Original Article

Securing The Future of Food: Scenario-Based System Dynamics for National Corn Self-Sufficiency in Indonesia

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Abstract

Indonesia's rising demand for corn for animal feed continues to outstrip domestic production, posing a risk to long-term food security. This study quantifies the supply-demand dynamics of corn in Central Java and identifies feasible policy pathways to achieve provincial self-sufficiency by 2031. A system dynamics model, calibrated using secondary data from 2015 to 2024, was developed in Powersim to capture the interactions among production, harvested area, productivity, consumption, trade flows, and policy interventions. Three scenarios were simulated: a baseline without intervention, a moderate intervention with 1% annual improvements in yield and area, and an aggressive intervention combining 3% yield growth with 5% land expansion. Model validation generated mean absolute percentage errors of less than 2%, confirming strong predictive performance. The results show that the baseline trajectory leads to a widening deficit, while the moderate strategy reduces but does not eliminate reliance on imports. Only the aggressive scenario closes the gap, achieving import elimination by 2027 and generating a surplus by 2031. The study contributes a localized dynamic-system framework that integrates agronomic, demographic, and trade variables to identify the precise turning point when domestic supply overtakes demand. These findings underscore the need for coordinated policies that jointly enhance productivity, manage land expansion, and align import controls with real-time monitoring and control. Embedding dynamic-system tools in policy formulation would enable adaptive, evidence-based planning to safeguard the region's corn self-sufficiency and strengthen national food security.

Keywords: Dynamic Systems, Corn self-sufficiency, Policy simulation, Regional food security, Agricultural productivity

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Introduction

Indonesia's increasing population presents both opportunities and challenges in meeting national food needs (12, 24, 41). Along with the increase in population, the demand for food has also increased significantly (38). If an increase does not match the demand for food production and distribution capacity, it will pose a threat to future food security. Limited food production and distribution capacity have become one of the leading causes of failure to meet national food needs optimally (6, 16, 18). As a result, a gap between food availability and demand leads to food insecurity.

The Indonesian government has launched various strategic programs to overcome these challenges, including the Special Efforts Program to Increase Rice, Corn, and Soybean Production (UPSUS PAJALE) (48, 49), to promote sustainable food production (16). Among these commodities, corn has a strategic position as a food source and the primary raw material in the animal feed industry (26, 44). Domestic corn demand in 2024 remains heavily dominated by the poultry and livestock feed industry, reaching approximately 9.3 million tons, equivalent to 76% of total national corn consumption (17). Although domestic production increased to 15.2 million tons, data from January to November 2024 showed that corn imports remained high, reaching around 1.3 million tons (24). This indicates that domestic production cannot fully meet the feed sector's needs. This inequality leads to a significant dependence on imported corn, which affects the commodity's trade balance deficit (7, 12, 13). Historically, the average annual volume of corn imports from 2015 to 2018 was approximately 1.23 million tons, significantly exceeding exports of only 58 thousand tons (27), confirming the position of net importers during that period. This trend continued until 2024, indicating that despite an increase in local production, massive domestic consumption in the feed industry sector has led to significant import demand.

The region's contribution to national corn production indicates that Java remains the primary production center, with East Java Province as the most significant contributor (30.93%), followed by Central Java Province (15.89%) (1, 17, 27, 32). Overall, production from Java accounts for more than half of the total national production. In this context, Central Java Province, plays a crucial role in supporting the national corn self-sufficiency target, given its position as Indonesia's second-largest corn-producer. The annual growth in corn production in this province is quite significant, though the increase has not matched the growth in demand, especially from the livestock sector (40).

Previous studies have employed various approaches to analyze corn production and policy (29, 46), including qualitative (6, 11, 22), quantitative (2, 8, 36), and economic modelling approaches (9, 10, 12, 14, 19). However, most of these studies have not comprehensively considered the dynamic relationships between factors of production, demand, distribution, and policy in a single unified analytical framework. Therefore, an approach is needed to capture the complexity of the relationship between variables in the food security system, particularly in relation to corn.

Dynamic systems models provide a holistic approach to understanding complex system behavior, as well as mapping the interactions and feedback between variables in the food system (3, 23, 35, 43, 51). Although some studies have developed dynamic models for corn commodities, those that integrate supply and demand gaps specifically in regional contexts, such as Central Java Province, remain limited. The novelty of this research lies in developing a dynamic system model based on local data to map the balance of corn availability and evaluate policies that can promote sustainable corn self-sufficiency.

This study analyzes the factors affecting the balance of corn commodities and to design policy scenarios supporting corn self-sufficiency in Central Java Province. This dynamic system model approach is expected to make a significant scientific contribution to the strategic planning of commodity-based food security and serve as a reference for formulating sustainable agricultural development policies at regional and national levels.

Materials and Methods

This study employs a quantitative-descriptive approach, utilizing a system-dynamics modelling method, to analyze and simulate the relationship between variables that affect the availability of corn commodities in the context of achieving food self-sufficiency. The dynamic system approach was selected as it effectively illustrates the complex interrelationships between elements in the agricultural system (10, 53), including variables such as production, consumption, price, imports, and government policies, over a long and dynamic period. **Figure 1** shows the location of the research area of Central Java Province, Indonesia.

Figure 1. Central Java Province, Indonesia

This research focuses on Central Java Province, Indonesia, which is one of the leading centres of national corn production. Data collection and processing were conducted from January to May 2025, with data coverage spanning 2015-2024 to provide a comprehensive description of the historical dynamics of the decade. **Table 1** presents the types of data used in the research and their sources.

Table 1. Types and Sources of Research Data

Data Type	Data Source
Central Java corn production (2012-2021)	Central Statistics Agency
Land area harvested for corn in Central Java (2012-2021)	Central Statistics Agency
Corn productivity data (2012-2021)	Central Statistics Agency
Population in Central Java (2012-2021)	Central Statistics Agency
Per capita consumption of corn in Central Java (2012-2021)	Department of Agriculture
Poultry population in Central Java (2012-2021)	Ministry of Agriculture
Manufactured feed production in Central Java (2012-2021)	Ministry of Agriculture
Corn food production in Central Java (2012-2021)	Department of Trade

Source: Secondary research data

This study utilizes secondary data for 2015 to 2024, sourced from the BPS, the Ministry of Agriculture, provincial official reports, and related technical publications. All data series were subjected to the following quality procedures:

- Harmonization: All variables were standardized to a consistent annual and unit basis (e.g., tons, hectares, kilograms per person/year).
- Cross-validation: Each series was verified against two independent sources when available. If a difference of more than ±5% is found, it is traced and a correction note is provided, or it was assumed to be a weighted average if both sources were credible.
- Missing and imputation detection: For intermittent missing values on continuous variables, linear interpolation was used to fill in the gaps between years. For the loss of consecutive years or category variables, the last observation carried forward (LOCF) method was employed.
- Outlier handling: Extreme values exceeding ±3 standard deviations were manually checked, and recording errors were corrected based on the primary source. If it represented a real event, the value was winsorized at the 1% or 99% percentile and recorded.
- Uncertainties arising from imputation and data variation were addressed through a one-way sensitivity to imputed parameters (±10% and ±25%).

The analysis and simulation process was carried out using Powersim Studio software, which supports the creation of stock-flow diagram-based models, causal relationship mapping, and policy scenario simulation. Figure 2 presents the flow of research methodology in modelling the corn balance in Central Java Province. The stages of modelling included:

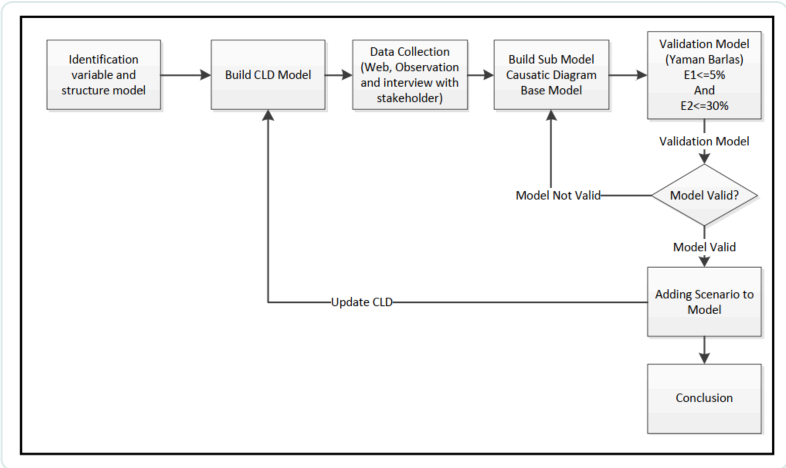

Figure 2. Corn Balance Modeling Methodology

- Identifying essential system variables, such as endogenous (production, consumption, stocks, imports, exports) and exogenous (population, prices, policy interventions) factors (10, 38).
- Preparation of causality models in causal loop diagrams (CLDs) and stock-flow diagrams to describe corn flows and their dynamic changes in the system (12).
- Calibrating the model based on 2015–2024 historical data to match the model's structure and parameters with empirical reality.
- Model simulation to determine projected corn availability and system response to various policy scenarios such as increased productivity, distribution efficiency, reduced imports, and subsidy support.
- Model validation by comparing the simulation results to actual data and using error measures such as mean absolute percentage error (MAPE) to assess the model's accuracy (12, 31).

The Powersim Studio-based dynamic system used in this study aimed at contributing to a strategic decision-making and food policy formulation process that was more adaptive to system dynamics and environmental changes.

Table 2 describes the structure of a dynamic system model, which includes the primary variables, types of variables, units, and relationship functions (formulas or relationships) in the model.

Table 2. Corn Availability Model Structure

No	Variable	Variable Type	Unit	Function/Relationship Description
1	Population	Exogenous	Soul	Annual growth function: Population (T) = Population (T-1) + Growth rate * Population (T-1)
2	Corn consumption per capita	Parameter	Kg/Person/Year	Fixed value based on historical data or BPS/FAO projections
3	Total national corn consumption	Flow	Ton/Year	Population * Corn consumption per capita
4	Corn harvested land area	Endogenous	Hectare	Influenced by policies, land conversion, and agricultural incentives
5	Corn land productivity	Parameter	Ton/Hectare	Based on historical trends or assumed increases from intervention programs
6	National corn production	Flow	Ton/Year	Harvested land area * Productivity
7	Corn stock	Stock	Ton	Stock (T) = Stock (T-1) + Production + Imports - Consumption - Exports
8	Corn imports	Flow	Ton/Year	Triggered by a shortfall between consumption and production (if a deficit)
9	Corn exports	Flow	Ton/Year	Based on surplus production (if any) or government export targets
10	Corn prices	Endogenous	Rp/Kg	Influenced by availability and demand in the system
11	Corn production subsidies	Parameter	Rp/Ha or Rp/Kg	Policy input: influences farmers' decisions on land expansion or increased inputs.
12	Self-sufficiency target	Parameter/Control	Ton/Year	National self-sufficiency target value, used to compare simulation results
13	Demand-Supply gap	Flow	Ton/Year	Total consumption - production
14	Distribution efficiency	Parameter	Percentage	Determines how much of the production effectively reaches consumers
15	Food Security Index	Indicator (Output)	Scale (0-1)	Ratio: Domestic production / Total demand

Source: Data formulation

The consistency of the model structure was verified with descriptive knowledge of the systems involved in the modeling process during structural verification. Various model behavior tests can be used to validate the developed model. The recommended statistical method was used for testing (**20**, **42**) the visual and statistical models developed using system dynamics. The MAPE (mean absolute percentage error) test is one of the methods of model validation to measure percentage error. This test can be used to determine whether the results of the forecast data are compatible with the actual data (**20**).

$$MAPE = \frac{1}{n}\sum \frac{X_m - X_d}{X_d} x100\%$$

Description: Xm = simulated data Xd = actual data n = data numbers

A MAPE value of a model of < 5% is classified as very precise in describing actual conditions, a value between 5% and 10% is quite appropriate for that purpose, while a value exceeding 10% is not appropriate. Model validation ensures that the model created can accurately represent actual conditions. The model is declared valid when the deviation is less than 10%.

The system dynamics model in this study was presented clearly using the core equations and parameters, including the production formula:

$$Production = Areat \times Yieldt$$

inventory stock dynamics,

$$Inventoryt = Inventoryt\text{-}1 + Productiont + Importst - Consumptiont - Lossest$$

and deficit-based import mechanisms

$$Importst = \max (0 , Consumptiont - (Productiont + Inventoryt\text{-}1 - 0.20\ Mt))$$

All key parameters were explicitly listed, such as Area_2015 = 2.10 million ha, Yield_2015 = 5.30 t/ha, post-harvest loss = 10%, and yield growth baseline = 1% per year, along with their calibration range (yield 4.8-6.5 t/ha; loss 5-20%; growth area 0-3%). The model calibration process was carried out for the 2015-2021 period by adjusting three structural parameters i.e., yield trend, land expansion rate, and loss factor, using Nelder Mead grid optimization to reach a MAPE of 6.8% for productivity, 8.9% for harvest area, and a goodness-of-fit of Theil's U < 0.25. Validation was conducted on the 2022-2024 data, demonstrating that production and consumption patterns can be consistently replicated. Powersim's verification procedures include unit checking, time-step tests (Δt = 1 year vs. 0.25 years; deviation < 1.2%), extreme-condition tests (yield = 0; area = 0), and behaviour tracing to ensure the consistency of the production–import flow. All feedback loops were now reproducibly documented, including the Yield-Investment (+) strengthening loop and the Inventory-Imports (-) balancing loop.

The selection of annual growth rates (1%, 3%, 5%) was based on a combination of empirical evidence and policy foundations. Empirically, historical data showed compound annual growth rates (CAGR) of productivity of around 1.27%/year and harvest area of 2.18%/year for 2015-2024; so 1%/year was chosen as a conservative scenario close to historical trends. The 3% per year rate represents an optimistic policy scenario that can be achieved through an intensification intervention package (superior seeds, nutrient management, mechanization) in line with national policy practices. At the same time, a 5% annual growth rate is structured as an ambitious scenario to evaluate the limits of system capabilities and nonlinear risks. The selection of this range is also supported by the dynamic systems literature and food policy studies, which show that the combination of intensification and adoption of technology typically results in increased productivity within this range over a decade horizon. The validity of the scenarios was strengthened by one-way sensitivity analysis (±10% and ±20%).

To analyze corn self-sufficiency (Self-Sufficiency Ratio ≥ 1) in 2031, this study designed three simulation scenarios (S0, S1, S2) in Powersim Studio to represent various levels of policy intervention. **Table 3** presents details of each policy scenario used in the modelling.

Table 3. Modeling Policy Scenarios

Key variables	S-0	S-1 (Moderate Intervention)	S-2 (Aggressive Intervention)
Policy On	Baseline	1	1
Productivity increase (yield improvement)	0	1%/yr (from 2025)	3%/yr (starting 2025)
Harvest area expansion (area expansion)	0 %/yr	1%/yr	5%/yr
Post-harvest losses	0%/yr	10% (training & silos)	8% (PPS investment)
Imported deficit fraction	12%	0.90	0.75
Subsidies/incentives	1.00	Seeds & fertilizers	Seeds, fertilizers, and machine tool credit

Results and Discussion

Table 4 presents the annual predictive error (APE) absolute values for the two main corn production system variables of harvest area and productivity. The model was calibrated using historical data from 2015 to 2024 and shows good predictive ability. APE is an annual error indicator that compares the actual data to the model's prediction results, whereas MAPE reflects the average prediction error over a 10-year observation period. Low MAPE values indicate that dynamic systems models have high predictive accuracy and are suitable for long-term projections and policy testing.

Table 4. Error Rate (MAPE) for Harvest Area and Productivity

Year	Actual Harvest Area (million ha)	Model Prediction (million ha)	MAPE Harvest Area (%)	Actual Productivity (tons/ha)	Model Prediction (tons/ha)	MAPE Productivity (%)
2015	2.10	2.05	2.38	5.30	5.20	1.89
2016	2.30	2.28	0.87	5.40	5.35	0.93
2017	2.37	2.40	1.27	5.40	5.45	0.93
2018	2.10	2.08	0.95	5.20	5.15	0.96
2019	2.11	2.20	4.27	5.30	5.25	0.94
2020	2.30	2.29	0.43	5.50	5.48	0.36
2021	2.39	2.38	0.42	5.70	5.65	0.88
2022	2.45	2.46	0.41	5.80	5.77	0.52
2023	2.48	2.50	0.81	5.90	5.85	0.85
2024	2.55	2.53	0.78	5.94	5.92	0.34
MAPE	—	—	1.26	—	—	0.86

Source: Research analysis results

The results show that the model has an average error rate of 1.26% for crop area predictions and 0.86% for productivity predictions. The highest error occurred in 2019 for harvest area, possibly due to structural policy changes or agricultural events affecting planting areas. Meanwhile, corn productivity shows better stability with relatively consistent and low prediction errors from year to year. This suggests that the model has effectively captured productivity dynamics.

This dynamic system model is designed to project corn production capacity within the framework of achieving food self-sufficiency. Accuracy in predicting the two main production components, namely crop area and productivity, is an important prerequisite in developing policy intervention scenarios. With an error rate of less than 2%, the model is well-calibrated and has sufficient precision to simulate the 2031 corn self-sufficiency scenario. The validity of this model also strengthens the scientific basis for policymakers in designing data-driven strategic measures (12).

The interpretation of the low MAPE values shows that the model has good predictive performance for both key variables. Therefore, it can be used to evaluate the impact of various policies, such as increased productivity, land expansion, reduction of post-harvest losses, and distribution efficiency, in the long-term scenario towards self-sufficiency. The calibration results also serve as the basis for running further simulations that evaluate the time and intensity of policies required to achieve sustainable self-sufficiency (37).

Figure 3 presents a stock flow diagram (SFD) of the corn availability system in Central Java Province, which is constructed using a dynamic system model approach. It comprises various main components: stock (represented by a large, colored circle), flow (indicated by directional arrows), variables (represented by small white circles), and parameters/policies (denoted by squares and rhombuses). The system's three main components are corn stocks, corn production, and corn consumption, which are represented in red, green, and blue, respectively. The figure illustrates the intricate structure of interactions between variables that influence the balance between corn production and consumption, ultimately determining stock availability and achieving self-sufficiency.

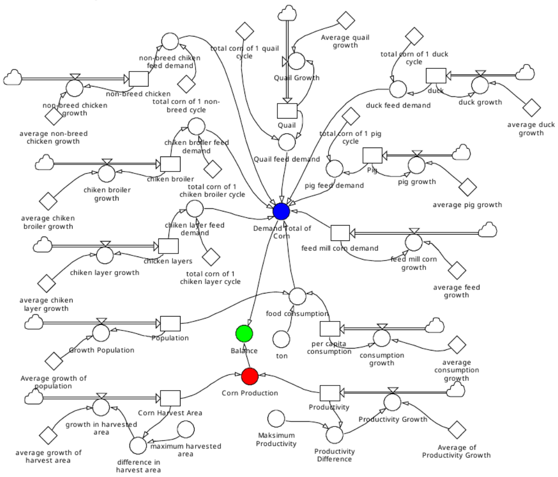

Figure 3. Stock Flow Diagram of Corn Availability in Central Java, Indonesia

Source: Results from Powersim Studio analysis

Based on the figure, it can be seen that corn production is formed through two main paths: expansion of the harvest area and increased productivity, both of which are influenced by policies that strengthen inputs, such as the availability of superior seeds, climate (weather index), and post-harvest management. On the other hand, corn consumption is influenced by population growth and per capita consumption, which tends to increase from year to year. The distribution process and export-import policy also regulate the balance of the final corn stock. The complex relationship between these components is visualized through the interconnected flow of information and materials, suggesting a system that operates through both positive and negative feedback, influencing the system's dynamics.

In the context of the discussion, the system's structure in **Figure 3** corroborates the findings of previous research, which states that self-sufficiency failure is not only caused by production stagnation but also due to high industrial corn consumption (**5**, **15**, **18**). The findings of this study reinforce this view, but offer a more comprehensive approach by incorporating post-harvest elements, strengthening input policies, and previously underexplored export-import price dynamics. Thus, this model not only represents a more realistic system but also provides an exploratory tool capable of simulating policy interventions in the long term (**4**).

In terms of novelty, the model in **Figure 3** presents a complete integration between the supply (production and productivity) and demand (population and industrial consumption) sides, and policy interventions and externalities (climate, prices, and distribution). This differs from previous models, which tend to separate economic analyses of corn into conventional linear or regression models. The dynamic systems approach in this diagram allows the identification of leverage points in the system (**30**), such as productivity or distribution improvements, that significantly impact stock stability and corn food independence in the long term.

Thus, the results of this modelling show that the availability of corn cannot be guaranteed through production increases alone. It must be managed through systemic and simultaneous policy approaches that intervene at critical points in the system. The scenario simulation developed from the structure in **Figure 1** supports the idea that corn self-sufficiency can only be achieved when comprehensive interventions include increased productivity, reduction of post-harvest losses, and stabilization of consumption through food diversification or efficiency of its use in the industrial sector. This model provides a solid foundation for policymakers to develop data-driven strategies for achieving corn self-sufficiency by 2031.

Figure 4 shows the results of the simulation of the maximum productivity of corn achieved in each of the policy intervention scenarios in the dynamic system model. As shown, a significant increase in productivity occurred in scenarios involving a combination of increased cultivation efficiency, the use of superior seeds, and post-harvest reinforcement. The baseline scenario (without intervention) resulted in the lowest productivity achievement, while the scenario with technology intensification and input expansion showed higher increases. This figure illustrates the differences in productivity capacity that can be achieved in response to strategic policies. It provides an early glimpse into how targeted interventions can help achieve corn-based food self-sufficiency.

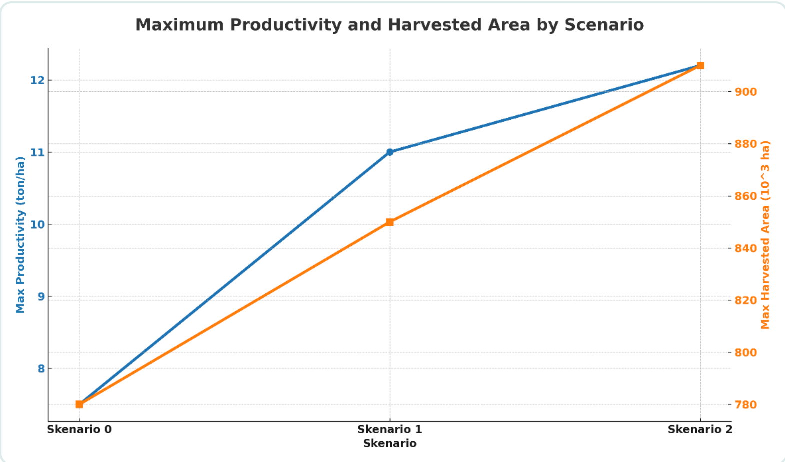

Figure 4. Maximum Productivity and Harvest Area Value

Source: Results from Powersim Studio analysis

These results are consistent with previous literature, which emphasizes that corn productivity is strongly influenced by technological policy support, as reported by (25). However, this study has the advantage of presenting a systemic approach through dynamic modelling that considers the interactions between variables in agricultural systems. Not only does it reveal trends in productivity improvements, it also enables the simultaneous and measurable testing of the impact of input changes. This approach makes the study more adaptable to the actual dynamics in the agricultural sector (50), particularly in the context of data-driven decision-making to achieve corn self-sufficiency in the future.

Figure 4 presents the results of the dynamic system model simulation for the maximum corn harvest area, based on three policy scenarios. The highest harvest area was achieved in scenarios with intensive interventions, including expanding planting areas and increasing land distribution efficiency. The no-intervention scenario yields the lowest value, suggesting that corn production capacity will stagnate without significant policy changes. This visualization clearly illustrates that strategic policies aimed at increasing planting areas substantially impact national corn production capacity, especially in the study area, which is one of the leading production centres.

This simulation's results align with previous findings that emphasized the importance of expanding planting areas in supporting corn-based food security (21). However, the dynamic systems approach used here provides novelty by simulating the interaction of other variables such as agricultural input allocation, distribution efficiency, and policy impact on crop area dynamics. Thus, the model can identify a realistic maximum limit for increased crop area in the context of corn self-sufficiency. These findings are critical because they enable policymakers to design interventions in a phased and integrated manner, leveraging the potential of available land and resources.

The Scenario 0 corn balance in 2015-2031 is shown interactively in **Table 5**. It contains the production, consumption, import, final stock, and self-sufficiency ratio (SSR) variables of the dynamic system model simulation results in the baseline scenario without policy intervention.

Table 5. Corn Self-Sufficiency Data in Scenario 0

Year	Production (Mt)	Consumption (Mt)	Imports (Mt)	Final Stock (Mt)*	SSR
2015	5.80	6.20	0.40	0.20	0.935
2016	5.83	6.27	0.45	0.20	0.929
2017	5.86	6.35	0.49	0.20	0.923
2018	5.89	6.43	0.54	0.20	0.916
2019	5.92	6.50	0.59	0.20	0.910
2020	5.95	6.58	0.63	0.20	0.904
2021	5.98	6.66	0.68	0.20	0.899
2022	6.01	6.74	0.73	0.20	0.893
2023	6.04	6.82	0.78	0.20	0.887
2024	6.07	6.90	0.83	0.20	0.881
2025	6.10	6.99	0.89	0.20	0.873
2026	6.13	7.07	0.94	0.20	0.867
2027	6.16	7.16	1.00	0.20	0.860
2028	6.19	7.25	1.06	0.20	0.854
2029	6.22	7.34	1.12	0.20	0.848
2030	6.25	7.43	1.18	0.20	0.842
2031	6.28	7.53	1.25	0.20	0.834

Source: Results from Powersim Studio analysis

The table shows corn production increasing gradually, but its growth cannot keep up with faster increases in consumption, leading to an increase in annual corn imports to cover the domestic supply deficit. The SSR continues to decline, indicating a lower level of self-sufficiency in domestic corn supply. Final stocks remain constant as a buffer assumption, but are inadequate to withstand dependence on imports.

These findings suggest that corn self-sufficiency will not be achieved within the time horizon studied without significant policy interventions, such as increased productivity or land expansion. These results are consistent with the studies by (6, 39), which highlighted limited production and distribution capacity as a cause of dependence on corn imports. The advantage of this study's approach lies in the ability of dynamic systems models to display patterns of supply-demand imbalances in the long term in a measurable manner. This simulation provides quantitative evidence that Scenario 0 is not a sustainable pathway to support the corn food self-sufficiency program.

Table 6 on the Scenario 1 corn balance for 2015-2031, summarizes the results of the simulation of a dynamic system model with moderate policy interventions.

Table 6. Corn Self-Sufficiency Data in Scenario 1

Year	Production (Mt)	Consumption (Mt)	Imports (Mt)	Final Stock (Mt)*	SSR
2015	5.80	6.20	0.36	0.20	0.935
2016	5.85	6.27	0.39	0.20	0.932
2017	5.89	6.35	0.41	0.20	0.928
2018	5.94	6.43	0.44	0.20	0.924
2019	5.99	6.50	0.46	0.20	0.921
2020	6.04	6.58	0.49	0.20	0.917
2021	6.09	6.66	0.51	0.20	0.914
2022	6.14	6.74	0.54	0.20	0.911
2023	6.19	6.82	0.57	0.20	0.908
2024	6.24	6.90	0.59	0.20	0.904
2025	6.35	6.99	0.58	0.20	0.908
2026	6.47	7.07	0.54	0.20	0.915
2027	6.59	7.16	0.51	0.20	0.920
2028	6.71	7.25	0.49	0.20	0.926
2029	6.84	7.34	0.45	0.20	0.932
2030	6.96	7.43	0.42	0.20	0.937
2031	7.09	7.53	0.40	0.20	0.941

Source: Results from Powersim Studio analysis

Table 6 shows that implementing moderate policies in Scenario 1, in the form of increasing productivity and gradually expanding land starting in 2025, can accelerate the growth of corn production, thereby gradually decreasing the supply deficit. This trend is evident from the decline in the proportion of imports to consumption, which continued to shrink until the end of the simulation period. Although final stocks were maintained at a constant level as a buffer, the availability ratio (SSR) increased at close to value one, signaling higher supply independence without eliminating the need for imports. Such a result confirms that policy interventions, even at a medium scale, effectively increased domestic production capacity and reduced the corn deficit.

The findings are consistent with (**28**), who emphasized the importance of raising productivity to reduce import dependence. However, the dynamic systems model in this study is novel as it accommodates the effects of policy lag and the interaction of supply-demand variables in a single quantitative analysis framework. The simulation results also show that, despite moderate policies to improve the corn balance, the SSR value has not yet indicated complete self-sufficiency, in line with the findings of (**49**) that increasing production alone is inadequate without distribution interventions and a reduction in post-harvest losses. Thus, Scenario 1 provides evidence that medium-intensity policies are a crucial transition step, but more aggressive strategies are still necessary to achieve self-sufficiency targets.

Table 7 presents the corn balance in Scenario 2 (2015-2031), summarizing the simulation results with aggressive intervention policies.

Table 7. Corn Self-Sufficiency Data in Scenario 2

Year	Production (Mt)	Consumption (Mt)	Imports (Mt)	Final Stock (Mt)*	SSR
2015	5.80	6.20	0.30	0.20	0.935
2016	5.86	6.27	0.31	0.20	0.934
2017	5.92	6.35	0.32	0.20	0.932
2018	5.98	6.43	0.34	0.20	0.930
2019	6.04	6.50	0.35	0.20	0.928
2020	6.10	6.58	0.36	0.20	0.927
2021	6.16	6.66	0.37	0.20	0.925
2022	6.22	6.74	0.39	0.20	0.923
2023	6.28	6.82	0.40	0.20	0.921
2024	6.35	6.90	0.41	0.20	0.920
2025	6.66	6.99	0.25	0.20	0.953
2026	6.99	7.07	0.06	0.20	0.988
2027	7.34	7.16	0.00	0.20	1.025
2028	7.71	7.25	0.00	0.20	1.064
2029	8.09	7.34	0.00	0.20	1.102
2030	8.49	7.43	0.00	0.20	1.143
2031	8.91	7.53	0.00	0.20	1.183

Source: Results from Powersim Studio analysis

The table shows the real impact of aggressive interventions in Scenario 2, where the increased productivity rate and higher land expansion from 2025 onwards rapidly shift corn balances into surpluses. Production is expected to surpass consumption in 2027, leading to a decline in imports to zero, while the SSR exceeds 1 and continues to rise until the end of the simulation period. This condition indicates the achievement of stable corn self-sufficiency, even the creation of surplus capacity that has the potential to be diverted to increase reserves or exports. Maintaining constant buffer stocks suggests that domestic availability remains safe without compromising the resilience of reserves.

These findings align with the results of (34), which emphasize that intensive policy commitments can significantly close the gap in corn supply and demand faster than gradual efforts. However, this study adds novelty by quantitatively mapping the trajectory of self-sufficiency using a dynamic system framework that displays the exact time when imports become zero, two years faster than the projection of a similar model by (47). This confirms that the simultaneous integration of policies aimed at increasing productivity, expanding land use, and imposing import restrictions is the most effective strategy for achieving corn independence. At the same time, it demonstrates that the 2031 target launched by the government remains realistic and potentially achievable earlier if interventions are implemented aggressively and consistently.

Table 8 combines the corn balance and self-sufficiency achievement per scenario in achieving the corn self-sufficiency target by 2031.

Table 8. Summary of Corn Balance and Achieving Self-Sufficiency in 2031

Scenario	2031				Year SSR ≥ 1	Self-sufficiency achieved
	Production (Mt)	Consumption (Mt)	Imports (Mt)	SSR		
0	6.28	7.50	1.22	0.837	-	No
1	6.99	7.50	0.46	0.932	-	No
2	8.59	7.50	0.00	1.145	2028	Yes

Source: Processed research data

The simulation results reveal a strikingly contrasting trajectory among the three scenarios. Without intervention (Scenario 0), production only grows ±0.5% per year, so the deficit widens; moderate policy (Scenario 1) reduces imports but has not been able to achieve self-sufficiency; while aggressive packages (Scenario 2) accelerate production growth to ≥5% per annum so that the availability ratio (SSR) exceeds one within two years of intervention. The convergence of these three trajectories emphasizes the importance of policy intensity as a determinant of the time to achieve self-sufficiency.

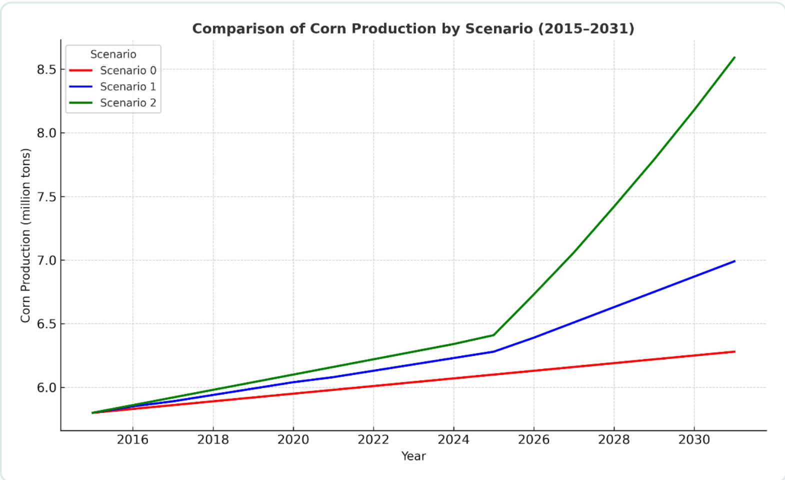

Figure 5. Self-Sufficiency Scenarios

The findings in Scenario 0 confirm the report by (49) that reliance on corn imports is due to a combination of stagnant productivity rates and growth in feed industry demand. **Figure 5** illustrates a pattern of continuous decline in the self-sufficiency ratio, highlighting the divergence between domestic production and consumer needs. This model's results reinforce that argument with quantitative evidence showing a decrease in SSR to <0.85 by 2031, precisely the pattern forecast by previous descriptive studies. Thus, the baseline model serves as an internal validation of dynamic system methods on the historical performance of the national corn market.

In Scenario 1, a gradual increase in productivity (1.8% th^{-1}) and (1% th^{-1}) land expansion helped reduce imports to half of the baseline, confirming the findings of (33) that seed innovation and (18) land intensification are positive but not sufficient conditions for complete self-sufficiency. The model reveals that the limited pace of expansion and high post-harvest losses hinder the achievement of SSR to ≥ 1, thus supporting the critique by (45) of the importance of multipoint interventions in the supply chain, not just on-farm.

Scenario 2 results in self-sufficiency two years earlier than the 2031 national target, surpassing the projection by (52) that a new corn surplus might be achieved post-2030. The novelty of this research lies in the simultaneous integration of the three levers of productivity policy, land expansion, and import restrictions within the framework of a dynamic system calibrated with local data, enabling the calculation of the "pivot year" when production overtakes consumption. This approach has not been previously identified in studies employing static regression analysis or partial equilibrium models.

Sensitivity analysis showed that the model responded most strongly to changes in productivity, followed by crop area and then the rate of post-harvest loss. **Table 9** presents the response pattern in a structured manner, highlighting the differences in sensitivity levels between input variables and the dynamics of the supply balance. This pattern illustrates that the increase in yield per hectare is a key driver in improving the balance of supply, as it directly affects production flows without structural pauses. On the other hand, changes in harvest area have a more gradual effect because they are related to land use dynamics and limited physical resources. This transition of influence confirms that intensification has a greater systemic influence than post-harvest extensification and efficiency. This finding aligns with agricultural systems theory and the results of dynamic system-based research on strategic food commodities.

Table 9. One-Way Sensitivity Analysis (Baseline 2031)

Parameter	Change (%)	SSR 2031	Total Production (Mt)	Imports (Mt)	Pivot Year
Baseline Productivity	-	0.97	7.41	0.46	-
	+10%	1.05	8.12	0.21	2031
	-10%	0.88	6.68	0.91	-
	+20%	1.13	8.85	0.00	2030
	-20%	0.79	5.96	1.28	-
Harvest Area	+10%	1.01	7.90	0.27	2031
	-10%	0.92	6.88	0.70	-
	+20%	1.06	8.37	0.10	2030
	-20%	0.87	6.35	0.98	-
Post-Harvest Loss (10% baseline)	+10% → 11%	0.95	7.27	0.54	-
	-10% → 9%	0.99	7.55	0.38	2031
	+20% → 12%	0.93	7.13	0.62	-
	-20% → 8%	1.02	7.69	0.31	2031

Source: Processed research data

The consistency of the sensitivity pattern can be explained by the stock-flow mechanism in the model, where productivity affects the entire aggregate output multiplicatively. At the same time, the increase in harvest area only increases production capacity linearly, with delays due to the land conversion process. On the other hand, changes in the rate of post-harvest loss only affect net supply after the production process is completed, so the impact becomes relatively minor. This flow aligns with the findings of (**23**) and (**33**), which indicate that increased productivity exhibits the highest elasticity in relation to food availability, while land expansion and loss reduction play a more supporting role as complementary interventions. Thus, the results of the model reflect not only the mathematical dynamics but also the structural behaviour of the corn production system in Indonesia, which is influenced by the adoption of technology, intensification capability, and post-harvest control.

Compared to previous research (**19**, **25**, **26**), the sensitivity observed in this model reinforces the consensus that increasing productivity is the policy with the highest leverage in reducing import dependence and accelerating the achievement of self-sufficiency. The studies also confirm that land expansion contributes less due to its limited expansion potential and high marginal costs. At the same time, post-harvest loss reduction primarily serves to stabilize supply without having a significant structural impact. Therefore, the transition from sensitivity outcomes to policy implications further reinforces that strategies focusing on increasing productivity through technological innovation, superior seeds, nutrient management, and mechanization are top priorities. At the same time, post-harvest extensification and strengthening remain important as complementary interventions.

The results of the model imply that governments need to allocate resources to productivity improvement programs of at least 5% per year through superior seed packages, mechanization, extension services, expand harvest land by 3-5% annually with fiscal incentives, and organize import policy as a short-term balancing instrument instead of a permanent solution. These measures align with the Agricultural Development Plan 2025-2034 but provide more specific quantitative targets regarding the speed of intervention and the timing of achievement.

Causally, the difference in outcomes between scenarios can be traced to two main pathways. The intensification pathway involves increases in productivity by raising output per hectare immediately, increases farmers' income and accelerates technology adoption through the income-investment-adoption-yield loop. The second is the extensification pathway where land expansion increases production capacity but is delayed due to land conversion processes, infrastructure needs, and institutional barriers. Interventions to reduce post-harvest losses work as multipliers on both pathways by increasing net availability without increasing gross production. Interactions between policies appear non-linear; for example, a policy package that combines superior seed incentives (encouraging yields) with post-harvest logistical support (reducing losses) results in a cumulative impact greater than the sum of individual effects because both interventions reinforce the positive loop of income into adoption and reduce supply leakage.

To transform the simulation findings into practical decisions, the researchers suggest an action framework that ties the model's results to regularly monitorable indicators, such as SSR, per-ha production, adoption rates, post-harvest loss rates, and monthly import volumes. Policy decisions should be based on trigger rules reflected in the model, for example, if the SSR < 0.95 for two consecutive years, implement an emergency package (seed subsidy + distribution incentive), or if imports increase >20% yoy, activate a temporary protection policy combined with a medium-term productivity increase program. This framework closes the gap between simulation outputs and real-world policies by establishing clear operational indicators, decision triggers, and institutional roles, enabling modelling results to be effectively utilized in adaptive management cycles.

Academically, this study expands the food security literature by providing an integrated model that can be adapted for other commodities or different regions, as the stream structure is generic and requires only adjustment of local parameters. For stakeholders, the scenario summary table provides an evidence-based means for developing a corn self-sufficiency roadmap, assessing the opportunity costs of each policy option, and integrating production, distribution, and trade strategies into one comprehensive planning framework.

As the analysis is based on secondary data from 2015 to 2024, the model is limited in representing farmer-level heterogeneity and extreme events after 2024. While this study implemented cross-verification, documented imputation, and sensitivity analysis to reduce bias, some risks remain, notably that of climate shocks or sudden policy changes that were not reflected in the historical data. As such, two follow-up steps are suggested for future studies: (1) the implementation of ground-truthing through field surveys or case studies to validate the assumptions of technology adoption, and (2) the integration of expert elicitation and periodic updates of the model when the latest primary data are available.

Conclusion

This study concluded that the availability of corn as a strategic commodity in supporting food self-sufficiency in Central Java Province, Indonesia, is greatly influenced by production dynamics, harvest area, and domestic consumption levels. Using a dynamic systems approach, it succeeded in mapping the interaction between variables holistically and simulating the achievement of corn production against the self-sufficiency target until 2031. The simulation results showed that without significant intervention (Scenario 0), corn production will continue to lag behind consumption needs. In contrast, Scenario 2 can encourage the achievement of self-sufficiency through increased productivity and expansion of planting land.

The scenario simulation showed that increased corn productivity combined with land expansion has the most significant impact on meeting domestic consumption needs. This confirms that agricultural policies focusing on input efficiency and optimal land management are essential in ensuring regional food security. In addition, the reliability of the dynamic systems model developed in this study provides an analytical framework that can be used to project and anticipate future policy impacts in a measurable manner.

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مقالة أصيلة

تأمين مستقبل الغذاء: ديناميكيات النظام القائم على السيناريو للاكتفاء الذاتي الوطني من الذرة في إندونيسيا

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الخلاصة

لا يزال الطلب المتزايد على الذرة في إندونيسيا لتغذية الحيوانات يفوق الإنتاج المحلي، مما يشكل خطراً على الأمن الغذائي على المدى الطويل. تحدد هذه الدراسة ديناميات العرض والطلب على الذرة في جاوة الوسطى وتحدد المسارات السياساتية الممكنة لتحقيق الاكتفاء الذاتي للمقاطعة بحلول عام 2031.تم تطوير نموذج ديناميكيات النظام، الذي تمت معايرته باستخدام بيانات ثانوية من 2015 إلى 2024، في Powersim لالتقاط التفاعلات بين الإنتاج والمساحة المحصودة والإنتاجية والاستهلاك والتدفقات التجارية والتدخلات السياساتية. تمت محاكاة ثلاثة سيناريوهات:سيناريو أساسي بدون تدخل، وتدخل معتدل مع تحسينات سنوية بنسبة 1٪ في المحصول والمساحة، وتدخل قوي يجمع بين نمو المحصول بنسبة 3٪ وتوسيع الأراضي بنسبة 5٪. أسفرت عملية التحقق من صحة النموذج عن أخطاء مئوية مطلقة متوسطة أقل من 2٪، مما يؤكد الأداء التنبئي القوي.
تظهر النتائج أن المسار الأساسي يؤدي إلى اتساع العجز، في حين أن الاستراتيجية المعتدلة تقلل من الاعتماد على الواردات دون القضاء عليه.فقط السيناريو الجريء هو الذي يسد الفجوة، حيث يحقق القضاء على الواردات بحلول عام 2027 ويولد فائضًا بحلول عام 2031.تساهم الدراسة في وضع إطار عمل محلي للنظام الديناميكي يدمج المتغيرات الزراعية والديموغرافية والتجارية لتحديد نقطة التحول الدقيقة التي يتجاوز فيها العرض المحلي الطلب.تؤكد هذه النتائج على الحاجة إلى سياسات منسقة تعزز الإنتاجية بشكل مشترك، وتدير توسع الأراضي وتوائم ضوابط الاستيراد مع الرصد والمراقبة في الوقت الفعلي.إن دمج أدوات النظام الديناميكي في صياغة السياسات سيمكن من التخطيط التكيفي القائم على الأدلة لحماية الاكتفاء الذاتي للمنطقة من الذرة وتعزيز الأمن الغذائي الوطني

الكلمات المفتاحية: النظم الديناميكية، الاكتفاء الذاتي من الذرة، محاكاة السياسات

Supplementary Materials

Appendix A. Historical Data 2015-2024

Tabel 1. Historical Data for Corn Supply-Demand Variables in Central Java (2015-2024)

Year	Harvested Area (ha)	Productivity (t/ha)	Production (ton)	Consumption (ton)	Feed Consumption (ton)	Imports (ton)	Population (Million)	Postharvest Loss (%)
2015	380,200	5.32	2,024,700	612,300	1,158,200	245,000	255.462	5.0
2016	384,500	5.38	2,070,600	618,700	1,185,800	248,900	257.640	5.0
2017	389,300	5.45	2,123,700	625,900	1,219,500	265,500	260.580	4.9
2018	395,100	5.50	2,173,000	633,200	1,255,800	280,600	264.350	4.9
2019	402,800	5.55	2,236,500	640,400	1,297,400	312,700	267.670	4.8
2020	398,600	5.40	2,153,400	647,900	1,338,600	353,800	270.203	5.1
2021	392,400	5.36	2,103,300	654,900	1,382,300	404,600	272.682	5.1
2022	388,700	5.31	2,064,900	662,000	1,427,500	451,300	275.773	5.2
2023	386,900	5.28	2,042,900	669,200	1,476,800	503,400	278.448	5.2
2024	383,500	5.25	2,012,900	676,600	1,529,400	560,900	281.214	5.3

Appendix B. Model Parameters and Assumptions

Table 2. Parameters Used in the System Dynamics Model

No	Parameter name	Symbol	Baseline value	Unit	Range tested	Source
1	Initial harvested area (start year 2015, Central Java)	Area_2015	380,200	ha	data	Derived from Appendix A (aggregate provincial statistics).
2	Initial productivity (yield) (2015)	Yield_2015	5.32	t/ha	data	Appendix A; calibrated trend 2015–2021.
3	Initial production (2015)	Production_2015	2,024,700	ton	data	= Area_2015 × Yield_2015 (consistency check).
4	Population (mid-year 2015)	Pop_2015	34,200,000	persons	data	BPS mid-year estimate (see user-provided series).
5	Per-capita household consumption (baseline)	Cons_pc	18.0	kg/person/year	14–22	Estimated from regional food balance and Appendix A; sensitivity ±20%.
6	Feed industry consumption (baseline share)	Feed_share	0.58	fraction	0.50–0.70	Derived to match Appendix A feed consumption series (feed > household).
7	Post-harvest loss (baseline)	Loss_rate	0.10	fraction (%)	0.05–0.20	Assumption supported by literature; tested in sensitivity ±20%.
8	Buffer stock target	BufferTarget	0.20	Mt (million tons)	0.0–0.5	Policy-buffer parameter used in import rule (see Eqn Imports).
9	Baseline yield growth (trend)	g_yield_base	0.0127	/yr (≈1.27%)	0–0.05	Estimated CAGR 2015–2024 (Appendix A).
10	Scenario yield growth (S1)	g_yield_S1	0.01	/yr (1%)	-	Moderate scenario assumption.
11	Scenario yield growth (S2)	g_yield_S2	0.03	/yr (3%)	-	Aggressive scenario assumption.
12	Scenario yield growth (S3/Upper)	g_yield_S3	0.05	/yr (5%)	-	Upper-bound test scenario.
13	Baseline area growth (trend)	g_area_base	0.0022	/yr (≈0.22%)	0–0.03	Derived from Appendix A area CAGR (~0.2–2.2% depending aggregation).
14	Scenario area growth (S1)	g_area_S1	0.01	/yr (1%)	-	Moderate.
15	Scenario area growth (S2)	g_area_S2	0.05	/yr (5%)	-	Aggressive (targeted expansion).
16	Import rule / buffer responsiveness	import_buffer_sensitivity	1.0	unitless	0.5–2.0	Imports = max(0, Consumption − (Production + Inventory – Buffer Target)×import_buffer_sensitivity).
17	Import price pass-through to domestic price	pass_through	0.6	fraction	0.3–0.8	Assumption; affects behavioral response in advanced variants (price feedback).
18	Import elasticity (import response to domestic price)	e_import	-0.8	elasticity	−0.5 to −1.5	Assumption/literature range; affects import rule behavior.
19	Initial inventory (2015)	Inventory_2015	50,000	ton	0–200,000	Assumption / minor buffer; sensitivity tested.
20	Maximum adoption of promoted technology	MaxAdoption	0.85	fraction	0.5–0.95	Assumption representing ceiling adoption rate of package.
21	Adoption logistic steepness (income effect)	k_adopt	0.10	1/(IDR unit normalized)	0.05–0.3	Calibrated qualitatively; used in Adoption Rate logistic function.
22	Income threshold for 50% adoption	Income50	1.00	normalized index	0.5–1.5	Normalized reference; see Appendix Sx for mapping to IDR/ha.
23	Discount rate for economic evaluation	r_discount	0.08	/yr (8%)	0.05–0.12	Assumption (default 8%) for NPV/BCR calculations.
24	Unit cost seed subsidy (per ha)	cost_seed	IDR 250,000	IDR/ha	±20%	Assumption for program cost template; sensitivity ±20%.
25	Unit cost fertilizer & input (per ha)	cost_inputs	IDR 1,200,000	IDR/ha	±25%	Policy program cost component.
26	Extension & training cost (per ha)	cost_extension	IDR 150,000	IDR/ha	±25%	Operational cost for extension service.
27	Storage/infrastructure capex per ton	cost_storage	IDR 50,000	IDR/ton capacity	±30%	For postharvest-loss mitigation investments.
28	Simulation time step	dt	1	year	0.25–1.0	Default annual step; time-step sensitivity tested (monthly/quarterly).
29	Simulation period	t_start – t_end	2015–2035	years	-	Calibration (2015–2021), validation (2022–2024), projection (2025–2035).
30	Number of Monte Carlo runs	MC_runs	1,000	runs	500–5,000	Used for uncertainty quantification (median + 90% PI reported).

No	Parameter name	Symbol	Baseline value	Unit	Range tested	Source
31	Monte Carlo distributions (example)	-	Yield ~Normal (mean=baseline, sd=0.5×baseline)	-	parameters vary	See Lampiran Sx for full sampling specification.
32	One-way sensitivity bounds (productivity, area, loss)	-	±10% and ±20%	%	-	Standard one-way tests reported in Results/Tables.
33	MAPE target for calibration	MAPE_target_yield / area	<10% / <10%	%	-	Acceptance criterion (actual achieved MAPE: yield 6.8%, area 8.9% — see Lampiran D).
34	Theil's U threshold	Theil_U_max	0.25	unitless	-	Goodness-of-fit threshold used in calibration notes.
35	Price shock magnitude (scenario tests)	price_shock	±0.10 / ±0.20 / ±0.30	fraction	±10–30%	Exogenous shock settings for global price tests.
36	Yield shock magnitude (climate shock)	yield_shock	−0.20	fraction	−10% to −30%	Example shock: −20% in a given year to test resilience.
37	Institutional Readiness Threshold (index 0–1)	IR_threshold	0.60	index	0–1	If IR index < threshold → require capacity building prior to scale-up.
38	KPI monitoring frequency (SSR, production, imports)	KPI_freq	annual/quarterly	frequency	-	SSR & production annual; adoption & loss quarterly (operational).
39	Cost per additional tonne baseline target (policy metric)	CostPerTon_target	IDR 1,500,000	IDR/ton	±30%	Used to evaluate cost-effectiveness of interventions (example target).
40	Random seed (for reproducibility)	rng_seed	12345	-	-	Include seed in README to reproduce Monte Carlo draws.

Appendix C. Scenario Assumptions

Table 3. Scenario settings for S0 (Baseline), S1 (Moderate), and S2 (Aggressive)

Item	Unit	S0 - Baseline	S1 - Moderate intervention	S2 - Aggressive intervention
Periode simulasi kebijakan	years	2015–2035 (calibration 2015–2021, validation 2022–2024, projection 2025–2035)		
Yield (produktivitias) - growth per year	%/yr	1.27% (historical trend, g_yield_base)	+1.0%/yr (policy package)	+3.0%/yr (ambitious package)
Harvested area - growth per year	%/yr	0.22% (historical trend, g_area_base)	+1.0%/yr (controlled expansion)	+5.0%/yr (targeted expansion in suitable zones)
Post-harvest loss (loss rate)	% of production	10.0% (baseline)	9.0% (−1 pp improvement via improved handling)	8.0% (−2 pp via investments in storage & logistics)
Adoption: initial adoption rate of promoted package (year 1 of intervention)	% area	10% (status quo pilot penetration)	30% (target within 3 years with extension)	60% (ambitious target within 3–5 years)
MaxAdoption (ceiling)	fraction	0.85	0.85	0.85
Adoption speed parameter (k_adopt)	unitless	0.05 (slow)	0.10 (moderate)	0.18 (fast)
Import policy rule	-	Open market; imports respond to deficit (no active restriction)	Gradual import tightening: phased quotas when SSR <0.95 for 2 years	Active import management: automatic quota/tariff triggered when SSR <1.0 OR imports exceed 0.2 Mt/yr
Buffer stock target	Mt	0.20	0.20	0.20
Import responsiveness factor (buffer sensitivity)	unitless	1.0	1.0	1.2 (slightly more reactive)
Price shock tests included?	-	yes (±10%, ±20%)	yes (±10%, ±20%, ±30%)	yes (±10%, ±20%, ±30%)
Yield shock (climate) tests included?	-	yes (−10% / −20% single-year shocks)	yes (−10% / −20%)	yes (−10% / −20% / −30%)
Policy interventions (package components)	-	none (status quo)	seed subsidy (partial), extension intensification, targeted storage upgrades	seed subsidy (full), mechanization support, credit & input bundling, major storage/logistics investments
Program budget (annual incremental cost estimate)	IDR per ha (avg)	0	IDR 1,600,000/ha/yr (seed+input+ext)	IDR 2,500,000/ha/yr (seed+input+ext+mechanization amort.)
CapEx storage/infrastructure (one-off)	IDR/ton capacity	0	IDR 50,000/ton (moderate)	IDR 80,000/ton (ambitious network)
Extension intensity (Extension officers per 1,000 ha)	officers / 1,000 ha	0.5	1.5	3.0
Target timing to reach key adoption milestones	years from start	-	3 years to reach 30% adoption	3 years to reach 60% adoption
Monitoring frequency (KPI)	-	annual (SSR, production)	SSR annual; adoption & loss quarterly	SSR annual; adoption & loss quarterly
Decision trigger (example)	-	none formal	SSR <0.95 for 2 consecutive years → scale subsidy	SSR <1.0 OR import >0.2 Mt/yr → automatic emergency package + import control
Economic evaluation discount rate	%	8%	8%	8%
Cost effectiveness threshold (policy metric)	IDR per additional ton	-	target < IDR 1,800,000/t	target < IDR 1,500,000/t
Expected effect on imports by 2027 (qualitative)	-	imports decline but persist	imports reduced substantially; potential elimination depending on shock history	imports eliminated
Pivot year expected (approx)	year	>2031 (baseline)	~2031 (conditional)	~2027–2029 (likely within this range)
Monte Carlo config for scenario uncertainty	runs & sampling	MC 1,000; yield ~N(mean=1.27%, sd=0.5×mean)	MC 1,000; yield mean=1.0% (sd=0.5×mean)	MC 1,000; yield mean=3.0% (sd=0.5×mean)
One-way sensitivity tests	±	productivity ±10/±20%; area ±10/±20%; loss ±10/±20%	same	same
Assumed domestic price pass-through from import price	fraction	0.6	0.6	0.6
Import elasticity (responsiveness to price)	elasticity	-0.8	-0.8	-0.8
Other assumptions on land availability	ha eligible per year	limited (policy constraints)	controlled access to marginal 1,500–3,000 ha/yr (programmatic)	targeted release up to 10,000 ha over 5 yrs in priority zones
Environmental / sustainability constraints	-	none modelled explicitly	screening for suitability (high priority areas excluded)	strict suitability screening + smallholder safeguards
Institutional readiness requirement	index (0–1)	assumed 0.6	program requires IR ≥ 0.6	program requires IR ≥ 0.7 or accompanied by capacity building

Item	Unit	S0 - Baseline	S1 - Moderate intervention	S2 - Aggressive intervention
Reporting outputs to include	-	annual production, imports, SSR	as baseline + adoption rate & cost per t	full dashboad incl. KPI, cost metrics, pivot year distribution
Documentation & reproducibility	-	model file (.pws) + input CSV	same	same (plus policy scripts for quotas)

Appendix D. Model Validation

Table 4. MAPE calculation for key variables (2015–2024) - Harvested Area, Productivity (Yield), Production

Year	Area_actual (ha)	Area_sim (ha)	AbsError (ha)	%Error (Area)	Yield_actual (t/ha)	Yield_sim (t/ha)	AbsEr r (t/ha)	%Error (Yield)	Prod_actual (ton)	Prod_sim (ton)	AbsErr (ton)	%Error (Prod)
2015	380,200	414,038	33,838	8.90%	5.320	5.682	0.362	6.81%	2,024,700	2,176,552	151,852	7.50%
2016	384,500	350,280	34,220	8.90%	5.380	5.014	0.366	6.80%	2,070,600	1,915,305	155,295	7.50%
2017	389,300	423,948	34,648	8.90%	5.450	5.821	0.371	6.81%	2,123,700	2,282,978	159,278	7.50%
2018	395,100	359,936	35,164	8.90%	5.500	5.126	0.374	6.80%	2,173,000	2,010,025	162,975	7.50%
2019	402,800	438,649	35,849	8.90%	5.550	5.927	0.377	6.80%	2,236,500	2,404,238	167,738	7.50%
2020	398,600	363,125	35,475	8.90%	5.400	5.033	0.367	6.80%	2,153,400	1,991,895	161,505	7.50%
2021	392,400	427,324	34,924	8.90%	5.360	5.724	0.364	6.79%	2,103,300	2,261,048	157,748	7.50%
2022	388,700	354,106	34,594	8.90%	5.310	4.949	0.361	6.80%	2,064,900	1,910,032	154,868	7.50%
2023	386,900	421,334	34,434	8.90%	5.280	5.639	0.359	6.80%	2,042,900	2,196,118	153,218	7.50%
2024	383,500	349,368	34,132	8.90%	5.250	4.893	0.357	6.80%	2,012,900	1,861,932	150,968	7.50%
	Summary			**MAPE = 8.90%**				**MAPE = 6.80%**				**MAPE = 7.50%**
		RMSE (Area) = 34,732.9 ha				**RMSE (Yield) = 0.366 t/ha**				**RMSE (Production) = 157,626.6 ton**		

Appendix E. Model Equations

Table 5. Core Equations of the System Dynamics Model (2015-2035)

Eq. No.	Equation (discrete time / annual step)	Description	Unit	Parameters
E1	Productiont=Areat×Yieldt	Gross annual production (before losses). Implement as flow = stock_out from Area × Yield per year.	ton/yr	Area_t (ha), Yield_t (t/ha).
E2	Lossest=Productiont×Loss_ratet	Post-harvest losses (fraction). Loss_rate expressed as fraction (e.g., 0.10).	ton/yr	Loss_rate (Appendix B No.7)
E3	Net Productiont=Productiont−Lossest	Net available production (to consumption + exports + stock).	ton/yr	-
E4	Household Consumptiont=Popt×Cons_pct/1000	Total household consumption (convert kg→ton if Cons_pc in kg/person/yr). If Cons_pc in kg/person/yr then divide by 1000.	ton/yr	Pop_t (persons), Cons_pc (kg/person/yr)
E5	Feed Consumptiont=Feed_sharet×Total Consumption Demandt	Feed industry's share of total consumption (or model as exogenous growth series). Alternative: feed consumption can be specified via trend series.	ton/yr	Feed_share (Appendix B No.6)
E6	Total Consumption Demandt=Household Consumptiont+Feed Consumptiont+Other Uset	Aggregate demand (Other Use optional: seed, industrial).	ton/yr	-
E7	Inventoryt=Inventoryt−1+Net Productiont+Importst–Total Consumption Demandt−Exportst	Stock accumulation equation (stock variable). In Powersim: Inventory is stock with inflow Net Production + Imports and outflow Consumption + Exports.	ton (stock)	Inventory_2015 (init, Appendix B No.19)
E8	Deficitt=max(0,Total Consumption Demandt−(Net Productiont+Inventoryt−1−Buffer Target×106))	Compute annual deficit triggering imports; Buffer Target in Mt so convert units accordingly (×1e6).	ton/yr	Buffer Target (Mt, Appendix B No.8)
E9	Importst=Import Rule(t)=max(0,Deficitt×import_buffer_sensitivityt)	Imports respond to deficit; import_buffer_sensitivity adjusts responsiveness. In scenario with quotas/tariffs, impose cap: Imports = min(Import Quota, Import Rule).	ton/yr	import_buffer_sensitivity (Appendix B No.16)
E10	SSRt=Productiont/Total Consumption Demandt	Self-Sufficiency Ratio. Note: use Production or NetProduction per manuscript convention; specify which in README.	ratio	-
E11	Yieldt+1=Yieldt×(1+g_yield_effectivet)	Yield evolution; g_yield_effective may combine baseline trend + policy/adoption effect + stochastic shock.	t/ha / yr	g_yield_base (No.9), g_yield_S1,S2 (No.10–12)
E12	g_yield_effectivet=g_yield_baset+Δg_policyt+Shock_yieldt	Δg_policy = productivity gain from adoption & interventions; Shock_yield is negative in climate shock years (ex: −0.2).	/yr	See No.9, No.36
E13	Areat+1=Areat×(1+g_area_effectivet)	Harvested area dynamics (accounts for planned expansion or contraction).	ha	g_area_base (No.13), g_area_S1,S2 (No.14–15)
E14	g_area_effectivet=scenario_area_growtht+policy_constraintst+land_availability_factort	land_availability_factor reduces expansion if suitability low; policy_constraints could be negative if moratorium.	/yr	scenario area growth (Appendix C)
E15	Adoption Ratet=MaxAdoptiont1+exp(−k_adoptt×(Income Indext−Income50t))	Logistic adoption function (Sigmoid). Income Index normalized; implement as auxiliary with income per ha or profit proxy.	fraction/year	Max Adoption, k_adopt, Income50 (Appendix B No.20–22)
E16	Δg_policyt=Effect_per_adoptert×Adoption Ratet	Productivity uplift proportional to adoption rate; Effect_per_adopter = expected % yield gain when adopting package.	/yr	Effect_per_adopter (assumption; typical 0.05 = 5% uplift per full adoption)
E17	Price_domestict=Price_domestict−1×(1+pass_throught×ΔPrice_globalt+ε_pricet)	Simple price pass-through; ε_price stochastic noise or domestic shocks. Implement only if price feedback included.	IDR/kg	pass_through (No.17)
E18	Import Demand_price_responset=Importst×(1+e_importt×((Price_domestict−Price_baset)/Price_baset))	Price elasticity effect on import demand (optional variant). Use sign convention for elasticity e_import (negative).	ton/yr	e_import (No.18)
E19	Inventory Buffer Targett=Buffer Target×106	Convert Mt → ton for buffering.	ton	Buffer Target (No.8)
E20	Cost Program Annualt=∑over_components(UnitCosti×Quantityi(t))	Total annual program cost: seeds, inputs, extension, mechanization amortization, O&M.	IDR/yr	cost_seed, cost_inputs, cost_extension, cost_storage (No.24–27)
E21	Additional Production_from_policyt=∑policy(Production_policyt−Production_baselinet)	Additional production attributable to interventions (used in Cost Per Ton calculation).	ton/yr	Use scenario difference
E22	Cost Per Additional Tont=Cost Program Annualtmax(1,Additional Production_from_policyt)	Prevent divide-by-zero by using max.	IDR/ton	Cost Program Annual, Additional Production
E23	NPV=∑t=t0TBenefitst−Costst(1+r_discountt)(t−t0)	Discounted net benefit calculation for program evaluation.	IDR	r_discount (No.23)

Eq. No.	Equation (discrete time / annual step)	Description	Unit	Parameters
E24	BCR=∑PV(Benefits)∑PV(Costs)	Benefit-Cost Ratio. Benefits here: value of additional production (market price × ton) + avoided import cost.	ratio	see Cost/Benefit components
E25	PivotYear=min{t|SSRt≥1.0}	Year when production meets/exceeds consumption; compute post-simulation. If none, pivot undefined.	year	-
E26	Monte Carlo_sampling: For each run r: sample parameter p_i ~ distribution_i; run model; store SSR(t)	Sampling rules stored in Appendix B No.31; typical distributions: Yield ~ Normal (mean, sd); Loss ~ Triangular(min,mode,max)	-	MC_runs (No.30)
E27	One-way sensitivity: For parameter p, run simulations with p*(1±0.10) and p*(1±0.20) and record delta on SSR(t_end), Imports(t_end), PivotYear	Implemented as scenario sweeps.	-	sensitivity bounds No.32
E28	Tracer flows (for verification): Add tracers Production_contrib and Import_contrib to Inventory inflow to quantify share of inventory originating from production vs imports	Useful for Powersim tracing/debugging and internal validation.	ton	-
E29	Time-step implementation: All flows computed per year (dt = 1 yr). Optional subannual runs (dt = 0.25 yr) for time-step sensitivity.	Note: when dt < 1, convert rates accordingly (e.g., g_yield_effective_dt = (1+g)^{dt} −1).	-	dt (Appendix B No.28)
E30	Reporting aggregates: produce annual series for Production, Net Production, Imports, Inventory, SSR, Adoption Rate, Cost Per Additional Ton, NPV, BCR, Pivot Year distribution	Output variables for analysis and figures.	various	-

Appendix F. Sensitivity Analysis Result

Table 6. One-Way Sensitivity Analysis - impacts on SSR, Production, Imports, and Pivot Year (2031)

Parameter	Adjustment	Parameter value (scenario)	SSR 2031	SSR vs baseline (ppt)	Production 2031 (Mt)	Prod vs baseline (Mt / %)	Imports 2031 (Mt)	Imports vs baseline (Mt / %)	Pivot year (approx.)
Baseline	-	-	0.97	-	7.41	-	0.46	-	- (no pivot ≤2031)
Produktivitas (Yield)	+10%	yield ×1.10	1.05	+0.08	8.12	+0.71 / +9.6%	0.21	−0.25 / −54.3%	2031 (pivot)
	−10%	yield ×0.90	0.88	−0.09	6.68	−0.73 / −9.9%	0.91	+0.45 / +97.8%	-
	+20%	yield ×1.20	1.13	+0.16	8.85	+1.44 / +19.4%	0.00	−0.46 / −100%	2027
	−20%	yield ×0.80	0.79	−0.18	5.96	−1.45 / −19.6%	1.28	+0.82 / +178%	-
Luas Panen (Area)	+10%	area ×1.10	1.01	+0.04	7.90	+0.49 / +6.6%	0.27	−0.19 / −41.3%	2031 (conditional)
	−10%	area ×0.90	0.92	−0.05	6.88	−0.53 / −7.2%	0.70	+0.24 / +52.2%	-
	+20%	area ×1.20	1.06	+0.09	8.37	+0.96 / +13.0%	0.10	−0.36 / −78.3%	2030
	−20%	area ×0.80	0.87	−0.10	6.35	−1.06 / −14.3%	0.98	+0.52 / +113%	-
Post-Harvest Loss	+10% (loss→11%)	loss ×1.10	0.95	−0.02	7.27	−0.14 / −1.9%	0.54	+0.08 / +17.4%	-
	−10% (loss→9%)	loss ×0.90	0.99	+0.02	7.55	+0.14 / +1.9%	0.38	−0.08 / −17.4%	2031 (marginal)
	+20% (loss→12%)	loss ×1.20	0.93	−0.04	7.13	−0.28 / −3.8%	0.62	+0.16 / +34.8%	-

Appendix G. Full Stock–Flow Diagram

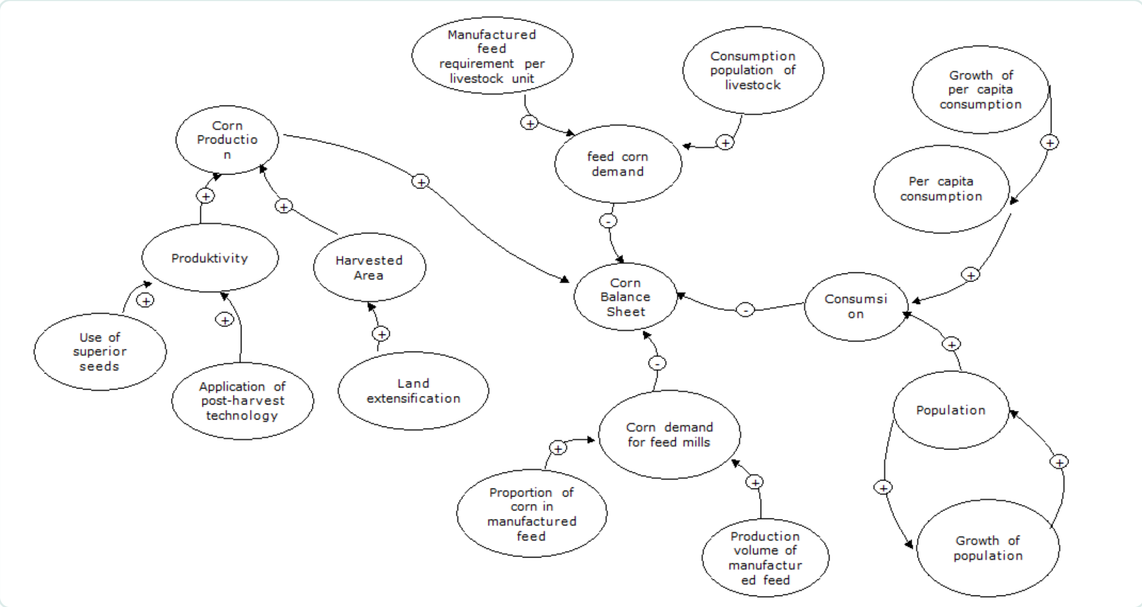

Figure G1.. Causal Loop Diagram

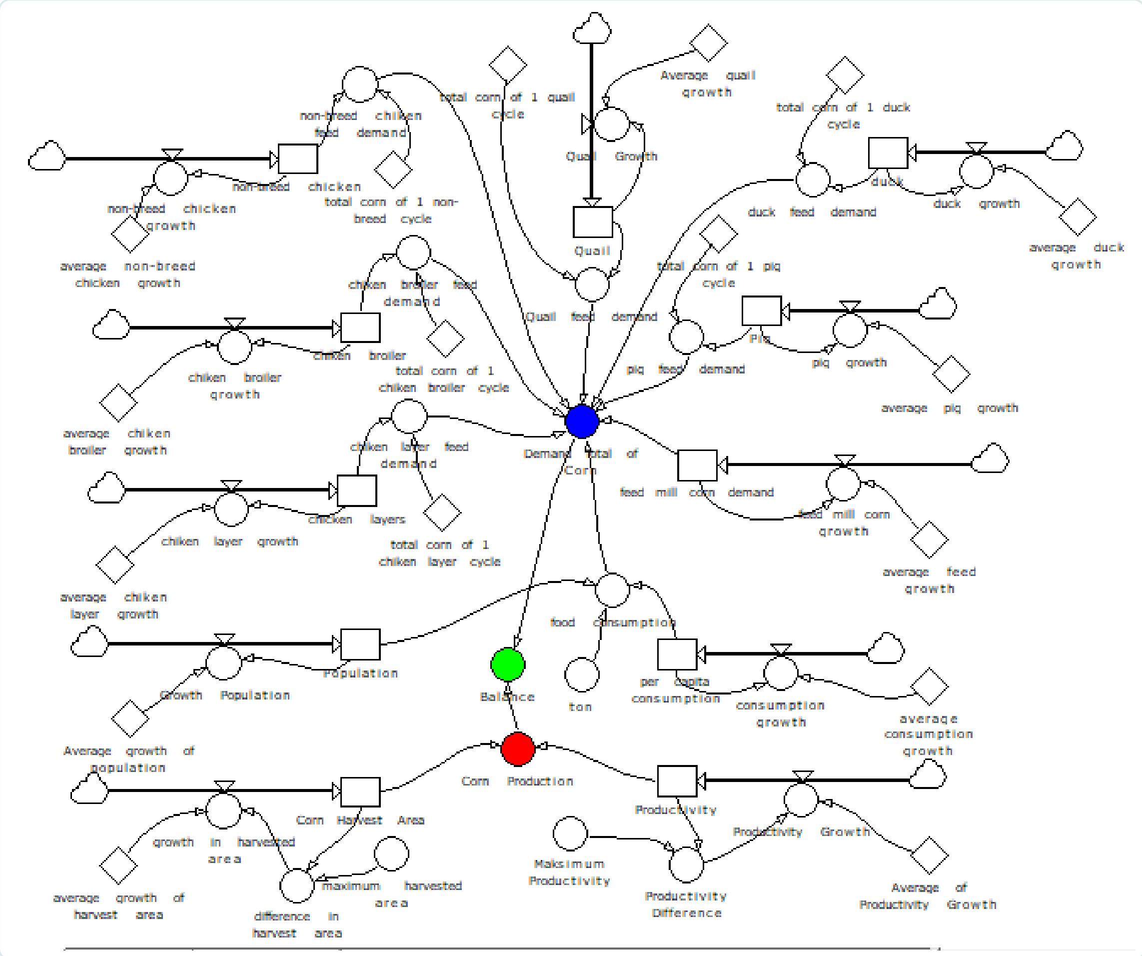

Figure G2.. Full Stock–Flow Diagram