPS Surabaya, 2020).

(7) Pests and diseases attack (Food Security Agency, 2009; Lewi et al., 2019; Seran, 2005).

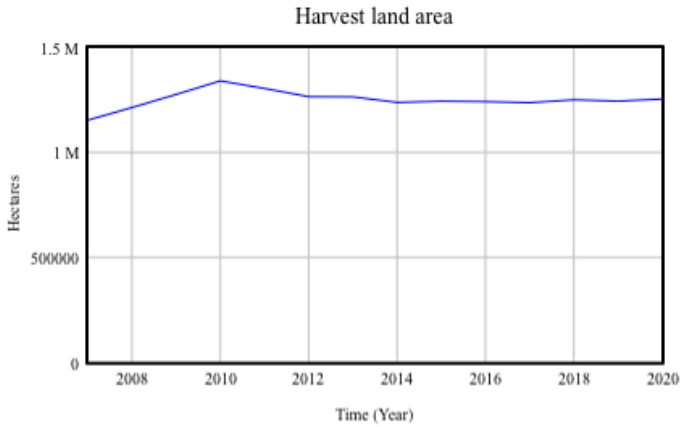


Figure 3. Harvest land area

Fulfillment ratio is a comparison between the maize production and the total demand. Farmers' gross income per hectare is influenced by productivity per hectare and the selling price of maize per kg at the producer level (Soullier & Moustier, 2018). The submodel of maize productivity and production can be seen in Figure 4.

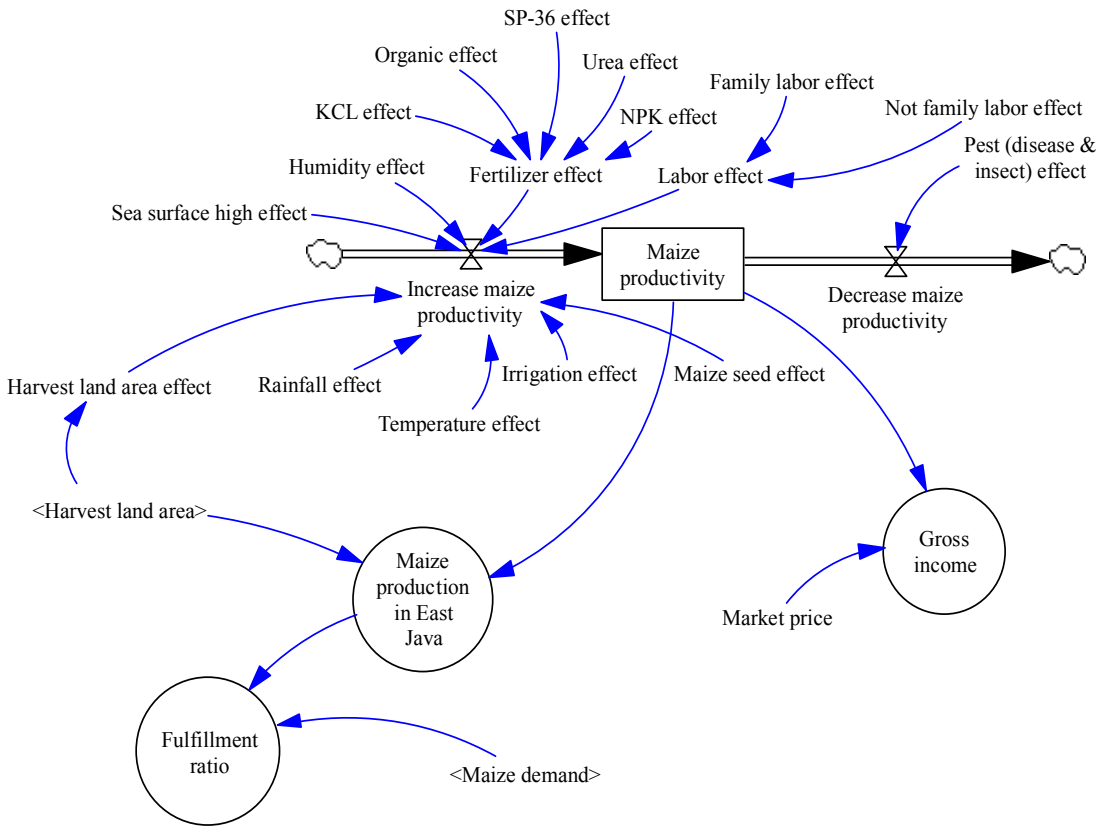


Figure 4. Submodel of maize productivity and production

The model formulation of the maize productivity and production can be seen in Equations (4)-(7):

$$Maize\ Production\ in\ East\ Java\ (t) = Maize\ productivity\ (t) \times Harvest\ land\ area\ (t) \tag{4}$$

$$Fulfillment\ ratio\ (t) = \frac{Maize\ Production\ in\ East\ Java\ (t)}{Maize\ demand\ (t)} \times 100 \tag{5}$$

$$Maize\ productivity\ (t+1) = Initial\ maize\ productivity\ (t0) + \int_{t0}^{t} [Increase\ maize\ productivity\ (t) - Decrease\ maize\ productivity\ (t)]\mathrm{dt} \tag{6}$$

$$Gross\ income\ (t) = [Maize\ productivity\ (t) \times 1000] \times Market\ price\ (t) \tag{7}$$

The simulation result of the maize production in East Java is shown in Figure 5. In this research, simulation is used because simulation has the ability to develop a model of a real system so that it can provide a better understanding of the system behavior. Maize production increased from 2007 to 2020 with an average increase of 4.40%. From the simulation results, the average of maize production in the period 2007 to 2020 was around 5,655,347 tons and the standard deviation is 826,763 tons. Maize production data can be useful in determining model parameter values and can be used to validate the model by comparing the model simulation result with the actual data.

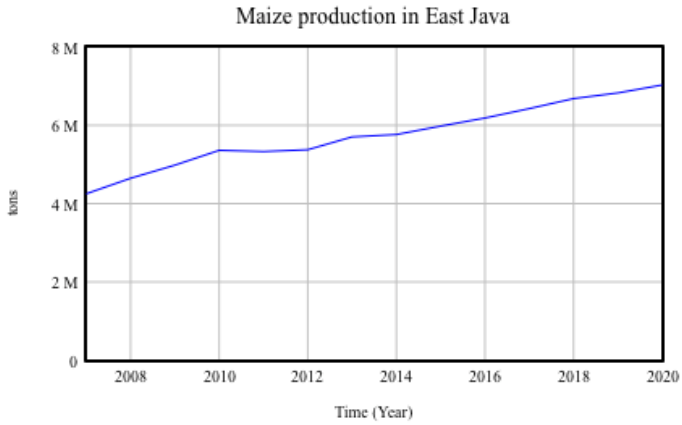


Figure 5. Maize production in East Java

Maize production which tends to increase is influenced by productivity and harvest area, as shown in the causes strip Figure 6. Maize productivity has increased from 2007 to 2020 with an average increase of 3.34% per year. The average productivity of maize in the period 2007 to 2020 was around 4.60 tons/ha. Furthermore, the harvest area experienced a slight fluctuation with an increase of 0.92% per year. The average harvest area in the period 2007 to 2020 was around 1,251,946 ha.

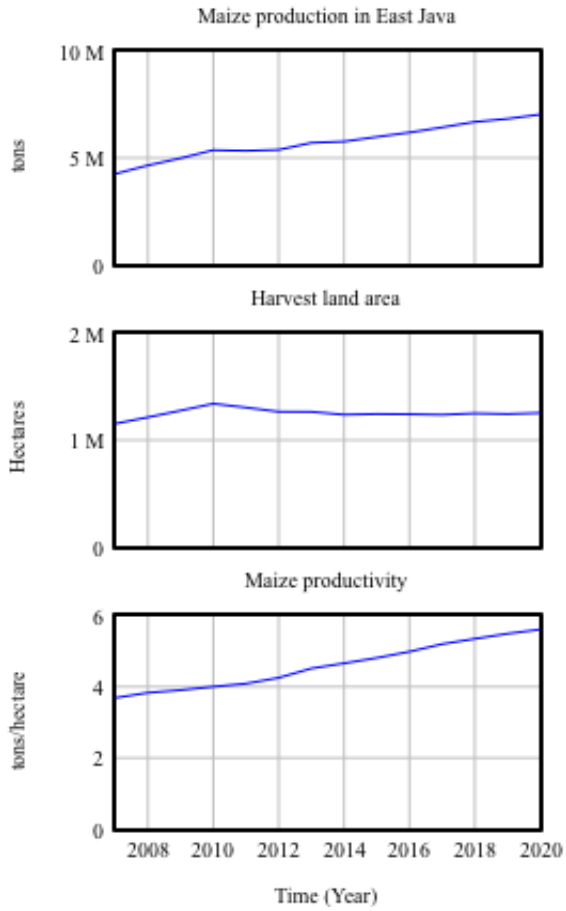


Figure 6. Causes strip of maize production in East Java

3.2.3 Population and Maize Demand Submodel

The population is affected by the birth rate, death rate, immigration rate, emigration rate, and the effect of the fulfillment ratio. The crude birth rate (CBR) of the population in East Java in the population projections for 2010 to 2035 is between 14.1% to 16.4%, while the crude death rate (CDR) of the population in East Java during this period is recorded between 8.1% to 8.6% (Central Bureau of Statistics, 2018). Maize demand is influenced by consumption with per capita consumption between 1,443 to 4,064 kg/capita/year, animal feed industry between 8,181,850 to 9,797,102 tons/year, and non-animal feed industry between 2,713,000 to 5,727,297 tons/year, as well as for independent animal feed around 992,680 up to 5,500,051 tons/year (Suwandi et al., 2016). SFD of population and maize demand submodel can be seen in Figure 7.

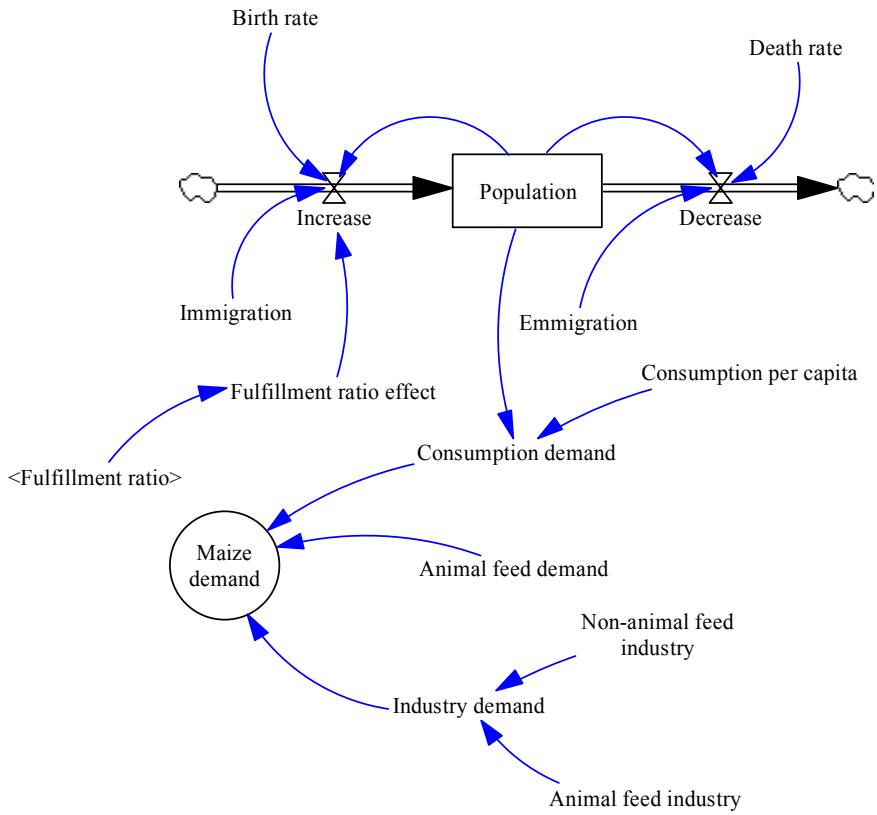


Figure 7. Submodel of population and maize demand

The model formulation of the population and maize demand can be seen in Equations (8)-(11):

$$Population\ (t+1) = Initial\ population\ (t0) + \int_{t0}^{t} [Increase\ (t)\ -\ Decrease\ (t)]\mathrm{dt} \tag{8}$$

$$Maize\ demand\ (t)\ =\ [Consumption\ demand\ (t)/1000]\ +\ Animal\ feed\ demand\ +\ Industry\ demand \tag{9}$$

$$Industry\ demand\ (t)\ =\ Animal\ feed\ industry\ (t)\ +\ Non\text{-}animal\ feed\ industry\ (t) \tag{10}$$

$$Consumption\ demand\ (t)\ =\ Population\ (t)\ \times\ Consumption\ per\ capita\ (t) \tag{11}$$

The simulation result of the population submodel is shown in Figure 8. The importance of using simulation because simulation provides a more realistic replication of the real system because it requires fewer assumptions (Chase & Aquilano, 1991). Figure 8 shows that population increased from 2007 to 2020 with an average increase of 0.66% per year. From the simulation results, the average population in the period 2007 to 2020 was around 37,945,350 people and the standard deviation was 1,096,555 people. Population data can be useful in determining model parameter values and can be used to validate the model by comparing the model simulation result with the actual data.

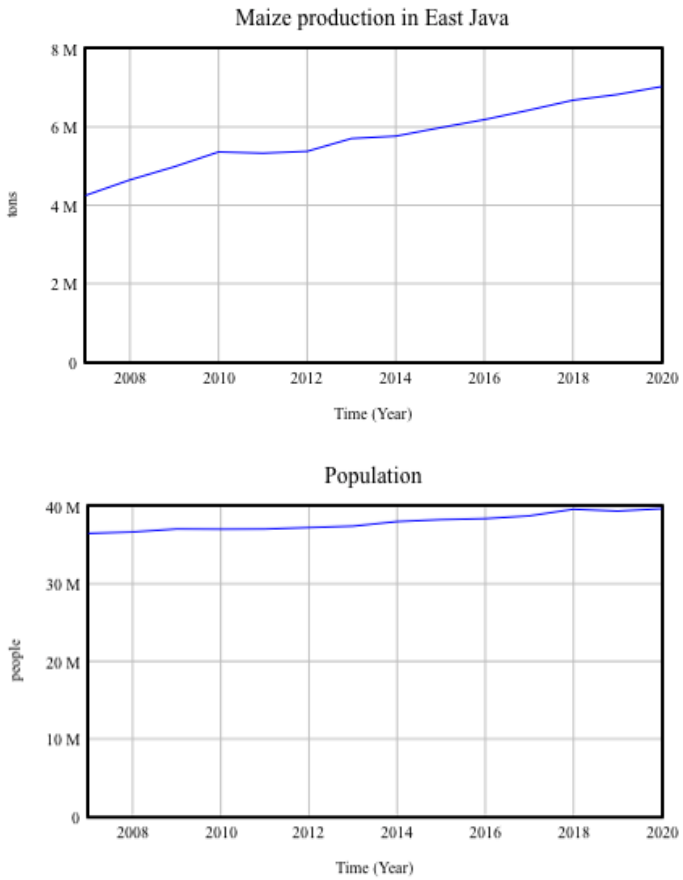


Figure 8. Population in East Java

Maize demand is influenced by demand for consumption, industrial demand, and demand for animal feed. Maize demand in East Java fluctuated during 2007 to 2020, with a minimum value of 13.77 million tons and a maximum of 19.15 tons. Causes strip of simulation result on maize demand is shown in Figure 9.

3.2.4 Farmers' Income and Cultivation Cost Submodel

Income indicators are profit per kilogram and price per kilogram (Soullier & Moustier, 2018). The net income of farmers is influenced by gross income minus the cost of cultivation. Meanwhile, cultivation costs are obtained from the accumulated input costs incurred for: (1) purchasing seeds; (2) purchase of fertilizers; (3) labor salaries; (4) other additional expenses (Food Security Agency, 2009; Kariyasa et al., 2018; Ojo & Baiyegunhi, 2020; Suwandi et al., 2016). The submodel of farmers' income and cultivation cost can be seen in Figure 10.

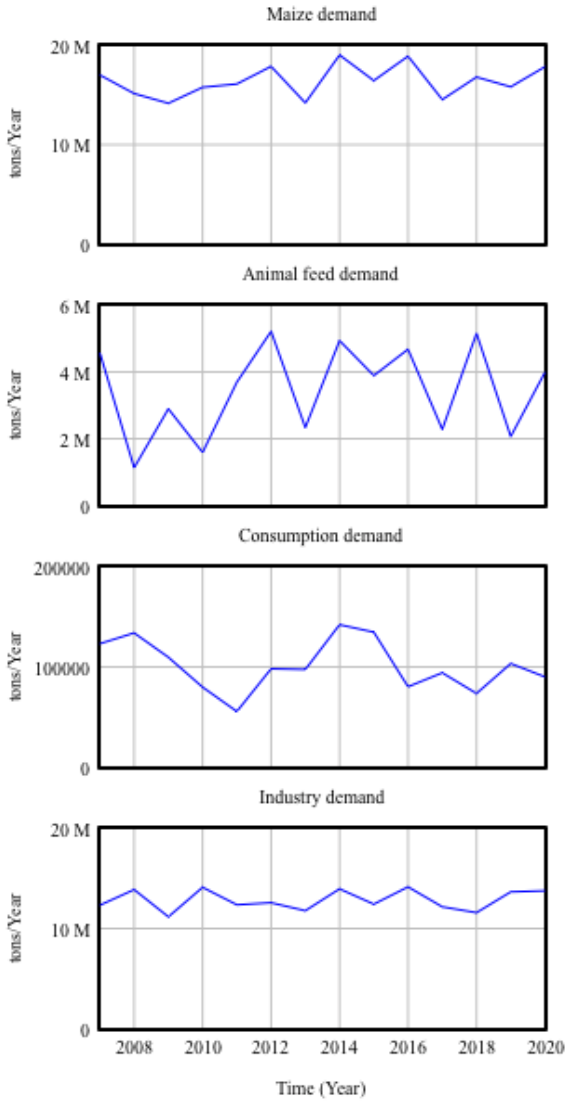


Figure 9. Maize demand in East Java

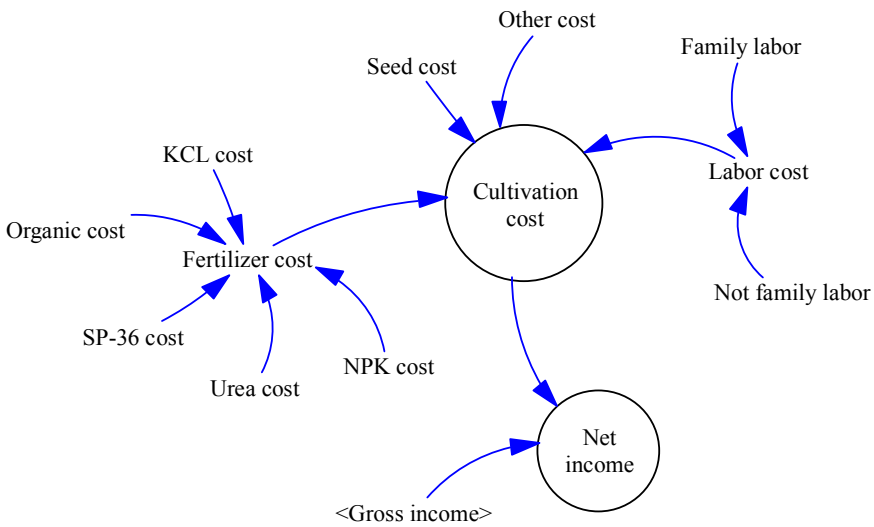


Figure 10. Submodel of farmers' income and cultivation cost

The formulation of the farmers' income and cultivation cost submodel can be seen in Equations (12) and (13):

$$Net\ income\ (t) = Gross\ income\ (t) - Cultivation\ cost\ (t) \tag{12}$$

$$Cultivation\ cost\ (t) = Fertilizer\ cost\ (t) + Labor\ cost\ (t) + Seed\ cost\ (t) + Other\ cost\ (t) \tag{13}$$

The net income received by farmer is the difference between the gross income of the farmer and the cost of cultivation. The simulation results of net income per hectare fluctuated from 2007 to 2020, with a minimum value of Rp7.6 million and a maximum value of Rp15.2 million. Causes strip of simulation results on net income per hectare is shown in Figure 11.

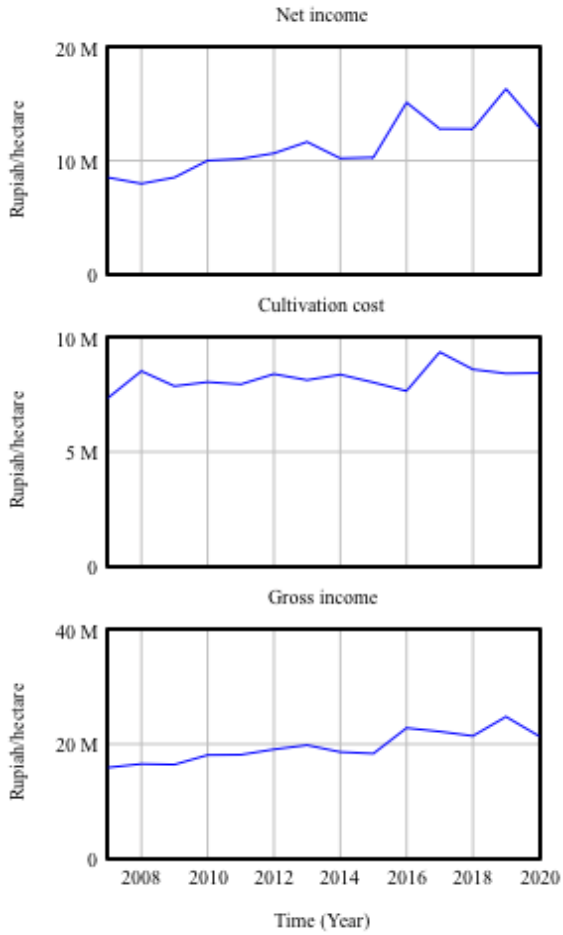


Figure 11. Causes strip of net income

4. Model Validation

Model validation was carried out using two methods, those are: (1) structural validation to identify the model credibility and to assess accuracy of the model equation; and (2) behavioral validity test to asess the substance of the model in accordance with the model's objectives (Sterman, 2000).

4.1 Structural Validation

This validation establishes several causal relationships in the causal loop diagram in Figure 1 which consists of three balancing feedback loops or B-Loops (B1, B2, and B3) and three reinforcing feedback loops or R-Loops (R1, R2, and R3). Based on the model formulation, the model consists of variables that are mutually influential and significant in shaping the maize cultivation model. In general, the model variables consist of level, auxiliary, and rate. Level variables include population, maize productivity, and harvest land area. Auxiliary variables include maize production, maize demand, fulfillment ratio, gross income, net income, and cultivation cost. The structure verification test is also carried out by checking for errors in the results of the model formulation that have been made. Structural validation is done by conducting a structure verification test by checking for errors in the model

formulation and dimensional consistency tests in the form of checking units of all model variables. Furthermore, a dimensional consistency test was conducted to check whether the mathematical equations in the research model had consistency in terms of dimensions. The results of testing the mathematical equations in the research model based on the real system/the results of data collection are on the increase in maize productivity as follows:

$$\text{Increase maize productivity} = \text{RANDOM UNIFORM } (0, 0.13, 0)$$

Units: dmnl.

From the data and literature study, it is found that the increase in corn productivity is between a minimum of 0% and a maximum of 13% (Kariyasa et al., 2018; Purwanto, 2007), this shows the correspondence of numbers and units between the simulated model and the data. The results of the validation of the structure of the maize production and farmers' income submodel can be seen in Figures 12 and 13.

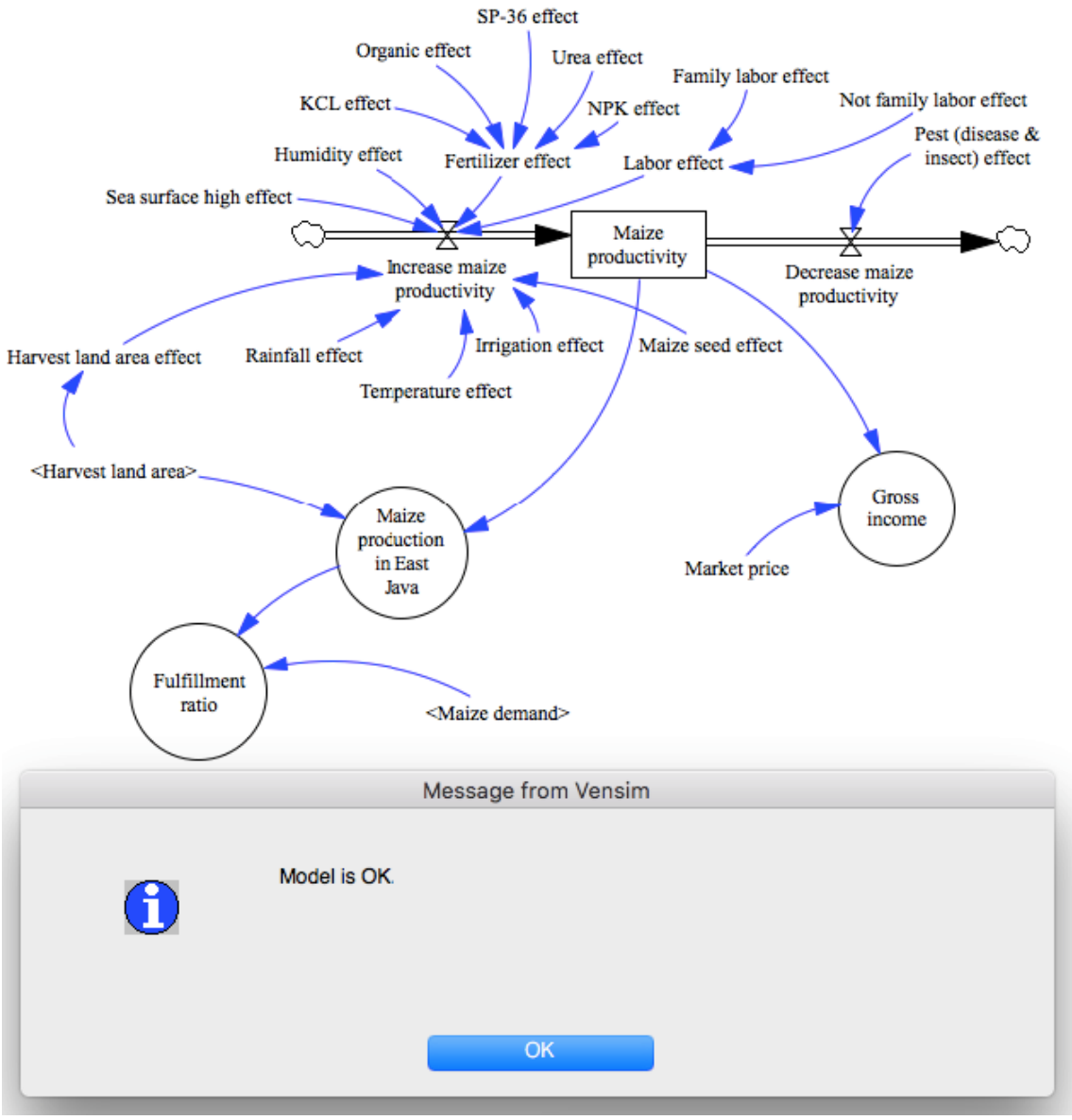


Figure 12. Structure verification test on maize production and farmers' income submodel

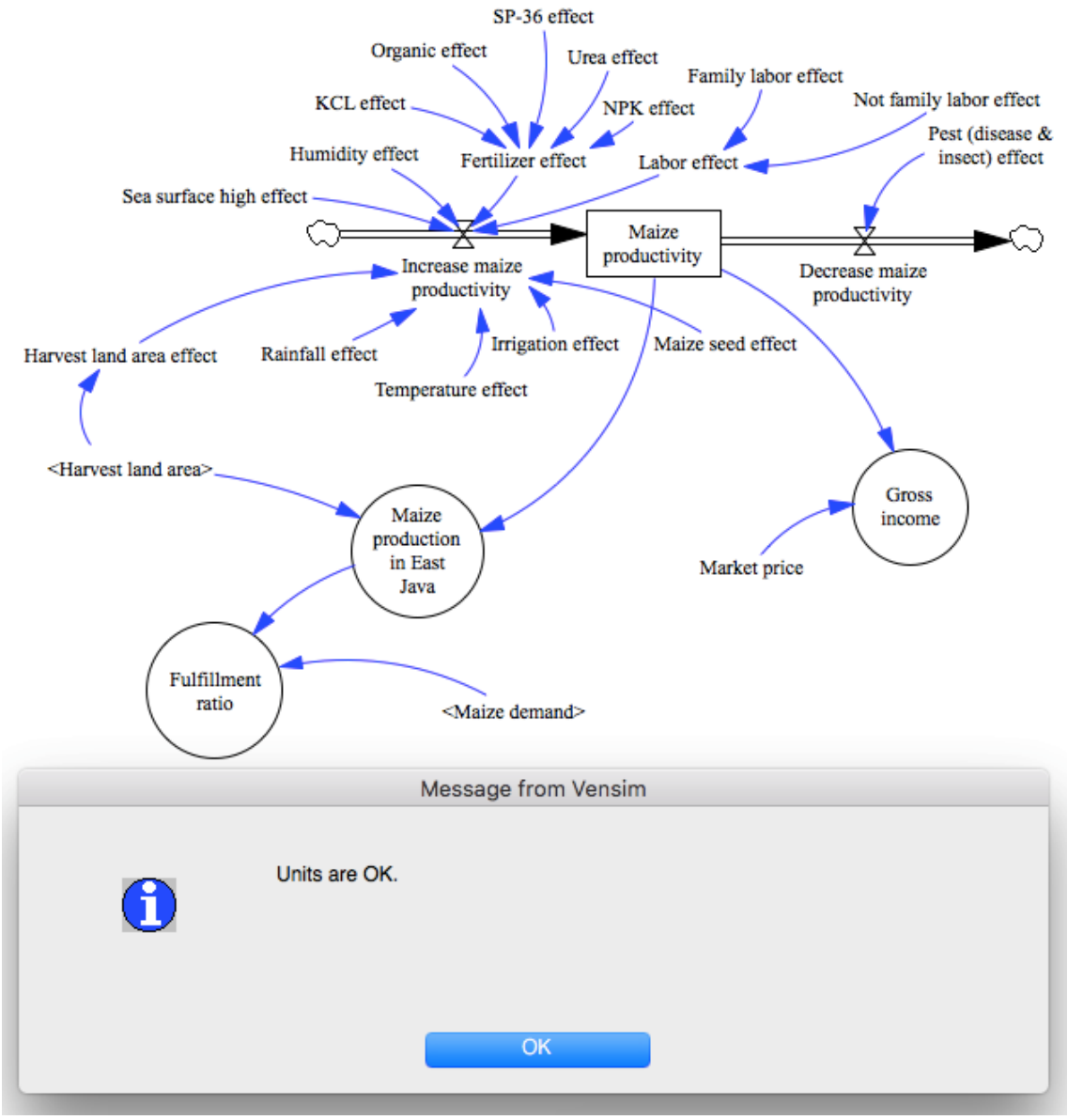


Figure 13. Dimensional consistency test of maize production and farmers' income submodel

4.2 Behavior Validity Test

Behavior validity tests are carried out by comparing the average or error rate and variations in amplitude or error variance (Barlas, 1989; Qudrat-Ullah, 2012). The model will be valid if the error rate is ≤ 5% and the error variance is ≤ 30%. The process of model validation by using behavioral validity tests can be seen in Equations (14) and (15).

$$Error\ rate = \left| \frac{\overline{S} - \overline{A}}{\overline{A}} \right| \times 100\% \tag{14}$$

where, $\overline{S}$ = The average value of the simulation results; $\overline{A}$ = The average value of data.

$$Error\ variance = \left| \frac{S_S - S_a}{S_a} \right| \times 100\% \tag{15}$$

where, S_S = Standard deviation of simulation; S_a = Standard deviation of data.

The results of the calculation of the error rate and error variance on maize productivity, harvested area, maize production, and population are shown in Table 2.

Table 2. The results of the calculation of error rate and error variance of some variables of the model

No.	Variable	The Average Rate of Data	The Average Rate of Simulation	Standard Deviation of Data	Standard Deviation of Simulation	Error Rate (%)	Error Variance (%)
1	Harvest Land Area (ha)	1,237,938	1,251,946	40,520	42,361	1.13	4.54
2	Maize Productivity (tons/ha)	4.77	4.60	0.54	0.64	3.68	20.19
3	Maize Production (tons)	5,923,477	5,655,347	788,710	770,955	4.53	2.25
4	Population (people)	38,408,289	37,945,350	1,042,447	1,096,555	1.21	5.19

From the results of the error rate and error variance test, all error rates are ≤ 5% and error variances are ≤ 30%, thus indicating that the model is valid. The comparison of simulation results with the data on maize productivity, harvested area, maize production, and population variables can be seen in Figures 14 to 17.

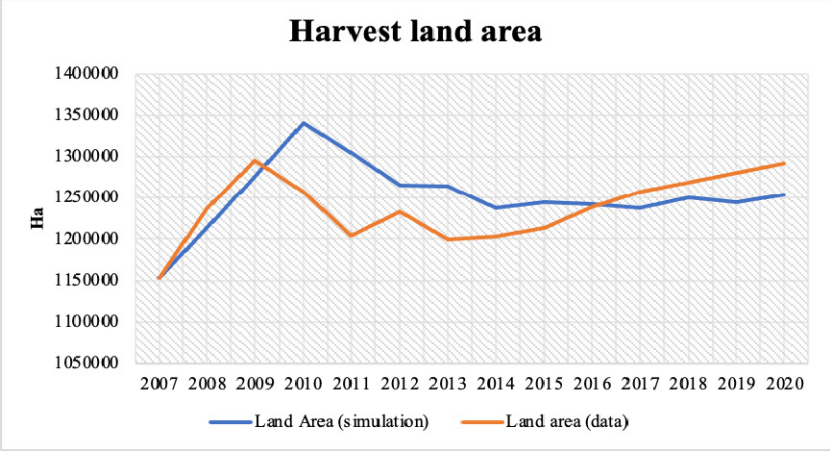


Figure 14. The comparison of simulation result of harvest land area model and data

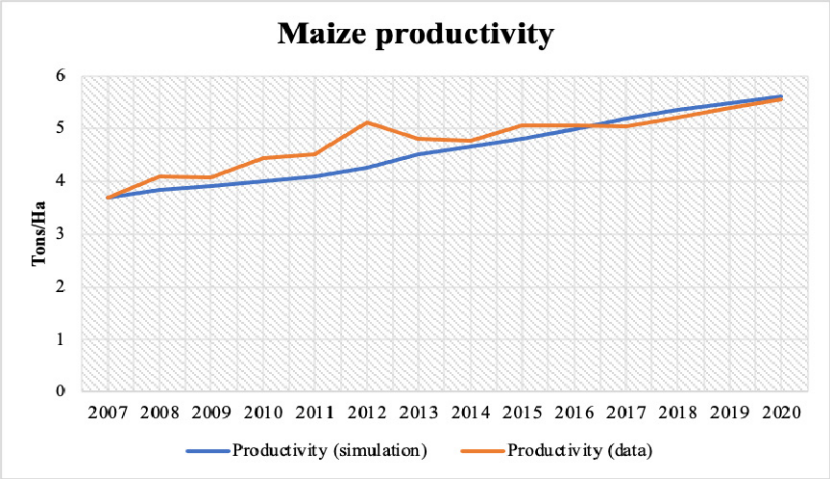


Figure 15. The comparison of simulation result of maize productivity model and data

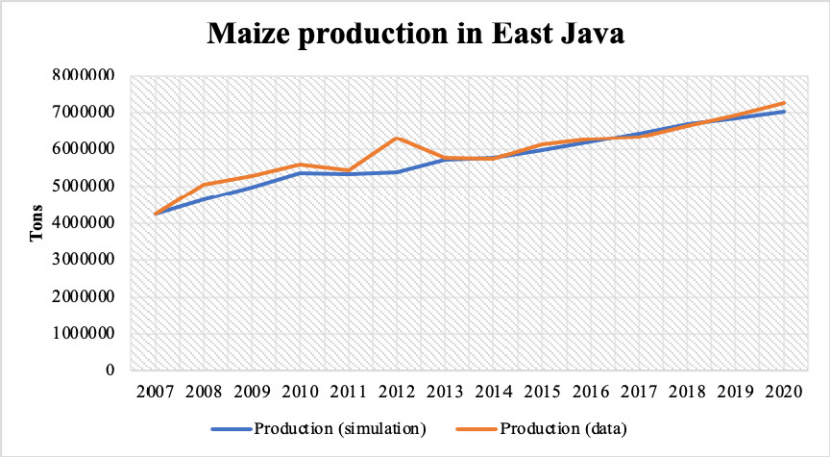


Figure 16. The comparison of simulation result of maize production model and data

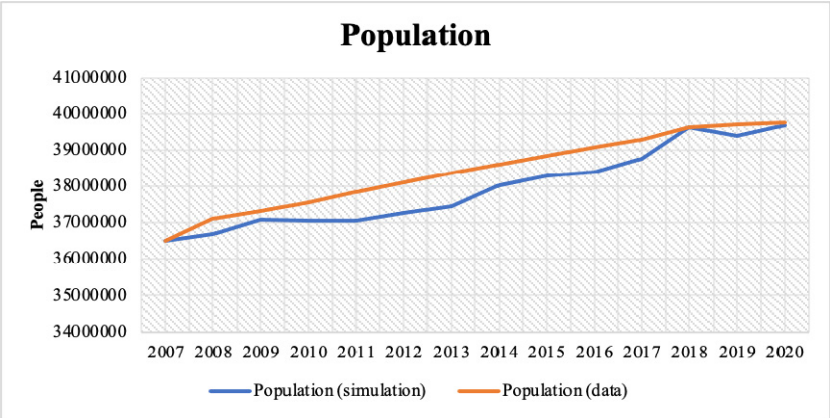


Figure 17. The comparison of simulation result of population model and data

5. Scenario Development

Scenarios were developed to increase maize production and farmers' income through (1) organic fertilizer scenario; (2) expansion and organic fertilizer scenarios; and (3) precision agriculture scenario.

5.1 Organic Fertilizer Scenario

The continuous use of inorganic fertilizers in maize farming can have a negative impact on soil productivity and the environment (Yoyo Sulaeman et al., 2017). The use of organic fertilizers, especially on dry land, is very important, given the large number of lands that have experienced degradation of organic matter, in addition to the high cost of inorganic fertilizers. Drought can reduce crop yields, while organic fertilizers rich in Zn and ZnO can increase yields under drought (Dimkpa et al., 2020). Effects caused by drought on food crops can be overcome by fertilizing with organic fertilizers rich in Zn and ZnO to increase production and quality. SFD scenario model of organic fertilizer can be seen in Figure 18. This scenario is developed by replacing inorganic fertilizers with organic fertilizers rich in Zn and ZnO. The simulation results of the maize productivity before (base model) and after the scenario can be seen in Figure 21 (a).

Through this scenario, maize productivity increases from an average of 5.90 tons/ha to 6.73 tons/ha. This scenario can increase maize productivity by around 14.02%. The comparison of maize production in East Java before (base model) and after scenario can be seen in Figure 22 (a).

Through this scenario, maize production in East Java is predicted to increase from an average of 7,847,972 tons to 9,086.265 tons. This scenario can increase maize production in East Java by around 15.78%. The comparison of maize cultivation costs before (base model) and after scenario can be seen in Figure 23 (a).

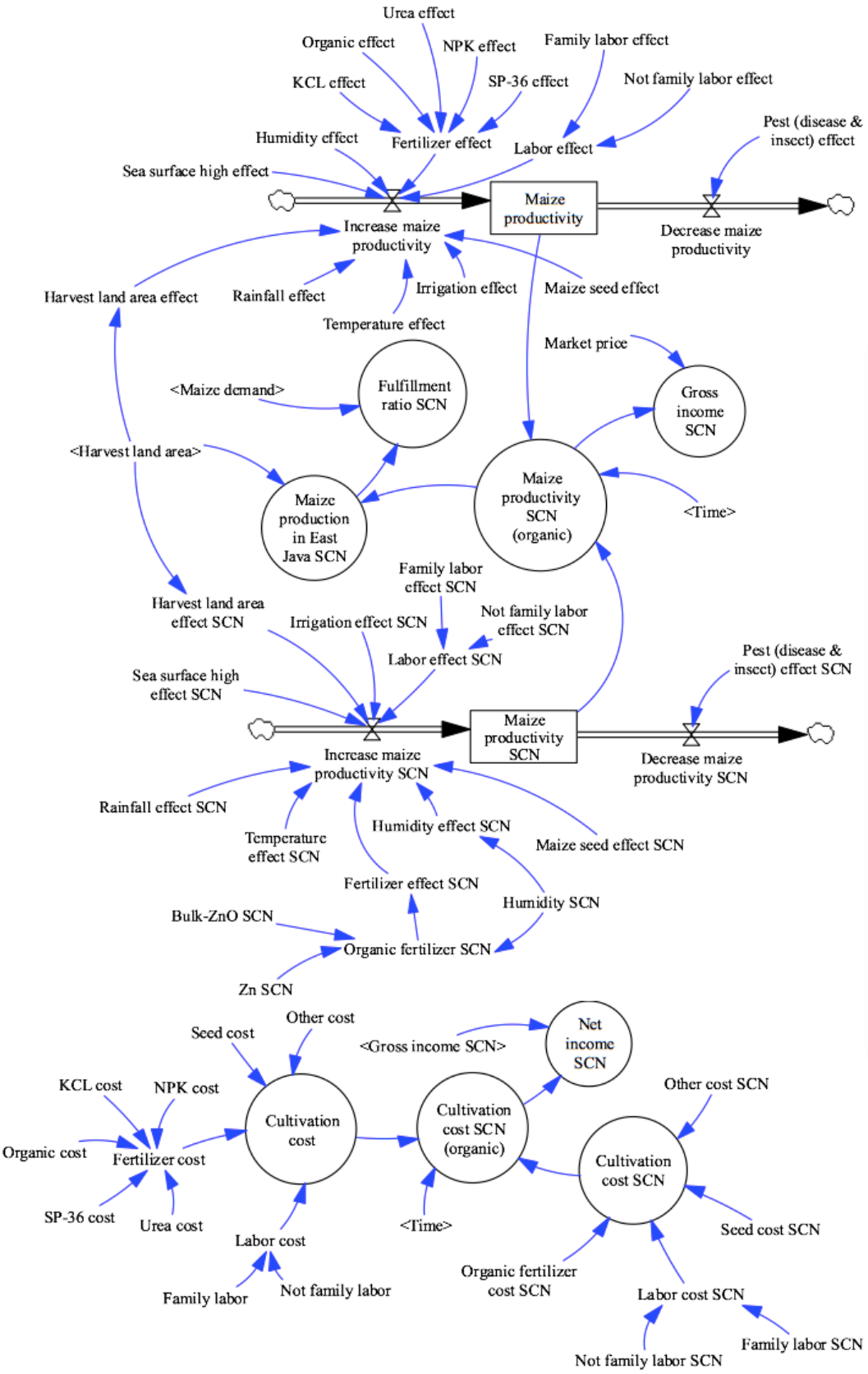


Figure 18. SFD of scenario model of organic fertilizer

5.2 Land Expansion and Organic Fertilizer Scenario

The addition of new land as a maize cultivation area can increase the availability of harvest area. New land clearing for maize cultivation is also influenced by farmers' income (Wang et al., 2018). Efforts to increase maize production can be pursued by expanding harvested areas and increasing productivity. Another problem is obtained from the use of fertilizers to increase productivity. The continuous use of inorganic chemical fertilizers has a negative impact on soil productivity and the environment. Membership in agricultural cooperatives, organic fertilizer subsidies, and farm size play a positive role in influencing farmers' choices of organic fertilizers instead of chemical fertilizers (Wang et al., 2018). The scenario model of land expansion and the use of organic fertilizer can be seen in Figure 19.

This scenario is developed by (1) replacing inorganic fertilizers with organic fertilizers; and (2) expanding agricultural land. The simulation result of the maize productivity before (base model) and after this scenario can be seen in Figure 21 (b).

The scenario simulation results show that through this scenario, maize productivity increases from an average of 5.90 tons/ha to 6.12 tons/ha. This scenario can increase maize productivity by around 3.80%. The comparison of maize production in East Java before (base model) and after this scenario can be seen in Figure 22 (b).

5.3 Precision Agriculture Scenario

The purpose of an application of technology in farming is to achieve higher agricultural productivity (Soekartawi, 1996). Precision agriculture technologies are a subset of agricultural practices that are economically efficient and environmentally sustainable (Kolady et al., 2021). The use of technology in farming will affect how many workers are required, but technological sophistication alone does not necessarily increase productivity without proper application of fertilizers (Nababan, 2009). To increase productivity and cost efficiency of farming, as well as farmer welfare, several initiatives are required such as the expansion of agricultural services, the availability of high-quality seeds, sufficient fertilizer at affordable prices, and provision of economical internet in remote areas (Elham et al., 2020). Female farmers, remittances, and agricultural machinery can increase agricultural efficiency, while the use of fertilizers tends to reduce agricultural efficiency (A. Gold & S. Gold, 2019). To develop a more competitive maize cultivation, it is necessary to apply the right technology (Food Security Agency, 2009). The perceived benefits of technology, facilitation conditions through the knowledge enhancement and training have a significant impact on increasing farmers' willingness to adopt precision agricultural technology (Li et al., 2020) such as the use of Global Navigation Satellite System (GNSS) and Unmanned Aerial Vehicle (UAV).

In this study, several strategies that need to be carried out related to the implementation of precision agriculture include: (1) the application of precision agriculture technology such as the Global Navigation Satellite System (GNSS) tractor, which offers many advantages for farmers including higher accuracy, higher operating speed, easier operation, less affected by bad weather, and accurate use of inputs (fertilizers, pesticides, seeds) (Keskin et al., 2018) and Unmanned Aerial Vehicle (UAV) for pest control, crop irrigation, and plant health monitoring (Yinka-Banjo, 2020); (2) increasing knowledge through socialization related to the use of precision agricultural technology (Li et al., 2020); and (3) training on the use of precision agricultural technology (Li et al., 2020). The SFD of the scenario model for precision agriculture can be seen in Figure 20.

This scenario was developed through the application of precision agricultural technology. The comparison of the maize productivity model before (base model) and after the scenario can be seen in Figure 21 (c).

Using this scenario, maize productivity is projected to increase from an average of 5.90 tons/ha to 6.66 tons/ha. This scenario can increase the productivity of maize by about 12.82%. The comparison graph of maize production in East Java before (base model) and after the scenario can be seen in Figure 22 (c).

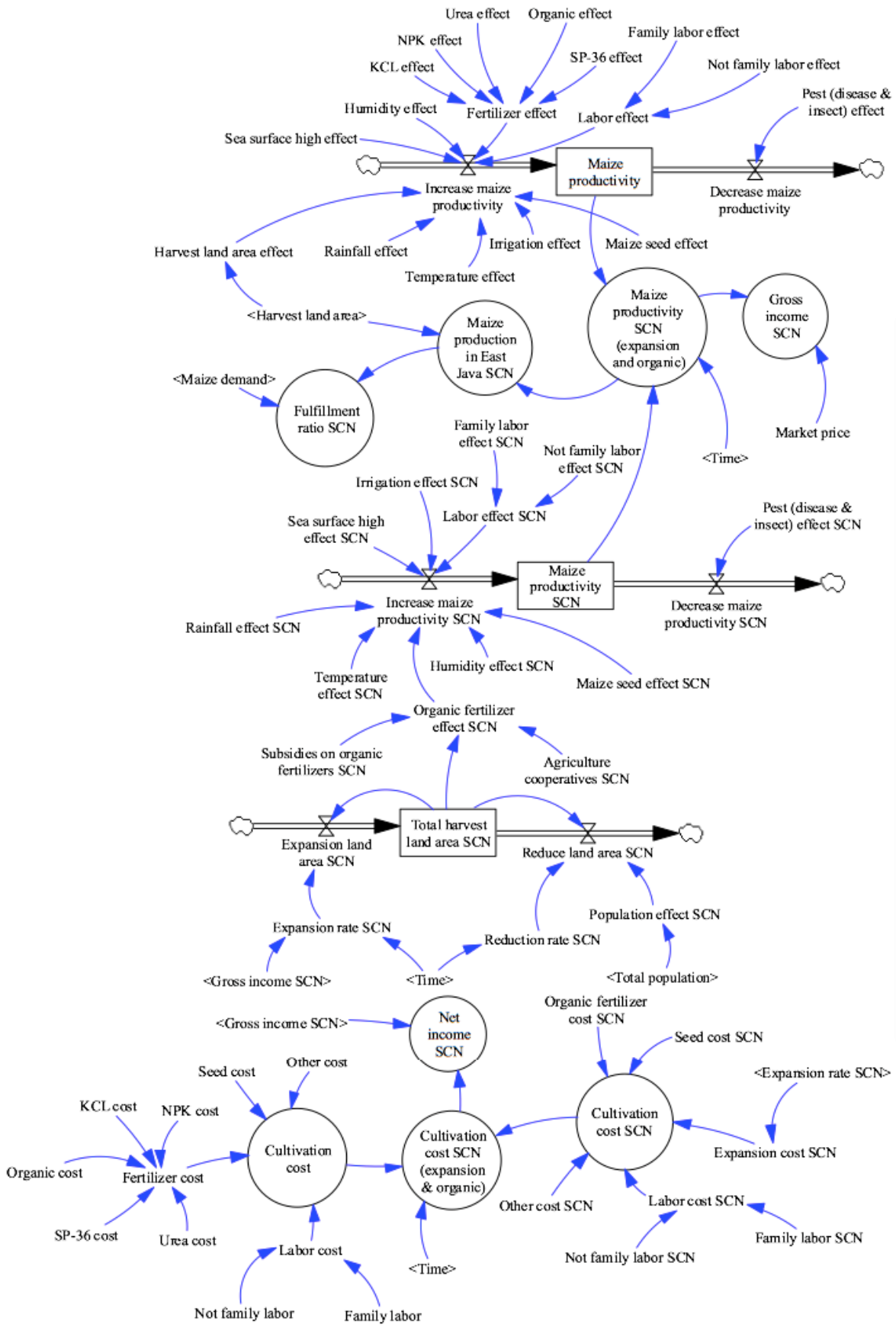


Figure 19. SFD of scenario model of land expansion and organic fertilizer

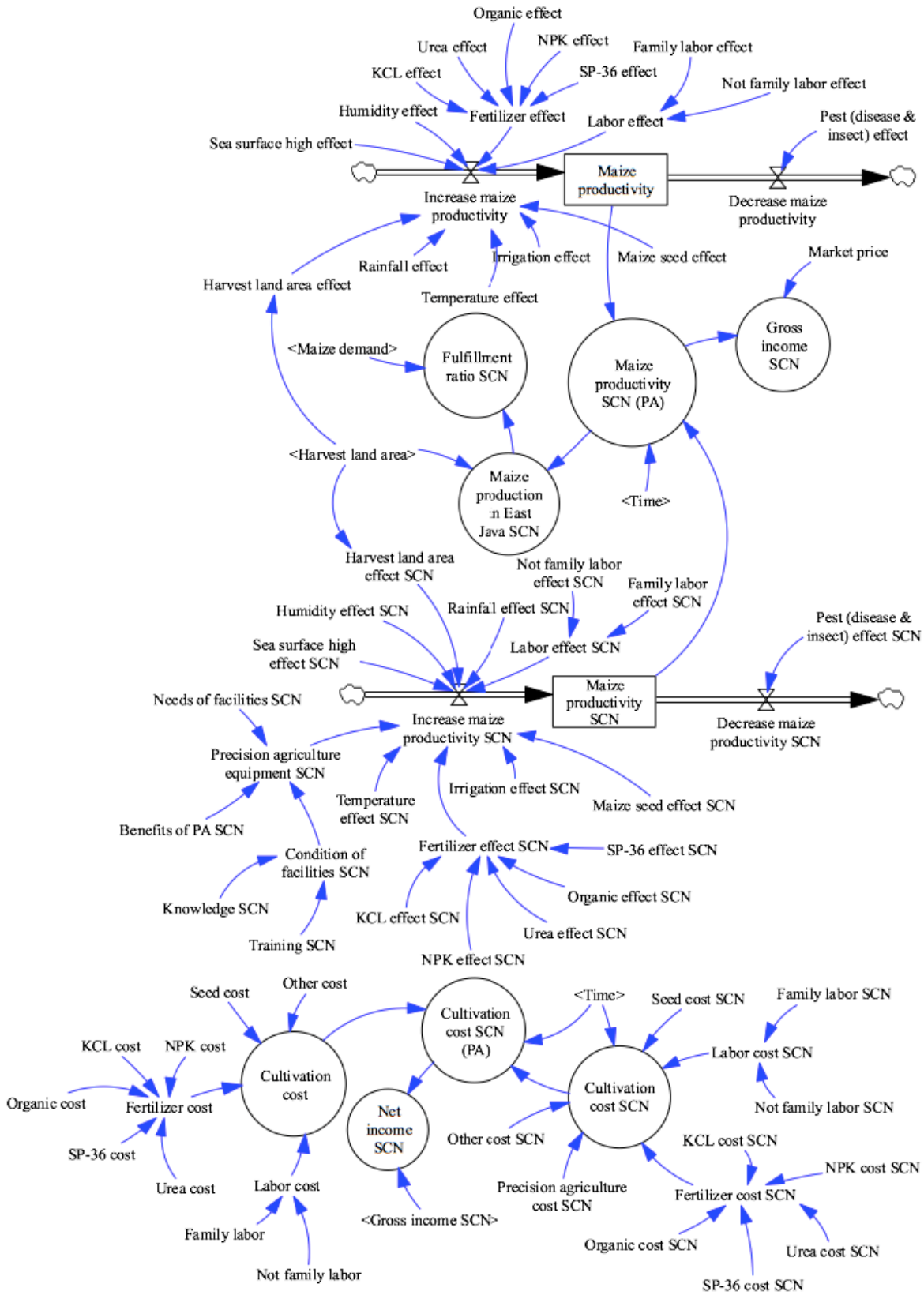
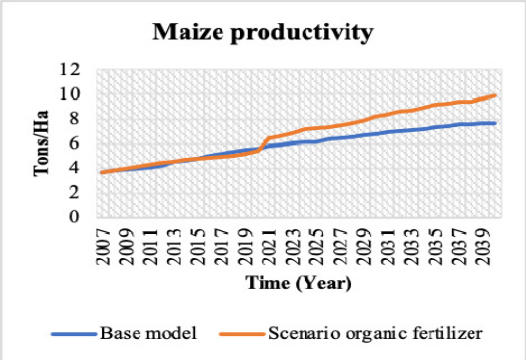
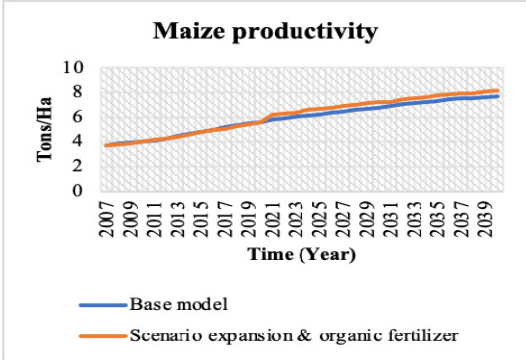


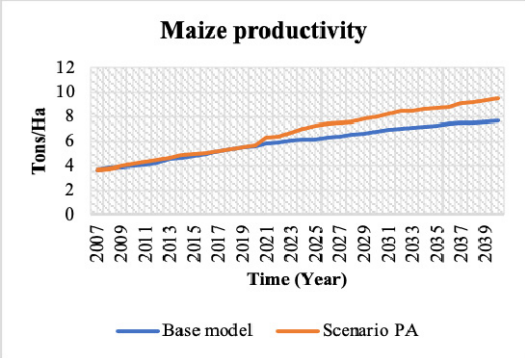
Figure 20. SFD of scenario model of precision agriculture



(a) Organic fertilizer

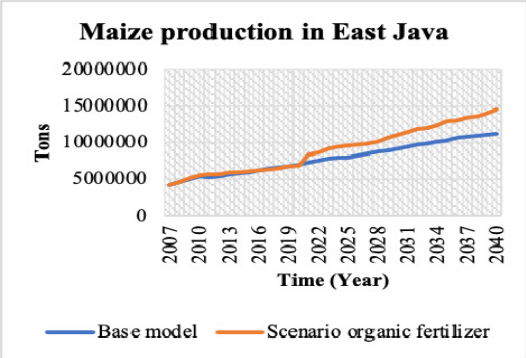


(b) Land expansion and organic fertilizer

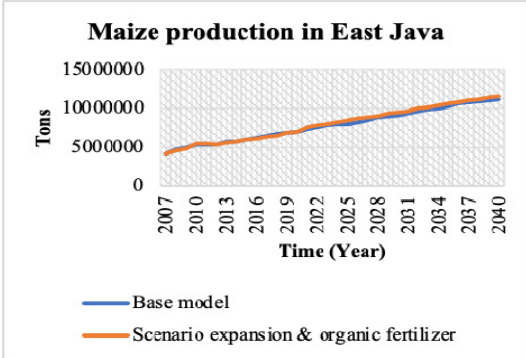


(c) Precision agriculture

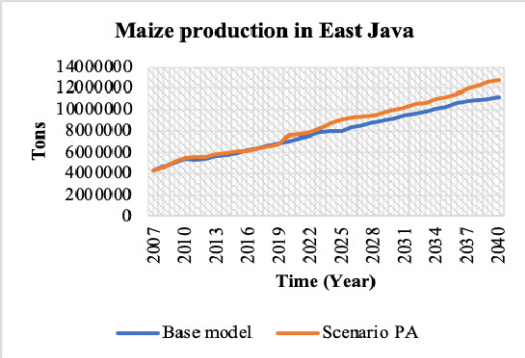
Figure 21. The comparison of the maize productivity model before (base model) and after scenarios



(a) Organic fertilizer



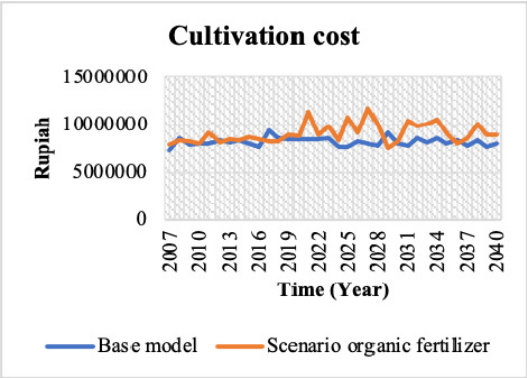
(b) Land expansion and organic fertilizer



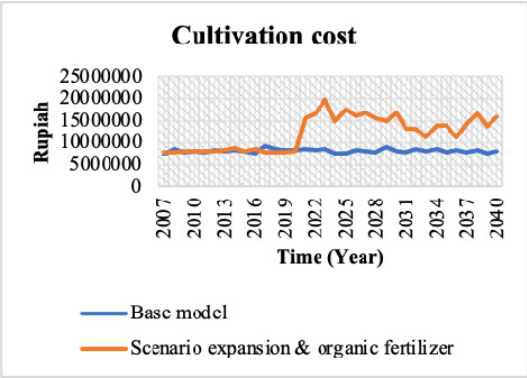
(c) Precision agriculture

Figure 22. The comparison of the maize production in East Java before (base model) and after scenarios

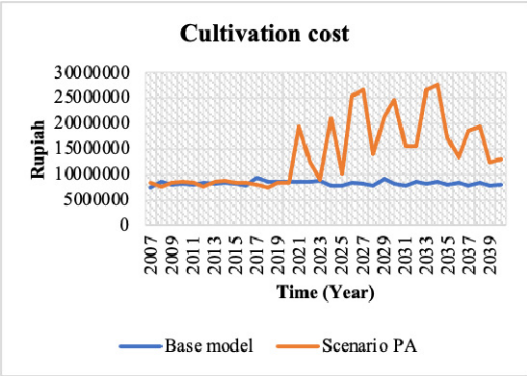
Using the land expansion and organic fertilizer scenario, maize production in East Java is predicted to increase from an average of 7,847,972 tons to 8,000,214 tons. This scenario can increase maize production in East Java by around 1.94%. Whereas if using the precision agriculture scenario, maize production in East Java is predicted to increase from an average of 7,847,972 tons to 8,413,554 tons. This scenario can increase maize production in East Java by around 7.21%. The comparison of maize cultivation costs before (base model) and after all scenarios are implemented can be seen in Figure 23.



(a) Organic fertilizer



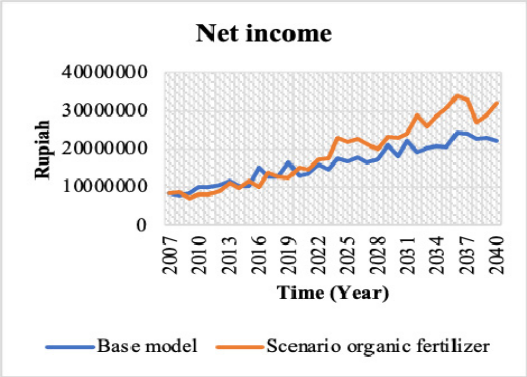
(b) Land expansion and organic fertilizer



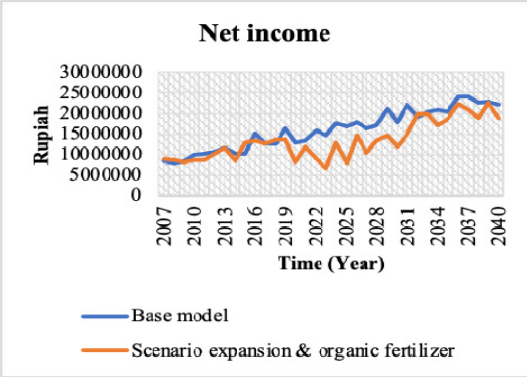
(c) Precision agriculture

Figure 23. The comparison of the maize cultivation costs before (base model) and after scenarios

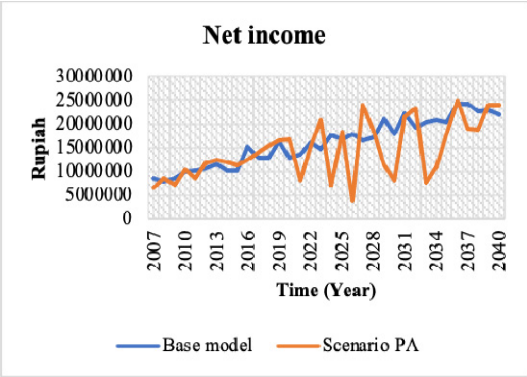
Using the organic fertilizer scenario, the cost of maize cultivation only increases slightly from an average of Rp8,205,199 to Rp9,069.978. This scenario has an impact on increasing the cost of maize cultivation by around 10.54%. Farmers' net income increased from an average of Rp15,794,534 to Rp18,919,286. This scenario can increase the net income of farmers by around 19.78%. Then if using the land expansion and organic fertilizer scenario, the cost of maize cultivation has increased quite a lot from an average of Rp8,205,199 to Rp12,226,361. The scenario has an impact on increasing the cost of maize cultivation by around 49.01%. The net income of farmers decreased from an average of Rp15,794,534 to Rp13,450,201. This scenario results in a decrease in the net income of farmers by around 14.84%. Whereas if using the precision agriculture scenario, the cost of maize cultivation has increased a lot from an average of Rp8,205,199 to Rp14,051,886. The scenario has an impact on increasing the cost of maize cultivation by around 71.26%. Farmers' net income decreased from an average of Rp15,794,534 to Rp14,468,461. This scenario results in a decrease in the net income of farmers by around 8.40%. The comparison of farmers' net income before (base model) and after all scenarios are implemented can be seen in Figure 24.



(a) Organic fertilizer



(b) Land expansion and organic fertilizer



(c) Precision agriculture

Figure 24. The comparison of farmers' net income before (base model) and after scenarios

6. Conclusions and Further Research

This research is designed to increase maize production and farmers' income through the development of sustainable maize productivity and production models to meet demand and increase farmers' incomes. This research was conducted by developing a system dynamics simulation model and scenario that can accommodate problems in the operational and strategic fields of the maize industry related to strategies to increase production and farmers' income.

Maize production is influenced by land harvest area and productivity. Several factors that affect the productivity and production of maize include harvested area, seed varieties, fertilizers, irrigation, climate and weather, labor, and pests and diseases. The demand for maize for consumption is calculated based on the calculation of consumption per capita multiplied by the total population. The fulfillment ratio is a comparison of maize production and the total demand. Farmers' net income per ha is the difference between gross income per ha and maize cultivation costs per ha. Gross income of farmers is obtained by multiplying the price of maize at the producer level with maize productivity. Meanwhile, the cost of cultivation per hectare is obtained from the accumulated total input costs for maize cultivation per hectare.

Several significant variables that affect maize production are the area of harvest, the use of fertilizers, and the use of technology. Scenario development is done by changing the structure of the validated model. Several scenarios were developed including: (1) organic fertilizer scenario by changing the use of inorganic fertilizers KCL, SP-36, Urea, NPK with organic fertilizers rich in Zn and ZnO; (2) land expansion and organic fertilizer scenarios by expanding the harvested area, changing the use of inorganic fertilizers to organic fertilizers, becoming membership in agricultural cooperatives, and using organic fertilizer subsidies; and (3) implementation scenarios of precision agriculture by utilizing precision agriculture technology, increasing farmer knowledge, and training in the use of agricultural cultivation technology. The results of scenario simulations show that: (1) the organic fertilizer scenario can increase productivity by 14.02%, production by 15.78%, and farmers' income increases by 19.78% with a fairly low increase in cultivation costs of around 10.54%; (2) the scenario of land expansion and organic fertilizer

can increase productivity by 3.80%, production by 1.94%, and farmers' income decrease by 14.84% with a fairly high increase in cultivation costs of around 49.01%; (3) the precision agriculture scenario can increase productivity by 12.82%, production by 7.21%, and farmers' income decrease by 8.40% with a very high increase in cultivation costs of around 71.26%.

The most optimal scenario is organic fertilizer which produces the highest productivity and production with the lowest cultivation costs because it replaces inorganic fertilizers with organic fertilizers rich in Zn and ZnO. The second optimal scenario is precision agriculture, which can increase productivity and production by reducing the number of workers but requiring the highest cultivation costs. The third optimal scenario is land expansion and organic fertilizer. The cost of cultivation under this scenario is quite expensive because of the need for land expansion. Future research is required to develop a sustainable agriculture by considering the environmental and social factors

Acknowledgements

The authors gratefully acknowledge financial support from the Institut Teknologi Sepuluh Nopember for this work, under project scheme of the Publication Writing and IPR Incentive Program (PPHKI).

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