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A System Dynamics Approach to Corn Production in indonesia: Causal Loop Diagram

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This study investigates the challenges facing corn production in Indonesia, using a system dynamics approach to address its role in national food security. The research focuses on declining domestic corn production, increasing reliance on imports, and limited market availability, all of which pose significant risks to food security. The study's primary objective is to analyze strategies for improving corn production, emphasizing harvested area expansion, productivity enhancements, and their combined effects. Time series data from 1980 to 2019 were sourced from the Central Bureau of Statistics (BPS), the Ministry of Agriculture, the Ministry of Trade, and the Food and Agriculture Organization (FAO). A quantitative descriptive approach was employed, utilizing system dynamics modeling—comprising input-output analysis and causal loop diagrams—to simulate key factors influencing corn production. Model verification was conducted using the Mean Absolute Percentage Error (MAPE) method, and simulations were performed with Powersim software to project future outcomes. The results indicate that without strategic interventions (Scenario 1), corn production is projected to decline to 31,863,838 tons by 2040, with productivity at 4.8 tons/ha, well below the potential 8 tons/ha. Scenario 2, which focuses on expanding harvested area by 3.5% per year while limiting land conversion, shows considerable potential if supported by sound management and policies. Scenario 3 aims to increase productivity to 5.87 tons/ha through advanced agricultural practices, with projected production reaching 44,761,157 tons by 2040. The combined strategy of area expansion and productivity improvement (Scenario 4) could result in corn availability of 15,063,006 tons by 2040. The study concludes that with proper government support, including the formation of farmer institutions, technical and financial assistance, and stronger partnerships between farmers and industry, Indonesia can significantly boost its corn production and enhance national food security.

Keywords: Corn production, system dynamics, national food security, agricultural productivity, causal loop diagram.

INTRODUCTION

Food is a fundamental human need that is essential for sustaining daily life. According to Food Law No. 18 of 2012, food security is defined as a condition in which food is available in sufficient quantities, of good quality, safe, diverse, nutritious, and affordable for all segments of society, thereby supporting an active and productive life. In Indonesia, food security is heavily influenced by government commitment and food self-sufficiency, which refers to the nation's ability to produce food by optimally utilizing local and natural resources (Dermawan and Lahming, 2018; Indah and Setyaningsih, 2020). The Indonesian government has implemented various policies to achieve food self-sufficiency, including the provision of agricultural land, fertilizers, pesticides, seeds, irrigation, farmer education, and financial support (Ika, 2016; Limenta and Candra, 2017; Megahwati and Priadana, 2023). Despite these efforts, Indonesia still relies on imports for key food staples such as rice, corn, soybeans, sugar, and meat, highlighting the challenges in achieving full self-sufficiency (Rozaki, 2021; Asriani and Herdhiansyah, 2023).

Corn is one of the strategic commodities in Indonesia's agricultural sector, playing a crucial role in the national economy. After rice, corn is the second-largest contributor to the agricultural sector's Gross Domestic Product (GDP), with a significant increase from IDR 9.4 trillion in 2000 to IDR 18.2 trillion in 2003 (Utomo *et al*., 2013). Corn serves multiple purposes (4F): as food, feed, fuel, and industrial raw materials (fiber). Currently, about 58% of corn is used for animal feed, 30% for food, and the remainder for various industries (Panikkai *et al*., 2017). Bulog, a state-owned

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enterprise, plays a vital role in ensuring food availability and security by maintaining buffer stocks and stabilizing prices, especially for low-income households (Anwar, 2022; Jamaludin, 2022).

Despite the increase in national corn production, Indonesia continues to face challenges in achieving self-sufficiency in corn due to fluctuations in production and harvested area. In 2019, corn production reached 30.69 million tons, but the harvested area grew by only 3.94% during the 2010-2019 period, leading to continued dependence on imports (Ministry of Agriculture, 2020). Meanwhile, there is a potential land area of 27 million hectares suitable for corn cultivation, but only about 5.16 million hectares were utilized in 2020 (Ministry of Agriculture, 2021). Low agricultural productivity, coupled with classic issues such as land-use changes, inadequate human resources, and insufficient inputs, hampers the achievement of food self-sufficiency (Warr, 2011; Asriani and Herdhiansyah, 2023).

Corn is a vital commodity in Indonesia, significantly impacting food security and the livestock feed industry. In 2020, corn production reached over 27 million tons, with more than 30% allocated for animal feed, particularly for poultry and cattle (Ariyanto *et al*., 2023). This reliance on corn for feed underscores its role in ensuring meat availability, which is crucial for food security. Additionally, corn serves as a staple food in regions like East Nusa Tenggara, where it substitutes rice. Economically, corn contributes to smallholder farmers' incomes, especially in production areas such as East Java and Central Java (Asriani *et al*., 2024). Enhancing corn productivity through improved agricultural practices can bolster rural economic resilience and support national food sovereignty (Asriani *et al*., 2023). However, challenges remain, including fluctuating production levels and the need for sustainable practices to maintain self-sufficiency in corn production, which is still below 100%.

In response to global changes and the increasing demand for corn, including the need for biofuels, Indonesia has significant opportunities to enhance production and become a major global corn exporter. The development of the corn commodity can be pursued through increasing productivity and expanding planting areas using innovative cultivation technologies and the Integrated Crop Management (ICM) approach (Asriani and Herdhiansyah, 2019). Indonesia has the potential to significantly boost corn production and emerge as a leading global exporter. Key strategies include improving transportation infrastructure, simplifying export procedures, and addressing barriers in agribusiness development (Kariyasa *et al*., 2014; Sulaiman *et al*., 2020; Astuti *et al*., 2022).

Advancements in technology and science also play a crucial role in supporting food security. Dynamic system-based forecasting models have been identified as effective tools for projecting future corn demand, considering the complexity of factors influencing production and demand. Key determinants that need to be incorporated into the dynamic model to estimate resource requirements and availability for corn production (Herdhiansyah *at al.*, 2022). Dynamic systems leverage software such as Stella and Vensim to simulate policy scenarios that support strategic planning in food security (Forrester *et al.*, 2010; Rahmah *et al.*, 2017; Shahhosseini and Archontoulis 2020; Eliw *et al.*, 2022; Tsiboe *et al.*, 2023). These models help simulate the impact of policies and future food security scenarios, aiding in strategic planning and decision-making in food security (Flies *et al*., 2018; Vanany *et al.*, 2021; Skinner and Blake 2023; Okhrimenko and Zhukovska, 2023). Therefore, this research aims to apply a dynamic system approach to corn production, with a focus on causal loop diagrams. This approach is expected to provide more comprehensive and adaptive solutions for advancing the agricultural sector and sustainably improving community welfare.

MATERIALS AND METHODS

This study was conducted in Indonesia, utilizing time series data from 1980 to 2019, obtained from various sources such as the Central Bureau of Statistics (BPS), the Ministry of Agriculture, the Ministry of Trade, and the Food and Agriculture Organization (FAO). The selection of the location was based on the availability of relevant and accessible secondary data to support comprehensive analysis.

***Research Design and Methodology*:** This research employs a quantitative descriptive approach to analyze numerical data related to corn production in Indonesia. The analysis was conducted using two primary methods: quantitative and qualitative, with a focus on factors influencing corn availability.

Research Stages

1. ***Needs analysis*:** This stage involves identifying the needs of various stakeholders involved in corn production and distribution, including local governments, farmers, entrepreneurs, traders, exporters, consumers, financial institutions, and research organizations.

Needs analysis in corn production and distribution is essential for identifying the requirements of various stakeholders, including farmers, traders, and consumers. This process involves several stages: organizational screening, data collection, data analysis, and action planning. Each stage plays a critical role in understanding stakeholder needs and ensuring effective interventions. For instance, the organizational screening phase helps identify potential issues and stakeholders, while the data collection phase focuses on gathering relevant information from targeted groups (Erma *et al*., 2022). Furthermore, stakeholders in the U.S. Corn Belt prioritize practical decision-making, emphasizing the need for credible and usable climate information to enhance agricultural outcomes (Chijina *et al.*, 2023).

This comprehensive approach ensures that the needs of all parties are addressed, leading to improved efficiency and productivity in corn production and distribution. The following points elaborate on the key aspects of needs analysis in this context. Identifying key stakeholders such as local governments, farmers, and financial institutions is crucial for effective needs analysis. Understanding the roles and influences of each stakeholder helps in tailoring interventions to meet their specific needs. Systematic data collection methods are essential for gathering accurate information on stakeholder needs. Analyzing this data allows for the identification of gaps and areas for improvement in corn production and distribution processes. Stakeholders require actionable information that can be applied to enhance agricultural practices and economic outcomes (Chijina *et al.*, 2023). Decision support tools should be developed based on stakeholder input to ensure relevance and usability. While needs analysis is vital for aligning stakeholder interests, it is also important to consider the potential for conflicting needs among different groups, which can complicate the decision-making process and require careful negotiation and prioritization.

2. ***Problem formulation*: This stage focuses on identifying the main issues affecting corn production, such as declining production, increased imports, decreased exports, and limited availability of corn in the domestic market.

The formulation of problems affecting corn production is crucial for addressing issues such as declining yields, increased imports, and limited domestic availability. A well-defined problem formulation can guide research and policy decisions, ensuring that the right questions are asked and relevant data is collected. A systems-based approach enables a holistic evaluation of environmental and resource factors that may impact corn production (Herdhiansyah *et al*., 2022). Factors such as climate change and soil degradation contribute to reduced corn yields. Research indicates that improved agricultural practices can mitigate these effects, enhancing productivity (Rahmawati *et al*., 2023).

3. ***System identification*:** The system being analyzed is identified through two main tools: the input-output diagram and the causal loop diagram. These tools are used to understand the interactions and causal relationships between the various variables influencing corn production.

System identification in corn production can be effectively achieved through the use of input-output diagrams and causal loop diagrams (CLDs). These tools facilitate the understanding of interactions and causal relationships among various influencing variables. Input-output diagrams provide a visual representation of how inputs (like seeds, fertilizers) lead to outputs (corn yield), while CLDs illustrate feedback loops that can be either reinforcing or balancing, crucial for understanding system dynamics (Crielaard *et al*., 2022). Visualize the relationship between inputs and outputs in corn production. Help identify key variables affecting yield, such as weather conditions and agricultural practices. Capture complex interactions and feedback mechanisms in the production system. Allow for scenario analysis to predict outcomes based on variable changes. In contrast, while these tools provide valuable insights, they may oversimplify complex agricultural systems, potentially overlooking critical external factors such as market dynamics and policy changes that also influence corn production outcomes (Deepali *et al*., 2023).

4. ***Model verification*:** Model verification is conducted to ensure the accuracy of the dynamic model developed. This verification involves testing the model using methods such as the Mean Absolute Percentage Error (MAPE) to ensure that the computer model accurately reflects the reality being studied.

Model verification is crucial for ensuring the accuracy of dynamic models, often employing techniques like the Mean Absolute Percentage Error (MAPE). This process involves several key steps to confirm that the model accurately represents the real-world phenomena it aims to simulate. A widely used metric for assessing prediction accuracy, particularly in time series forecasting, which quantifies the error as a percentage of the actual values. Essential in Computational Fluid Dynamics (CFD) to ensure that the model's results are not dependent on the mesh size or configuration. Adjusting model parameters iteratively to align model outputs with experimental or analytical data. Ensuring that the model accurately reflects the physical system it represents, often through comparison with experimental results (Mohamad, 2024).

While model verification is vital for accuracy, it is also important to recognize that models may still produce errors due to limitations in data or assumptions made during their development. This highlights the need for continuous improvement and adaptation in modeling practices to enhance reliability and accuracy in predictions (Rahmawati *et al*., 2023).

5. ***Model simulation*:** The simulation is conducted to project the future performance of the corn production system. This simulation uses Powersim software and involves relevant variables and assumptions. The simulation results are expected to provide insights for formulating policy strategies that support national food security.

he simulation of corn production systems using Powersim software is crucial for projecting future performance and informing policy strategies aimed at enhancing national food security. Various studies highlight the importance of simulation models in understanding the dynamics of maize production and the factors influencing it. Increasing land area for maize cultivation significantly impacts production levels. The application of organic fertilizers enhances yield and farmer income. Precision agriculture techniques improve efficiency and output. Studies indicate that government interventions can affect maize food security, with simulations predicting increased reliance on imports by 2030 (Eliw *et al*., 2022). While simulation models provide valuable insights, they also face challenges, such as accurately predicting soil water content under different conditions, which can affect overall reliability (Deepali *et al*., 2023).

***Data and data collection techniques*:** The data used in this study is secondary data in the form of time series from 1980 to 2019. This data encompasses various aspects such as production, productivity, harvested area, prices, and import volumes of corn. Data collection was carried out through literature reviews from official sources and historical documentation.

***Research instruments*:** The instruments used in this research include various literature sources such as books, scientific journals, and Powersim software for data analysis.

***Data analysis*:** The data is analyzed using a descriptive quantitative approach and dynamic system modeling (Morcillo *et al*., 2018; Freebairn *et al*., 2019; Franco *et al*., 2018; Guizzi *et al*., 2019). The analysis process includes:

a. The development and validation of the dynamic system model using Powersim software.

b. Model simulation to project policy scenarios.

c. Policy recommendations based on the model simulation results, aimed at supporting national food security strategies.

Through this approach, the research is expected to provide more comprehensive and adaptive solutions to address the challenges of corn production in Indonesia.

RESULTS AND DISCUSSION

Introduced by Professor Jay Forrester from MIT in the 1950s, dynamic systems are a conceptual tool for understanding and modelling complex and dynamic systems. This method is well-suited for building effective computer simulations that contribute to better policymaking and organizational improvement (Sterman, 2000; Legaard *et al*., 2021; Ghadami and Epureanu, 2021; Cassidy *et al*., 2019; Vespignani, 2011). In dynamic system modeling, the relationships and behaviors of complex systems are analyzed through Causal Loop Diagrams (CLDs). CLDs are simple maps that depict cause-and-effect relationships between variables using arrows. This tool is useful for: (a) illustrating hypotheses about dynamic processes; (b) capturing individual or group mental models; and (c) communicating important feedback (Crielaard *et al*., 2022; Abram and Dyke, 2018; Bureš, 2017).

Feedback in a CLD can be either positive (Reinforcing loop), which strengthens the system, or negative (Balancing loop), which produces the opposite effect. Stock and flow diagrams are used to test the behavior and impact of changes in system structure and policies (Ryan *et al*., 2019; Bala *et al*., 2017; Lin *et al*., 2020). The dynamic model scenarios for corn availability in support of national food security include: (1) input-output diagrams, (2) causal loop diagrams, (3) model verification, and (4) model simulation.

***Input-output diagram for corn production*:** The input-output diagram provides a detailed representation of the system by identifying both controlled and uncontrolled input and output variables. This diagram facilitates understanding of the real system by establishing model boundaries that encompass problem analysis and related causal relationships (Rodgers and Oppenheim, 2019; Chong *et al*., 2021; Xu and Dang, 2020; Junglas, 2016). The components of the diagram include uncontrolled inputs, controlled inputs, environmental inputs, desired outputs, undesired outputs, and system controls.

Table 1. System dynamics approach boundaries for corn production.

No.	Main attributes	Sub-attributes	
1	Corn commodity harvest area	a.	Corn cultivation area
		b.	Land use conversion (conversion) of corn cultivation
		c.	Expansion of cultivation area (extensification) of corn
2	Corn commodity productivity	a.	Use of superior corn seeds
		b.	Use of superior corn seeds
		c.	Pest and disease management for corn
		d.	Fertilization for corn
		e.	Use of agricultural machinery and equipment for corn**
		f.	Climate impact on corn cultivation
		g.	Labor in corn cultivation
3.	Corn commodity production	a.	Corn productivity
		b.	Corn harvested area
		c.	Corn yield loss

In the System Dynamics Approach to Corn Production, environmental inputs include government policies and global climate changes. Uncontrolled inputs are land-use conversion, while controlled inputs include production. (Figure 1).

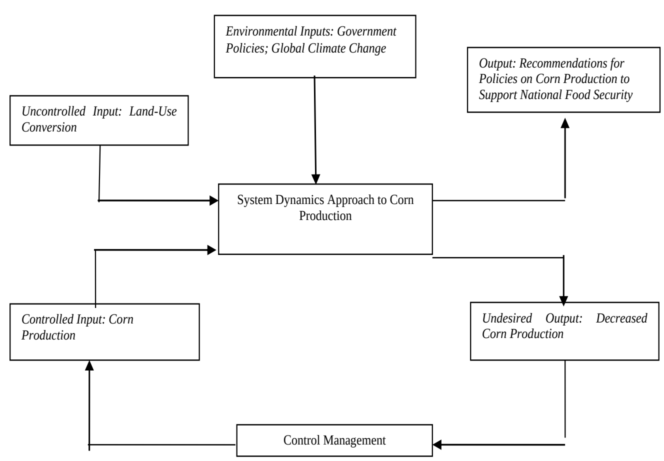

Figure 1. Input-output diagram of the system dynamics approach to corn production.

Figure 1 shows that the desired output of the System Dynamics approach to corn production is the development of strategic scenarios to support national food security. The undesired output includes a decrease in corn production.

***Causal loop diagram of corn production*:** The causal loop diagram is used to map the interconnections between variables in the system dynamics approach (Amiri *et al.*, 2020; Kopainsky *et al.*, 2017; Abidin *et al.*, 2023; Alvarado *et al.*, 2023). for corn production to support national food security. The corn production model is influenced by factors such as harvested area, land productivity, and yield loss, with a constant representing the fraction of yield loss. The government can enhance production through the expansion of harvested area and improvements in corn productivity (Fig. 2).

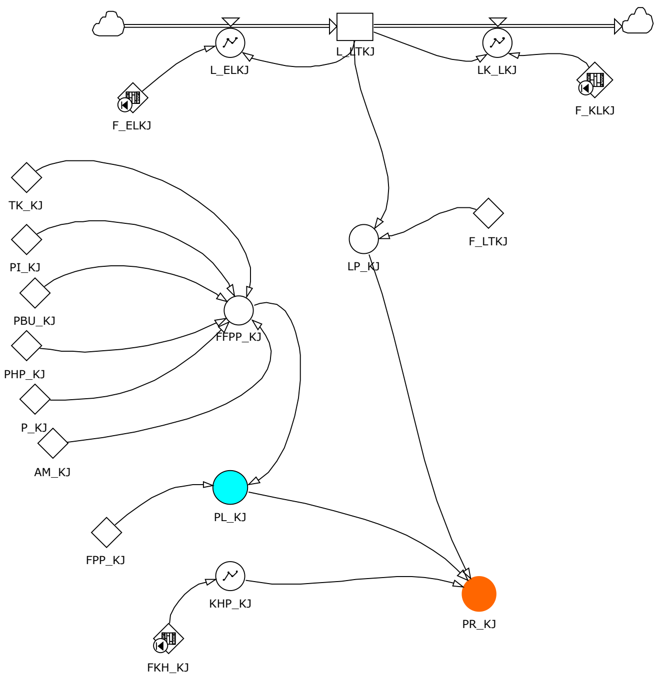

Figure 2. Causal loop diagram model of corn production.

Increased harvested area and corn productivity have a positive impact on production, which in turn enhances the availability of raw materials for household consumption, animal feed, self-sustaining feed, seeds, and processing industries. Harvested area is influenced by factors such as planting area, potential area, extensification, and land conversion. Constants like the fraction of land area, extensification, and conversion are used to facilitate model modifications according to real conditions. As extensification increases, the harvested area expands, which can be supported by the government through the utilization of potential areas.

Corn productivity is influenced by variables including: the fraction of corn land productivity and the fraction of potential production factors for corn. These variables also require constants as inputs for the model, making it easier to adjust the model in response to changes that align with real-world conditions. Constants for corn productivity include: (1) percentage of use of superior corn seeds, (2) percentage of pest and disease management for corn, (3) percentage of fertilization for corn, (4) percentage of agricultural machinery and equipment usage for corn, (5) percentage of labor, and (6) percentage of climate change impact. Corn productivity indicates that the greater the increase in potential production factors for corn, the higher the productivity of the corn itself. This is related to various alternatives for enhancing corn productivity that the government can pursue, including: (1) the use of superior seeds; (2) pest and disease management; (3) fertilization; (4) the use of agricultural machinery and equipment; (5) the impact of climate on corn cultivation; and (6) labor involved in corn cultivation.

***Formulation of the system dynamics approach to corn production*:** Model formulation involves translating the problem into a mathematical representation to represent the real system, connecting the identified variables in the conceptual model with symbols. This model formulation utilizes Powersim software. The corn production model is formulated with the following equations:

PR_KJ = L_PKJ*PL_KJ * KHP_KJ ………………… (1)

Information:

- PR_KJ = Corn Production
- LP_KJ = Harvested Area of Corn
- PL_KJ = Land Productivity of Corn
- KHP_KJ = Corn Yield Loss

Equation 1 states that corn production is the product of land productivity, harvested area, and yield loss, with yield loss being 2% per year. The harvested area of corn is formulated as:

LP_KJ = L_LTKJ * F_LTKJ ………………………… (2)

Information:

- LP_KJ = Harvested Area of Corn
- L_LTKJ = Area of Land Dedicated to Corn Cultivation
- F_LTKJ = Fraction of the Corn Cultivation Area

Equation 2 indicates that the harvested area of corn is the product of the land area dedicated to corn cultivation and the fraction of the cultivation area, which is assumed to be 98.3%. Land conversion from corn to non-corn use occurs at a rate of 1.2% per year. The area of land dedicated to corn cultivation is calculated using the following equation:

L_LTKJ = L_ELKJ - LK_KJ ....…….. ………… (3)

Information:

L_LTKJ = Area of Land Dedicated to Corn Cultivation

L_ELKJ = Rate of Extensification of Corn Land

L_KJ = Rate of Conversion of Corn Land

Equation 3 indicates that the area of land dedicated to corn cultivation is derived from the difference between the rate of extensification (1.8% per year) and the rate of land conversion (1.2% per year). Extensification involves increasing the corn cultivation area through new land and community forests, while conversion reduces corn land for non-corn uses. Corn productivity is formulated as:

PL_KJ = FP_KJ*FFPP_KJ………………………… (4)

Information:

-PL_KJ = Land Productivity of Corn
- FP_KJ = Fraction of Corn Productivity
- FFPP_KJ= Fraction of Potential Productivity Factors for Corn

Equation 4 states that the fraction of potential productivity factors for corn (FFPP_KJ) is the sum of various factors affecting productivity, namely:

FFP_KJ = PBU_KJ + PHP_KJ + P_KJ + AM_KJ + PI_KJ + TK_KJ…….(5)

Information:

- FFP_KJ = Fraction of Productivity Factors for Corn
- PBU_KJ = Use of Superior Corn Seeds
- PHP_KJ = Pest and Disease Management for Corn
- P_KJ = Fertilization for Corn
- AM_KJ = Use of Agricultural Machinery for Corn
- PI_KJ = Climate Impact on Corn Cultivation
- TK_KJ = Labor in Corn Cultivation

Equation 5 states that corn land productivity is the total of the percentages of the use of superior seeds, pest management, fertilization, use of machinery, climate impact, and labor.

Verification of the dynamic system model for corn commodity availability**:** The verification of the dynamic system model for corn ensures that the model adheres to the established procedures. The verification process includes: (a) dimensional checks of model variables (levels, rates, constants) against secondary data; and (b) evaluation of the accuracy of the integration methods and time steps used. The results of the verification indicate that the model functions well and is accurate according to the mathematical equations that have been developed.

Simulation of the dynamic system model for corn commodity production**:** The simulation begins with the prediction of parameters from 1980 to 2019 that have been verified. The simulation for the period 2020-2040 evaluates several scenarios for corn production in Indonesia. The scenarios tested include: (1) no strategy, (2) increase in corn planting area, (3) increase in corn production, and (4) a combination of increased planting area and corn production.

Scenario 1: Without strategy implementation**:** This scenario depicts a situation with no government intervention in corn production management. Without a strategy, there is no increase in the planting area or production.

a. Simulation of the corn harvest area subsystem**:** In 2020, the corn planting area is 5,977,362 hectares per year. The simulation indicates an increase to 6,875,595 hectares per year by 2040, with an average annual growth rate of approximately 1.64%, considering land conversion to non-corn commodities.

Table 2. Simulation results of corn planting area under scenario 1.

Years	Land conversion rate of corn commodities (LK_LKJ) (ha)	Corn planting area (L-LTKJ) (ha)	Corn land expansion Rate (L_ELKJ) (ha)
2020	98.028,74	5.977.362,00	139.870,27
2021	98.717,34	6.019.349,98	140.852,79
2022	99.410,78	6.061.632,90	141.842,21
2023	100.109,09	6.104.212,84	142.838,58
2024	100.812,31	6.147.091,89	143.841,95
2025	101.520,46	6.190.272,13	144.852,37
2026	102.233,59	6.233.755,70	145.869,88
2027	102.951,73	6.277.544,72	146.894,55
2028	103.674,92	6.321.641,33	147.926,41
2029	104.403,18	6.366.047,70	148.965,52
2030	105.136,56	6.410.766,00	150.011,92
2031	105.875,09	6.455.798,43	151.065,68
2032	106.618,81	6.501.147,18	152.126,84
2033	107.367,76	6.546.814,49	153.195,46
2034	108.121,96	6.592.802,59	154.271,58
2035	108.881,47	6.639.113,73	155.355,26
2036	109.646,30	6.685.750,19	156.446,55
2037	110.416,51	6.732.714,24	157.545,51
2038	111.192,13	6.780.008,19	158.652,19
2039	111.973,20	6.827.634,36	159.766,64
2040	112.759,76	6.875.595,07	160.888,92

Table 2 demonstrates that the increase in land conversion for corn is driven by the conversion of land to fields or plantations, resulting in a reduction in the area of corn cultivation. However, the simulation indicates that the corn cultivation area increases from 5,977,362 ha in 2020 to 6,875,595 ha by 2040, with an average annual increase of 0.115%. This growth is attributed to new land development and regional government policies that provide support for opening new lands, including physical infrastructure and superior seeds. Details of the simulated harvest area can be found in Table 3.

Table 3 shows that the corn harvest area under Scenario 1 increases from 5,606,765 ha in 2020 to 6,449,308 ha by 2040, with an average annual increase of 0.115%. The area of potential corn cultivation, which represents 10% of the total land, is expected to decrease each year. The expansion area for corn rises from 139,870 ha in 2020 to 160,688 ha in 2040, maintaining the same average annual increase of 0.115% **(**Figure 3).

The simulation results indicate that the corn cultivation area increases each year. In 2020, the area was 5,977,362 hectares, and it is projected to reach 6,875,595 hectares by 2040, with an average annual increase of 0.115%. This increase is assumed under the condition that there are no changes in land conversion for other purposes or settlement.

Table 3. Simulation results of corn commodity harvest area in scenario 1.

Years	Area of planted land for corn commodities (L_LTKJ) (ha)	Corn commodity harvest area (LP_KJ) (ha)
2020	5.977.362,00	5.606.765,56
2021	6.019.349,98	5.646.150,28
2022	6.061.632,90	5.685.811,66
2023	6.104.212,84	5.725.751,65
2024	6.147.091,89	5.765.972,19
2025	6.190.272,13	5.806.475,26
2026	6.233.755,70	5.847.262,85
2027	6.277.544,72	5.888.336,94
2028	6.321.641,33	5.929.699,57
2029	6.366.047,70	5.971.352,74
2030	6.410.766,00	6.013.298,51
2031	6.455.798,43	6.055.538,92
2032	6.501.147,18	6.098.076,06
2033	6.546.814,49	6.140.911,99
2034	6.592.802,59	6.184.048,83
2035	6.639.113,73	6.227.488,68
2036	6.685.750,19	6.271.233,67
2037	6.732.714,24	6.315.285,96
2038	6.780.008,19	6.359.647,68
2039	6.827.634,36	6.404.321,03
2040	6.875.595,07	6.449.308,18

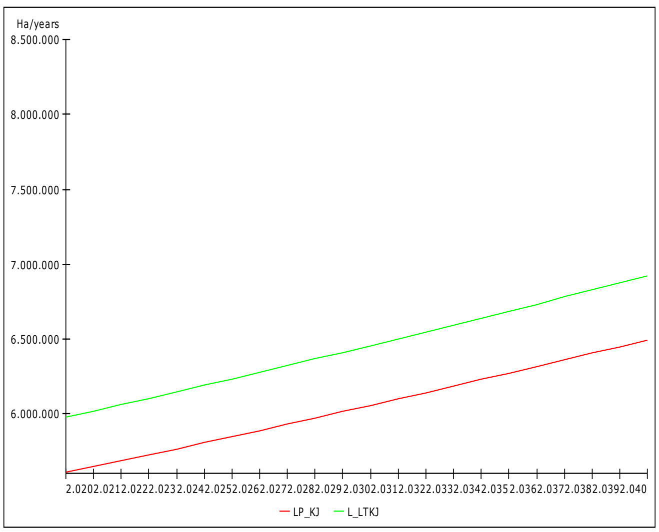

Figure 3. Simulation results of the harvest area for corn commodities in scenario 1.

Economic factors significantly influence corn production in Indonesia, particularly through market prices and government subsidies. The relationship between domestic and international corn prices is crucial, as fluctuations in global markets directly affect local prices, which can lead to increased imports when domestic supply falls short (Kariyasa, 2014; Rahmawati *et al*., 2023). Government interventions, such as import tariffs and subsidies for fertilizers, play a vital role in stabilizing prices and enhancing production efficiency (Rahmawati *et al*., 2023; Ariyanto *et al*., 2023).

***b. Simulation of the corn commodity production subsystem*:** The potential productivity of corn is 8 tons per hectare, but in reality, it is only 5.27 tons per hectare in Indonesia. This decrease is due to suboptimal utilization of: (1) superior seeds (65%), (2) fertilization (65%), (3) pest and disease control (60%), (4) labor (60%), (5) climate influence (70%), and (6) agricultural tools and machinery (60%). Corn production in 2020 reached 27,701,122 tons and is projected to increase to 31,863,838 tons by 2040, with an average annual growth rate of only about 0.115% (Table 4).

Table 4. Results of corn commodity production simulation in scenario 1.

Years	Corn commodity production (PR_KJ) (ton)	Corn commodity harvest area (LP_KJ) (ha)
2020	27.701.122,31	5.606.765,56
2021	27.895.708,85	5.646.150,28
2022	28.091.662,25	5.685.811,66
2023	28.288.992,13	5.725.751,65
2024	28.487.708,16	5.765.972,19
2025	28.687.820,07	5.806.475,26
2026	28.889.337,66	5.847.262,85
2027	29.092.270,81	5.888.336,94
2028	29.296.629,47	5.929.699,57
2029	29.502.423,64	5.971.352,74
2030	29.709.663,41	6.013.298,51
2031	29.918.358,94	6.055.538,92
2032	30.128.520,46	6.098.076,06
2033	30.340.158,25	6.140.911,99
2034	30.553.282,69	6.184.048,83
2035	30.767.904,23	6.227.488,68
2036	30.984.033,37	6.271.233,67
2037	31.201.680,71	6.315.285,96
2038	31.420.856,92	6.359.647,68
2039	31.641.572,73	6.404.321,03
2040	31.863.838,95	6.449.308,18

Climate change poses significant threats to corn production in Indonesia, primarily through altered precipitation patterns, increased temperatures, and extreme weather events. These changes can lead to reduced yields and increased vulnerability for farmers. Changes in rainfall patterns disrupt planting and harvesting schedules, leading to crop failures. Studies indicate a correlation between rising temperatures and decreased maize yields, particularly in regions like Majalengka (Jinheon *et al*., 2023). El Niño and La Niña events exacerbate droughts and floods, further threatening food security.

Adoption of climate-resilient crop varieties, adjusted planting times, and improved water management can help mitigate these impacts (Rahmawati *et al*., 2023). Continuous collaboration among stakeholders is essential for effective adaptation strategies. While these strategies can alleviate some impacts, the unpredictability of climate change necessitates ongoing research and adaptation efforts to ensure sustainable corn production in Indonesia.

Scenario 2: Expansion of corn harvest area**:** In this scenario, efforts to increase the harvest area for corn include: (1) expanding the area through extensification by 3.5% per year, and (2) limiting land conversion to other commodities by 1.64% per year (Table 5). This expansion is feasible due to: (1) the availability of potential land for corn, (2) utilization of forest areas for development, and (3) conversion of non-corn land to corn cultivation. The area to be developed is based on land suitability characteristics in each region.

Table 5. Simulation results for corn commodity land in scenario 2.

Years	Corn commodity land conversion rate (LK_LKJ) (ha)	Corn commodity planting land area (L_LTKJ) (ha)	Rate of land extensification for corn commodities (L_ELKJ) (ha)
2020	98.028,74	5.977.362,00	209.207,67
2021	99.869,03	6.089.574,90	213.135,12
2022	101.743,87	6.203.894,37	217.136,30
2023	103.653,90	6.320.359,95	221.212,60
2024	105.599,80	6.439.011,94	225.365,42
2025	107.582,22	6.559.891,38	229.596,20
2026	109.601,86	6.683.040,09	233.906,40
2027	111.659,41	6.808.500,67	238.297,52
2028	113.755,59	6.936.316,52	242.771,08
2029	115.891,12	7.066.531,85	247.328,61
2030	118.066,74	7.199.191,71	251.971,71
2031	120.283,21	7.334.341,99	256.701,97
2032	122.541,28	7.472.029,45	261.521,03
2033	124.841,75	7.612.301,71	266.430,56
2034	127.185,40	7.755.207,29	271.432,26
2035	129.573,05	7.900.795,65	276.527,85
2036	132.005,52	8.049.117,12	281.719,10
2037	134.483,66	8.200.223,04	287.007,81
2038	137.008,32	8.354.165,66	292.395,80
2039	139.580,37	8.510.998,25	297.884,94
2040	142.200,71	8.670.775,05	303.477,13

The simulation results of the area of corn commodity harvest in scenario 2 can be seen in Table 6.

The simulation results for Scenario 1 show that the corn cultivation area in 2040 will be 6,875,595 hectares. In contrast, the simulation for Scenario 2 indicates an increase in the corn cultivation area to 8,670,775 hectares. For the harvest area, Scenario 1 predicts 6,449,308 hectares in 2040, while Scenario 2 shows an increase to 8,133,186 hectares.

The simulation results for Scenario 1 indicate that the availability of corn in 2040 will be 3,674,442 tons. In contrast, Scenario 2 predicts a corn availability of 11,020,744 tons in 2040, showing an increase each year. This increase in corn availability by 2040 is attributed to the expansion of the corn harvest area.

Table 6. Simulation results of corn commodity harvest area in scenario 2.

Years	Corn commodity planting land area (L_LTKJ) (ha)	Corn commodity harvest area (LP_KJ) (ha)
2020	5.977.362,00	5.606.765,56
2021	6.089.574,90	5.712.021,25
2022	6.203.894,37	5.819.252,91
2023	6.320.359,95	5.928.497,63
2024	6.439.011,94	6.039.793,20
2025	6.559.891,38	6.153.178,12
2026	6.683.040,09	6.268.691,61
2027	6.808.500,67	6.386.373,63
2028	6.936.316,52	6.506.264,89
2029	7.066.531,85	6.628.406,87
2030	7.199.191,71	6.752.841,82
2031	7.334.341,99	6.879.612,79
2032	7.472.029,45	7.008.763,62
2033	7.612.301,71	7.140.339,00
2034	7.755.207,29	7.274.384,44
2035	7.900.795,65	7.410.946,32
2036	8.049.117,12	7.550.071,86
2037	8.200.223,04	7.691.809,21
2038	8.354.165,66	7.836.207,39
2039	8.510.998,25	7.983.316,36
2040	8.670.775,05	8.133.186,99

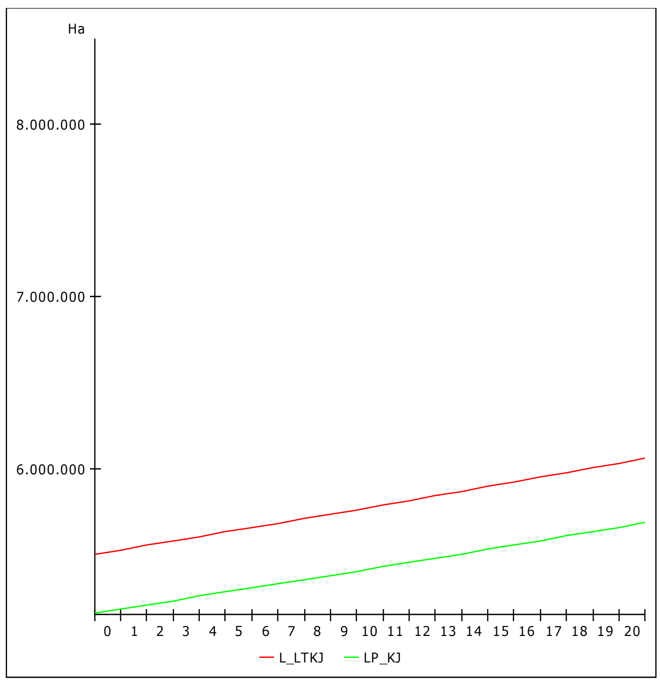

Figure 4. Simulation results of corn commodity harvest area in scenario 2.

Stakeholder engagement is crucial for enhancing corn production strategies, involving farmers, government agencies, and consumers in a collaborative framework.

Effective engagement ensures that diverse perspectives are integrated into decision-making processes, fostering sustainable practices. Implementing frameworks that facilitate iterative interactions among stakeholders can enhance knowledge co-production, as seen in studies focused on climate resilience (Jinheon *et al*., 2023). Engaging stakeholders through semi-structured interviews allows for the identification of context-specific goals and innovative solutions (Moataz *et al*., 2022).

Active involvement of stakeholders from strategy development to implementation is essential for realizing sustainable bioeconomy benefits. Engaging diverse groups, including farmers and NGOs, ensures that all voices are heard and considered (Nurul *et al*., 2023). Utilizing systems thinking can help develop strategic interventions that address competing interests holistically. Group model building exercises can facilitate stakeholder involvement in creating effective strategies. While stakeholder engagement is vital, challenges such as time commitments and the need for efficient communication infrastructures can hinder effective collaboration (Loes *et al*., 2022).

***Scenario 3: Increasing corn production by improving productivity to 5.87 tons/ha per year*:** This scenario involves efforts to: (1) increase the average corn productivity to 5.87 tons per hectare per year, and (2) reduce corn harvest losses by 2% per year. The simulation results for corn production under Scenario 3 can be seen in Table 7.

Table 7. Results of corn commodity production simulation in scenario 3.

Years	Corn commodity production (PR_KJ) (ton)	Corn commodity harvest area (LP_KJ) (ha)
2020	31.908.887,73	5.606.765,56
2021	31.959.982,79	5.615.743,56
2022	32.011.159,67	5.624.735,94
2023	32.062.418,50	5.633.742,71
2024	32.113.759,41	5.642.763,91
2025	32.165.182,53	5.651.799,56
2026	32.216.687,99	5.660.849,67
2027	32.268.275,93	5.669.914,28
2028	32.319.946,48	5.678.993,40
2029	32.371.699,76	5.688.087,05
2030	32.423.535,92	5.697.195,27
2031	32.475.455,08	5.706.318,08
2032	32.527.457,37	5.715.455,49
2033	32.579.542,94	5.724.607,54
2034	32.631.711,91	5.733.774,24
2035	32.683.964,42	5.742.955,61
2036	32.736.300,60	5.752.151,69
2037	32.788.720,58	5.761.362,50
2038	32.841.224,50	5.770.588,05
2039	32.893.812,50	5.779.828,38
2040	32.946.484,70	5.789.083,515

The increased productivity indicates that the implementation of corn production innovations among farmers is progressing. For example, the number of farmers using hybrid seeds has increased, although not all have adopted them yet. Additionally, some farmers who previously used local seeds have started switching to composite seeds. The improvement in corn productivity is also due to better farm management by farmers, although it is not yet optimal.

Table 7 shows that Scenario 3, which aims to increase corn productivity in Indonesia to 5.87 tons per hectare, involves the following measures: (1) use of superior seeds (75%), (2) fertilization (75%), (3) pest and disease control (70%), (4) labor in corn cultivation (70%), (5) climate impact on corn cultivation (75%), and (6) agricultural tools and machinery in corn cultivation (75%). The simulation results for Scenario 1 show that corn production in 2020 reached 27,701,122 tons, and is projected to increase to 32,946,484 tons by 2040, with an average annual growth of only about 0.115%. Meanwhile, the simulation results for Scenario 3 show that corn production in 2040 will reach 32,946,484 tons.

***Scenario 4: Expansion of corn cultivation area and increase in corn production*:** This combined scenario involves: (1) expanding the corn cultivation area by 3.5% per year while limiting land conversion to other uses by 1.68% per year, and (2) increasing the average corn productivity to 5.87 tons per hectare per year (Table 8).

Table 8. Results of corn commodity production simulation in scenario 4.

Years	Corn commodity production (PR_KJ) (ton)	Corn commodity harvest area (LP_KJ) (ha)
2020	30.856.946,37	5.606.765,56
2021	31.436.223,21	5.712.021,25
2022	32.026.374,80	5.819.252,91
2023	32.627.605,29	5.928.497,63
2024	33.240.122,67	6.039.793,20
2025	33.864.138,83	6.153.178,12
2026	34.499.869,63	6.268.691,61
2027	35.147.535,00	6.386.373,63
2028	35.807.358,97	6.506.264,89
2029	36.479.569,80	6.628.406,87
2030	37.164.400,04	6.752.841,82
2031	37.862.086,57	6.879.612,79
2032	38.572.870,77	7.008.763,62
2033	39.296.998,50	7.140.339,00
2034	40.034.720,27	7.274.384,44
2035	40.786.291,27	7.410.946,32
2036	41.551.971,50	7.550.071,86
2037	42.332.025,83	7.691.809,21
2038	43.126.724,10	7.836.207,39
2039	43.936.341,23	7.983.316,36
2040	44.761.157,29	8.133.186,99

Scenario 4 aims to increase corn productivity in Indonesia to 5.87 tons/ha by enhancing the use of superior seeds, fertilization, pest and disease control, labor, and agricultural tools and machinery, each up to 75%, and by improving climate impact management to 70%. The simulation results show that in 2020, corn production reached 27,701,122 tons and increased to 31,863,838 tons by 2040, with an average annual growth of 0.115%. In contrast, with the implementation of Scenario 4, corn production in 2040 is estimated to reach 44,761,157 tons.

Technology plays a crucial role in enhancing corn productivity and sustainability through precision agriculture and biotechnology. Precision agriculture utilizes data-driven approaches to optimize farming practices, leading to improved crop yields and resource efficiency. For instance, technologies like remote sensing and IoT sensors enable farmers to make informed decisions, reducing inputs such as fertilizers and pesticides while maintaining productivity. Additionally, biotechnology contributes by developing crops resistant to pests and diseases, addressing challenges posed by biotic and abiotic stresses (Dewa *et al*., 2017).

The long-term outlook for Indonesia's food security and agricultural sector is significantly influenced by climate change, land use, and technological advancements. Projections indicate that climate change, particularly through phenomena like El Niño and La Niña, will adversely affect agricultural productivity, leading to reduced food availability and increased vulnerability (Faisal and Latief, 2023). Additionally, land conversion for industrial purposes and urbanization pose challenges to maintaining agricultural land, which is crucial for food production (Dewa *et al*., 2017). The need for increased protein production to meet the demands of a growing population further complicates the situation, necessitating optimization of existing agricultural land rather than expansion (Garib *et al*., 2022). Moreover, the institutional framework and technological adoption play vital roles in enhancing food security, with policies aimed at sustainable land use and support for farmers being essential for long-term resilience (Diah *et al*., 2019).

Climate change leads to droughts and floods, disrupting planting seasons and reducing crop yields. Increased temperatures and pest prevalence further threaten food production. Industrialization and land conversion reduce available agricultural land, impacting food security. Effective land use policies are necessary to balance agricultural needs with development. Adoption of technology, such as tractors and improved agricultural practices, can enhance productivity. Institutional support is crucial for implementing these technologies effectively. While these challenges are significant, opportunities exist for improving food security through increased awareness of food waste and leveraging local resources, which can foster resilience in the agricultural sector (Rozaki, 2021).

***Conclusion*:** This study evaluates various scenarios to increase corn production to support national food security in Indonesia. Without any strategy (Scenario 1), corn production is projected to decline, reaching only 31,863,838 tons by 2040, with productivity at 4.8 tons/ha, far below the potential of 8 tons/ha. In contrast, expanding the cultivated area by 3.5% per year and limiting land conversion (Scenario 2) could significantly increase the corn cultivation area, utilizing community forests, potential lands, and underutilized areas, provided there is proper management and supportive policies. Scenario 3 suggests that increasing productivity to 5.87 tons/ha through the use of superior seeds, fertilization, pest control, and advanced cultivation technology could boost production to 44,761,157 tons by 2040, highlighting the importance of research and development in agricultural technology to improve yields and farmer incomes. Finally, the combined strategy (Scenario 4) of expanding both area and productivity could result in corn availability of 15,063,006 tons by 2040, with farmer cooperatives and institutions playing a crucial role in bridging the gap between farmers and industry, enhancing partnerships, and providing necessary support such as technical guidance and capital. Local governments should facilitate the formation of farmer institutions and provide technical support and capital assistance. The implementation of efficient cultivation technology and the development of adequate infrastructure are crucial to achieving production targets. Additionally, strengthening partnerships between farmers and industry, as well as expanding the cultivated area, can significantly increase the availability of corn in Indonesia. This study demonstrates that with the right strategies—both in expanding cultivation areas and improving productivity—corn production can be significantly enhanced to support national food security.

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