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Decision-Making Systems in Smart Agriculture Based on Forecasting Supply Chain: A New Approach in the Business of Technopreneurship

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Abstract

The agricultural sector contributes significantly to Indonesia's economy 12.4% GDP, 29% workforce, yet faces persistent challenges including climate uncertainty, market fluctuations, and inefficient supply chains due to inadequate decision-making systems. This study aims to analyze the relationship between decision-making and agricultural supply chains integrated with technopreneurship, determine integrated strategies for improving efficiency and sustainability and develop plans to reduce crop failure risks and market demand uncertainty. A quantitative approach was employed using Structural Equation Modeling, Interpretive Structural Modeling and ARIMA forecasting methods with 300 farmer samples and 7 experts from Solok Regency, West Sumatra, during January-September 2025. SARIMAX models successfully predicted potato production and prices with high accuracy. ISM analysis identified hierarchical relationships among objectives, needs, constraints, activities, and actors, revealing seed independence and superior variety development as key drivers. Integrating forecasting-based decision-making systems with technopreneurship principles enhances agricultural supply chain efficiency, though data quality and model validation remain critical challenges.

Keywords

ARIMA, Decision-Making Systems, Interpretive Structural Modeling, Supply Chain Forecasting, Technopreneurship.

1. Introduction

The agricultural sector is a cornerstone of Indonesia's economy, significantly contributing approximately 12.4% to the national GDP and employing over 29% of the workforce (BPS, 2023). Despite this crucial role, agricultural productivity continues to face challenges stemming from inefficient supply chains, market fluctuations, and disparities in technology access between smallholders and supply chain actors. These issues often arise from farmers' difficulties in making informed decisions regarding their agricultural practices. Effective decision-making within the agricultural supply chain is vital for addressing these challenges, as it encompasses various aspects, including climate-based planting strategies, efficient resource allocation, and marketing efforts that align with market demand.

The complexity and unique dynamics of the agricultural sector necessitate a nuanced approach to decision-making that spans production, distribution, and consumption. Informed decisions can lead to increased efficiency, reduced risk, maximized profits, and enhanced sustainability. A well-structured decision-making process not only boosts productivity and profitability but also underpins food security, environmental sustainability, and the welfare of farmers. By leveraging technological advancements, fostering stakeholder collaboration, and implementing supportive policies, agricultural supply chains can become more resilient in the face of global challenges (Kamble et al., 2021; Sawitri & Pujiyana, 2024).

Farmers frequently encounter issues stemming from flawed decision-making strategies, resulting in suboptimal agricultural supply chains. A notable gap in this context is the lack of effective forecasting mechanisms to meet market demand. An effective decision-making strategy is essential for balancing cost-efficiency, resilience, sustainability, and customer satisfaction. Without a systematic approach, farmers risk resource inefficiencies, reduced ability to respond to market shocks, and diminished competitiveness (Dubey et al., 2021; Zia et al., 2022; Chowdhury et al., 2022). Moreover, inaccurate demand predictions can lead to significant operational inefficiencies, contributing to 20-30% of supply chain cost overruns due to challenges like unused inventory or emergency deliveries (Ren et al., 2019). These inaccuracies can result in overstocking, stockouts, inflated logistics costs, and diminished customer satisfaction (Ivanov & Dolgui, 2021; Wang et al., 2021).

The urgency for research is amplified by the dual demands of sustainability and farmers' welfare, which introduce new dimensions to decision-making processes. Farmers often grapple with risks of crop failure, uncertain market demand, and unfair pricing, trapping them in a cycle of poverty. Therefore, integrating principles of sustainability and social justice into decision-making is not merely an option but a necessity. The advent of the fourth industrial revolution presents opportunities through technological integration, such as smart agriculture, which can enhance agricultural efficiency. This includes developing strategies for supply chain decision-making, predicting production planning, and minimizing crop failure risks (Yazdani et al., 2021; Zhou et al., 2022; Han et al., 2024).

In this landscape, the concept of technopreneurship becomes increasingly relevant. It merges entrepreneurial principles with technological innovation, emphasizing the empowerment of smallholder farmers and business sustainability (Klerkx & Rose, 2020; Rafiki et al., 2024). However, in many developing countries, farmers have yet to fully embrace these technologies, hindered by inadequate infrastructure, cultural resistance, insufficient training, education, and fragmented collaboration networks. Consequently, existing business models often lack cohesion. Research on supply chains frequently overlooks socio-cultural contexts, while technological approaches fail to fully harness the potential of technology in decision-making. This results in strategic decisions that are not holistic; for instance, technology investments may disregard farmers' adoption capacities or ecological impacts, while planting schedules may not account for climatic conditions and market trend predictions. Furthermore, there is often a lack of standardized agricultural products.

To address these challenges, this research proposes an integrative decision-making system that incorporates the principles of technopreneurship with technological innovation, grounded in supply chain forecasting. This model aims to bridge the gap between technological and business innovation by providing an analytical framework that combines quantitative data, such as crop predictions and market analysis, with qualitative considerations, including stakeholder participation and sustainability. Collaboration among stakeholders, farmers, business leaders, government entities, academics, and the private sector is essential for the successful implementation of this model.

Ultimately, this integrative decision-making system is expected to enhance business efficiency while also fortifying the resilience of agricultural ecosystems against global disruptions. This study aims to analyze the relationship between decision-making and agricultural supply chains integrated with technopreneurship, determine integrated strategies for improving efficiency and sustainability, and develop plans to reduce crop failure risks and market demand uncertainty.

2. Methods

This research will be conducted in three main stages. First, the Structural Equation Modeling (SEM) method will analyze factors influencing decision-making in the agricultural supply chain. Second, Interpretive Structural Modeling (ISM) will develop technology-based decision-making models incorporating social entrepreneurship values. Finally, the Autoregressive Integrated Moving Average (ARIMA) method will optimize market demand forecasting to help farmers anticipate trends and reduce crop failure risks. The study will take place in four sub-districts of Solok Regency from January to September 2025, involving 300 farmers and 7 experts selected through saturated sampling. Solok was chosen because, according to BPS (2023), it is the largest horticultural production center in West Sumatra. Data collection will utilize both primary and secondary sources through literature reviews (scientific journals, documents, books, and the internet), field surveys, in-depth interviews, and questionnaires.

Agricultural supply chains face complex challenges including climate uncertainty, logistics inefficiencies, and market pressures. According to FAO, around 30% of global agricultural products are wasted due to poor supply chain management, while BPS (2023) reports post-harvest losses in Indonesia of 20–40% for horticultural commodities. These issues demand integrated decision-making that accounts for technical, social, economic, and environmental interdependencies. Structural Equation Modeling (SEM) was employed to analyze relationships between latent variables (farmer satisfaction, technology adoption, climate risk) and manifest variables (infrastructure availability, price fluctuations). SEM effectively identifies indirect impacts of sustainability factors on supply chain performance. This study examines technology, institutions, and stakeholder behavior as independent variables, with decision-making as the dependent variable. Without structural understanding, stakeholders' decisions tend to be reactive and ineffective in achieving long-term goals.

In the globalization era, where competition intensifies, supply chain optimization is crucial to improving efficiency, reducing costs, and maintaining competitive advantages (Deperiky, 2022). Complex supply chains involve multiple stakeholders, uncertain demand, disruption risks, and dynamic environments, requiring systematic strategies to identify key factors and hierarchical relationships (Jain et al., 2022). Interpretive Structural Modeling (ISM) maps hierarchical relationships among sub-elements in agricultural business systems and applies collaborative learning to create structural models visualizing interrelated elements (Eriyatno, 2012). This method helps stakeholders identify key drivers, address root problems, and avoid focusing on surface symptoms. ISM effectively maps complex relationships through participatory approaches, identifying hierarchical structures, dependencies, and driving factors (Attri et al., 2013; Singh & Kumar, 2020; Raut et al., 2021; Jain & Ajmera, 2021; Sharma et al., 2023).

Market demand uncertainty and crop failure are major challenges requiring technological and managerial approaches for supply chain optimization. Seasonal cropping patterns complicate farmers' planting decisions, making demand forecasting essential to identify commodities with strong market potential. The ARIMA method combines Autoregressive (AR), differencing (I), and Moving Average (MA) components (Ahmed, 2020; Bandara et al., 2020; Alamsyah et al., 2021). ARIMA is suitable for non-stationary data with changing trends or variances, transforming data through differencing before modeling autoregressive and moving average patterns (Makridakis et al., 2018; Zhang et al., 2018; Smith et al., 2022). Forecasting results support decision-making in selecting planting commodities based on future market demand trends. Model accuracy was validated using Root Mean Squared Error (RMSE), a standard metric for evaluating predictive models (Kim & Park, 2019; Singh & Agarwal, 2020; Shankar et al., 2025). The market demand forecasting model is validated using RMSE to assess its accuracy, measuring deviations between predicted and actual values, as illustrated in Figures 1 and 2.

$$RMSE = \sqrt{\frac{\Sigma(y_i - \hat{y}_i)^2}{N - P}}$$

Figure 1. RMSE Equation

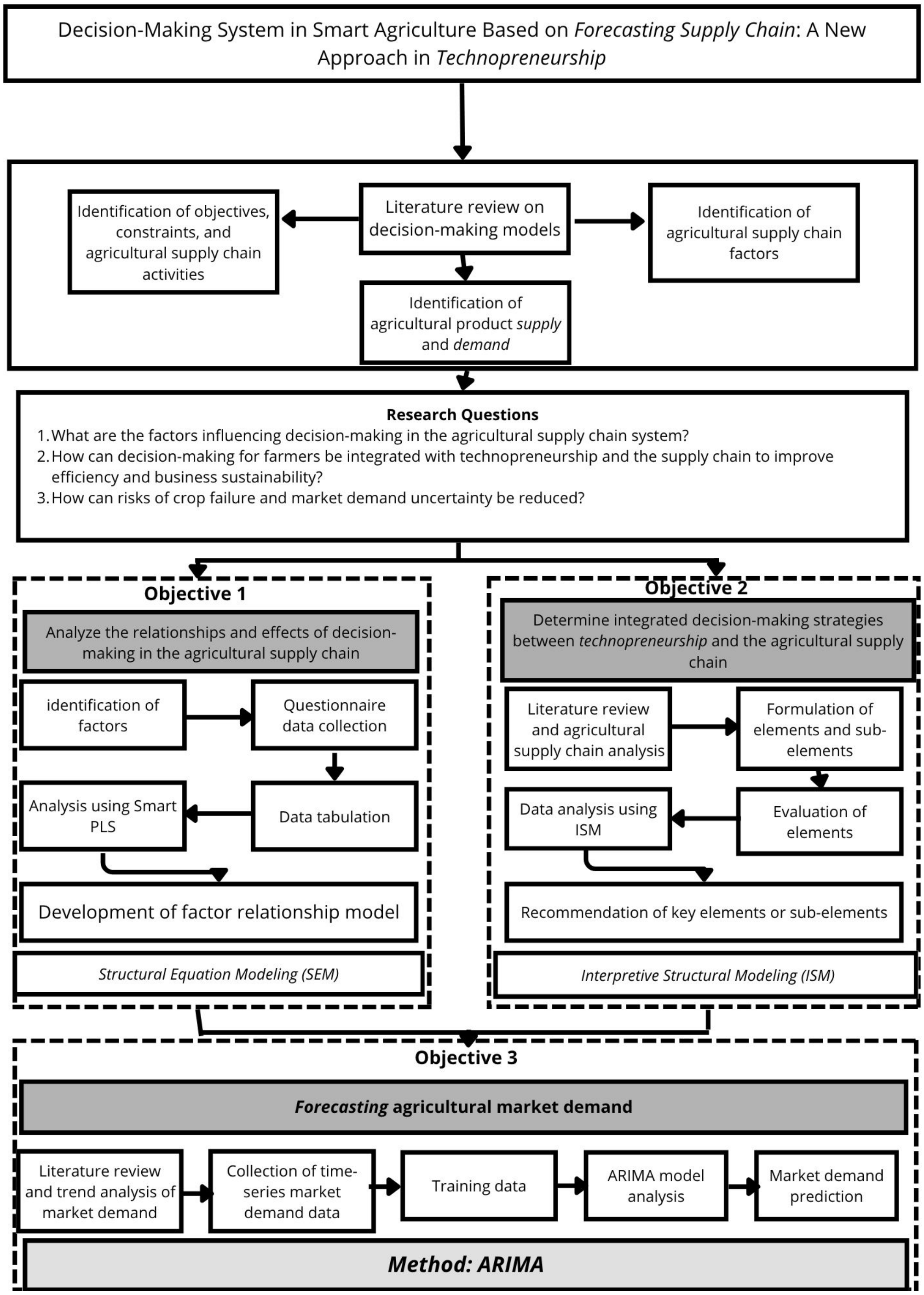

Figure 2. Flow Chart of Research Objectives

3. Results

Figure 3 presents the research roadmap for the next five years, illustrating the progressive development from foundational decision-making system analysis through technopreneurship integration to advanced supply chain forecasting applications and sustainability frameworks.

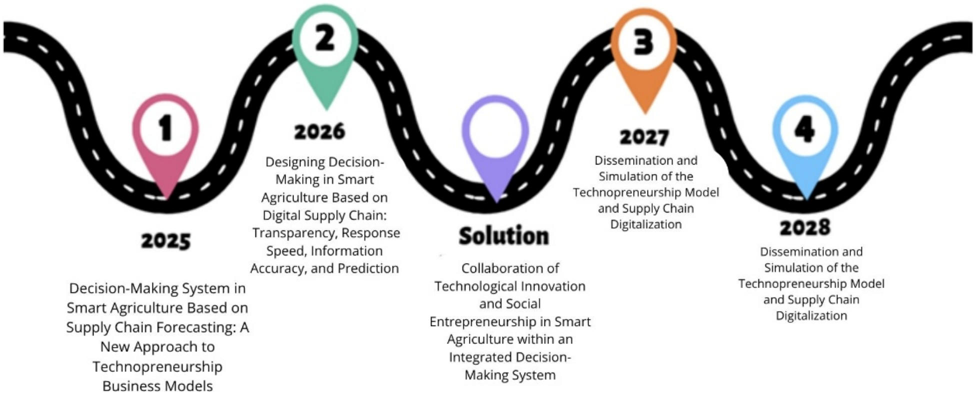

Figure 3. Research Road Map

The outputs expected from the Beginner Lecturer Research activities, along with their target achievement indicators. The mandatory external outputs include scientific publications in national journals with an ISSN, which are expected to appear, as well as the availability of activity videos and research activity logbooks. Additionally, there are supplementary external outputs such as the registration of Intellectual Property Rights (IPR) related to the Decision-Making System Model.

The research activities are scheduled over a 12-month period. Proposal preparation and data collection take place during the first three months, followed by Focus Group Discussions (FGDs) with key stakeholders in months 3 to 5. The analysis, planning, validation, and simulation of the decision-making system model occur from months 5 to 8. Evaluation, data analysis, and reporting activities begin in month 8 and continue through month 12, including the preparation of articles, IPR documentation, and seminars for progress and final reports.

3.1. Potato Production Prediction

After a series of identification, estimation, and verification steps, the Seasonal Autoregressive Integrated Moving-Average with Exogenous Variables (SARIMAX) model was selected as the most appropriate for modeling potato production in West Sumatra. This section presents the parameter estimation results, focusing on the statistical interpretation of significant coefficients, model fit evaluation, and residual diagnostics to ensure validity and reliability. Figure 4 illustrates potato production trends from 2012 to 2024, showing quarterly data with clear seasonal fluctuations.

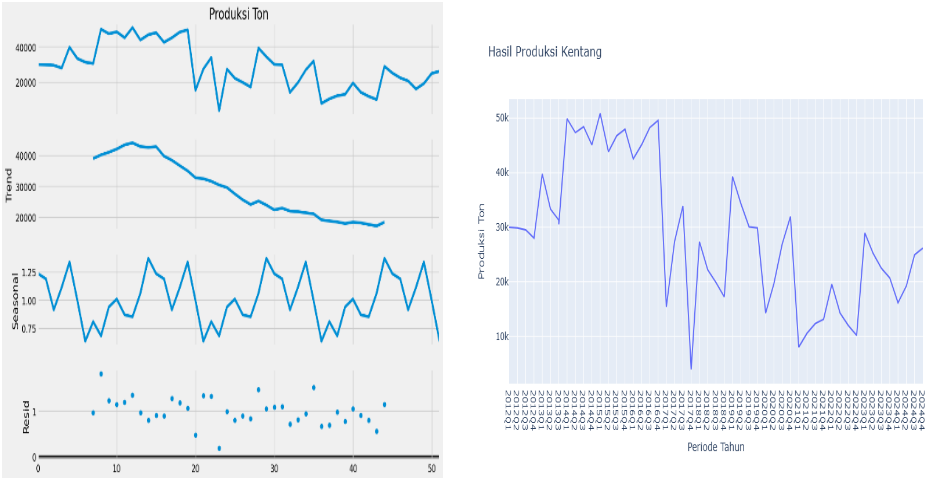

Figure 4. Potato production graph 2012-2024

Based on Figure 4, the results of the graph analysis determine that in predicting potato production in the following year, the SARIMAX model can be used because it is seasonal. Auto Arima is run to create an Arima model to predict annual potato production. From this model, several iterations were carried out, which were used to find the best model based on the AIC (Akaike Information Criterion) value. Some of the models tried include ARIMA(2,0,2), ARIMA(0,0,0), ARIMA(1,0,0), ARIMA(0,0,1), ARIMA(0,0,0) (no mean), ARIMA(2,0,0), ARIMA(3,0,0), and so on. Models with lower AIC values are considered better. The best model is obtained with the smallest AIC value among the other orders, namely ARIMA(1,0,1).

Table 1. SARIMAX Model

Parameter	Coef.	Std. Error	Z-Stat	Prob. (P>|z|)	Lower Limit (0.025	Upper Limit (0.975)
AR(L1)	0.9979	0.0100	102.595	0.000	0.979	1.017
MA(L1)	-0.5144	0.5430	-0.948	0.343	-1.578	0.549
AR.S(L4)	0.6002	0.3940	1.523	0.128	-0.172	1.373
MA.S(L4)	-0.8408	0.3610	-2.327	0.020	-1.548	-0.132
Sigma^2	9.082e+07	8.64e-09	1.05e+16	0.000	9.08e+07	9.08e+07

Based on Table 1 the SARIMAX(1,0,1)x(1,0,1,4) model estimation for potato production data (2012–2024), patterns and key factors influencing production fluctuations were identified. The quarterly time series (52 observations) reflects four harvests per year, with a strong seasonal component (m=4). The regular autoregressive parameter (ar.L1=0.9979, p<0.01) indicates strong dependence on the previous period's production, while the moving average parameter (ma.L1=–0.5144, p=0.020) shows that past shocks negatively affect current production. For the seasonal part, the seasonal AR (ar.S.L4=0.6002, p=0.128) is positive but insignificant, whereas the seasonal MA (ma.S.L4=–0.8402, p=0.020) is significant, suggesting strong corrective effects of shocks from the same quarter in the previous year.

Table 2. Model Fit Statistic

Information	Value
Dependent Variable	Production Ton
No. Observations	52
Model	SARIMAX(1,0,1)x(1,0,1,4)
Log Likelihood	-548.062

Information	Value
AIC	1106.125
BIC	1115.881
HQIC	1109.865
Covariance Type	opg

Table 3. Statistic Probability

Statistical test	Probabilitity (Prob)
Ljung-Box (L1) Q	0.00
Prob (Q)	0.95
Heteroskedasticity (H)	0.97
Prob (H) (two-sided)	0.96
Jarque-Bera (JB)	23.37
Prob (JB)	0.00
Skew	-0.91
Kurtosis	5.73

Based Table 2 and 3, Model fit statistics (AIC=1106.125; BIC=1115.881) indicate good adequacy, supported by the Ljung-Box test (Prob(Q)=0.95), showing no autocorrelation in residuals. However, the Jarque-Bera test (Prob(JB)=0.00) with skewness –0.91 and kurtosis 5.73 indicates non-normal, left-skewed, and leptokurtic residuals. The model effectively captures both basic and seasonal patterns of potato production. The results of the sarimax model continue to predict the next year's production results. These results suggest that potato production in tons in 2025 is Q1 = 23888.75, Q2 = 24183.56, Q3 = 22408.37 Q4 = 24166.16 and in 2026 potato production in tons is Q1 = 23595.88, Q2 = 23753.61, Q3 = 22668.97, Q4 = 23704.86).

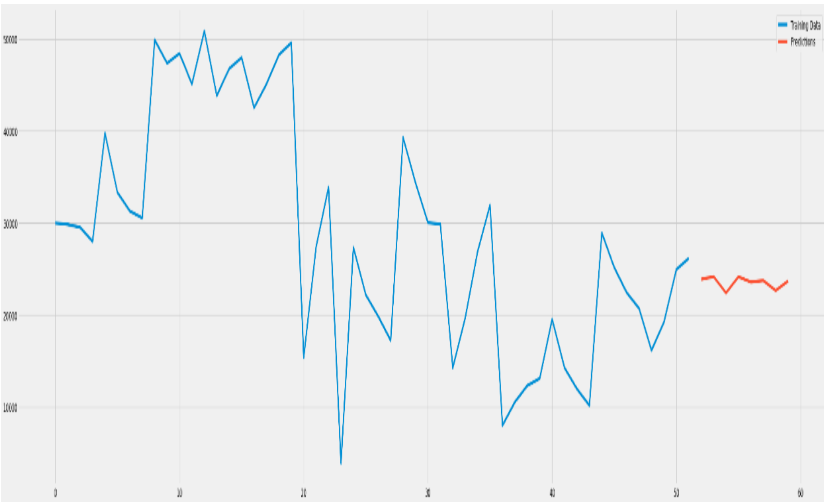

Figure 5. Potato Production Prediction

3.2. Potato Price Prediction

Price fluctuations in horticultural commodities such as potatoes are influenced by dynamic interactions of demand-supply factors, harvest seasons, and external shocks like climate and policy, creating uncertainty for farmers, distributors, and consumers. Accurate price forecasting is crucial for strategic planning and risk management. This study applies the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) model to potato price data from 2012–2024, as it effectively captures autoregressive, moving average, and strong seasonal patterns linked to the four annual harvests. The model aims to provide a reliable forecasting tool and deeper insight into the temporal dynamics influencing potato prices.

Figure 6 shows a graph of potato prices from 2012 to 2024 in each quartile (4 times a year). This graph shows that potato prices in West Sumatra have fluctuated. The results of the graph analysis show that the price of potatoes is seasonal because the chart pattern is similar to that of the pattern.

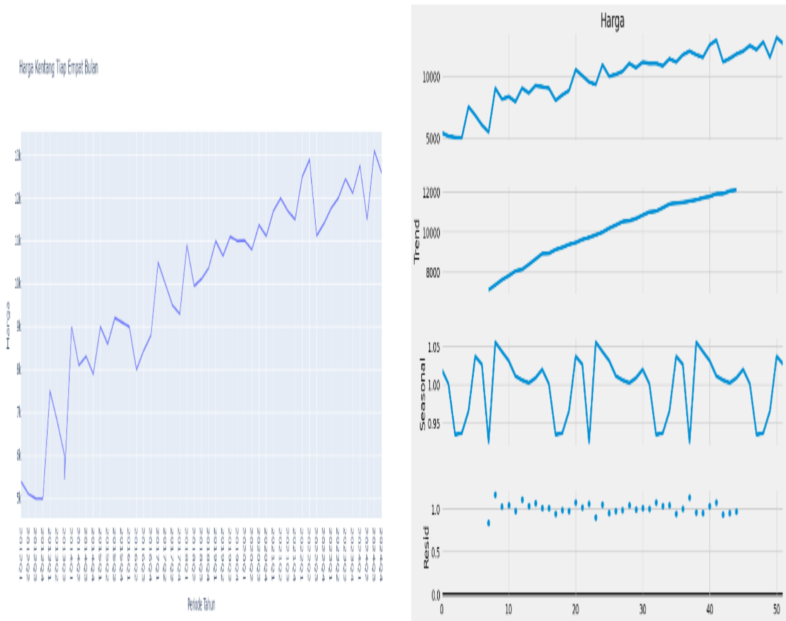

Figure 6. Potato Price Prediction

Figure 6 shows that this study employs a time series modeling approach using the seasonal AutoRegressive Integrated Moving Average (ARIMA) model, implemented computationally via Google Colaboratory (Colab). Colab was chosen for its accessibility, sufficient computing power, and comprehensive Python libraries such as statsmodels and pandas for statistical and machine learning analysis. Within this environment, processes from data import, stationarity testing, model identification, parameter estimation, validation, to forecasting are conducted efficiently and systematically. The seasonal ARIMA model is specifically designed to capture regular patterns from the quarterly harvest cycle, enabling more reliable and realistic projections of potato price dynamics.

Table 4. Model Fit Results

Statistic	Value
Log Likelihood	-417.930
AIC	845.859
BIC	855.615
HQIC	849.599
Ljung-Box (L1) Q	0.30
Prob(Q)	0.58
Heteroskedasticity (H)	0.84
Prob(H)	0.58
Jarque-Bera (JB)	2.44
Prob(JB)	0.30
Skew	-0.54
Kurtosis	3.93

Table 5. SARIMAX Results

Parameter	Coeff.	Std. Error	Z-Stat	Prob. (P>|z|)	Lower Limit (0.025	Upper Limit (0.975)
AR(L1)	0.9930	0.014	72.220	0.000	0.966	1.020
MA(L1)	-0.5688	0.145	-3.912	0.000	-0.854	-0.284
AR.S(L4)	0.9384	0.076	12.291	0.000	0.789	1.088
MA.S(L4)	-0.6763	0.190	-3.554	0.000	-1.049	-0.303
Sigma^2	4.753+05	9.7e+04	4.902	0.000	2.85e+05	6.65e+05

Based on Table 4 and 5, the estimation results, the SARIMAX(1,0,1)x(1,0,1,4) model was identified as a robust tool for analyzing and forecasting potato price dynamics. The dataset consisted of 52 quarterly observations from 2012–2024, representing four harvests per year. A high Log-Likelihood value (417.930) indicates strong goodness-of-fit, meaning the model effectively explains most of the variation in potato prices. Model quality is further supported by information criteria AIC (845.859), BIC (855.615), and HQIC (849.599) which consistently validate the model selection. The relatively small gap between these values suggests that the chosen model complexity is optimal, being neither too simple to miss key patterns nor too complex to risk overfitting.

The model parameters (1,0,1) for the non-seasonal component and (1,0,1,4) for the seasonal component illustrate the temporal structure of potato prices. The non-seasonal AR(1) term indicates that prices in the current quarter are strongly influenced by those in the previous quarter, while the MA(1) term shows that random shocks from the previous quarter also affect current prices. The seasonal component with a period of s=4 captures the annual cyclical pattern linked to the harvest season. The seasonal AR(1) parameter reflects the influence of prices from the same quarter in the previous year, and the seasonal MA(1) indicates that shocks occurring in the same season a year earlier continue to affect current price movements.

The differentiation parameters for both trend (d=0) and seasonal (D=0) being zero indicate that the potato price time series is already stationary at both the level and seasonal components. This stationarity implies that key statistical properties such as mean and variance remain relatively stable over time. Consequently, the model can be applied directly to the level data without requiring differencing to remove trends or seasonality, simplifying interpretation. These results demonstrate that potato prices exhibit strong temporal persistence, reflecting both short-term dependencies between consecutive quarters and long-term linkages across the same quarters in different years.

Based on the estimated SARIMAX(1,0,1)x(1,0,1,4) model, potato price projections for the next two years are presented on a quarterly basis. The forecasts for 2025 are: Q1 (Rp 12,967.64), Q2 (Rp 12,648.94), Q3 (Rp 12,939.91), and Q4 (Rp 12,726.36). For 2026, the predicted prices are: Q1 (Rp 13,161.61), Q2 (Rp 12,855.60), Q3 (Rp 13,121.75), and Q4 (Rp 12,914.51). Presenting forecasts quarterly aligns with the four annual harvest cycles, enabling stakeholders to better plan production and distribution activities in accordance with seasonal market patterns.

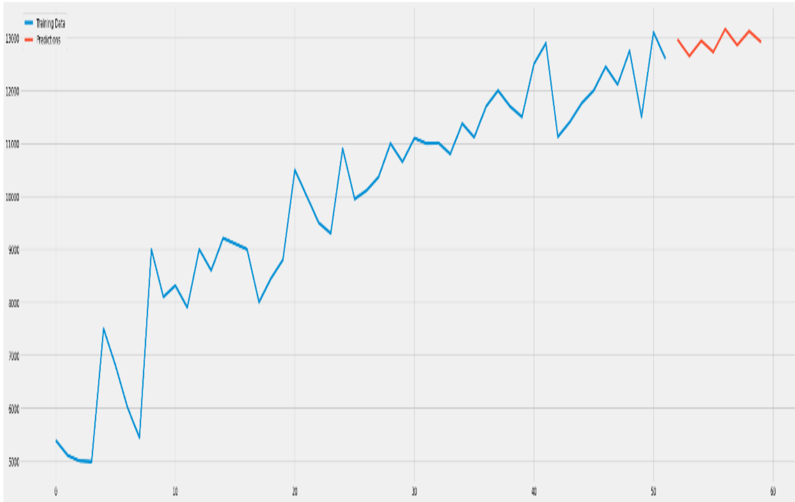

Figure 7. Potato Price Prediction

Based on Figure 7, the SARIMAX-based predictions indicate that the relationship between potato production and price in West Sumatra is complex and not strictly linear. While both production and price exhibit strong seasonal patterns linked to quarterly harvests, price fluctuations do not always correspond directly to changes in production. For instance, despite typically lower production in Q3, prices are projected to rise, as seen in 2025 when Q3 prices reach IDR 12,939.91. To optimize these insights, farmers and farmer associations are advised to integrate the production and price forecasts into planting and harvest planning. Specifically, the Q3 period, characterized by lower production but potential price increases, offers opportunities for strategies such as partial harvest storage or rescheduling to maximize revenue.

3.3. Institutional Strategy of Potato Farming Business

The Interpretive Structural Modeling (ISM) analysis of institutional strategies in potato farming revealed a clear hierarchical and dependency structure among ten objective elements across eight levels. The foundational drivers are Potato Seed Independence (E8), Development of Superior Potato Varieties (E10), and Formation of Cluster-Based Agroindustry (E6). This indicates that prioritizing investments in seed development, superior varieties, and agro-industrial cluster formation is essential, as their success underpins and facilitates the achievement of higher-level objectives.

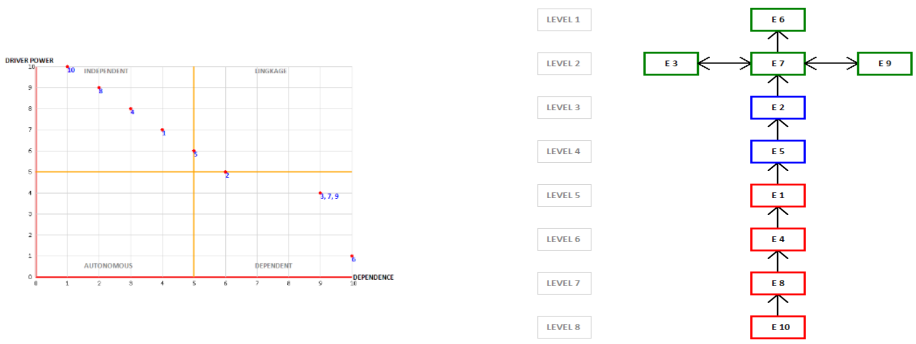

Figure 8. The Formulation of Key Sub-Elements on Each Objective Element is Based on (A) the Structure of the Objective Element and (B) the Matrix of the Objective Element

Based on Figure 8, the propulsion-dependency matrix analysis reinforces the hierarchical structure by categorizing elements into four quadrants. The driver elements Potato Seed Independence (E8), Development of Superior Potato Varieties (E10), and Formation of Cluster-Based Agroindustry (E6) fall into the Independent quadrant, characterized by high influence and low dependency. Dependent elements, such as Integrated Supply Chain Development (E3), Price Stabilization (E7), Value Addition through Agroindustry (E9), and Potato-Based Agroindustry Formation (E6), rely heavily on the realization of these drivers. Linkage elements, including National Standard Quality Implementation (E5) and Post-Harvest Loss Reduction (E2), both influence and are influenced by other elements, requiring careful coordination to prevent systemic instability.

This implies that implementation should begin with the driver elements, starting with superior potato variety development (E10), followed by seed independence (E8), adoption of precision farming technology (E4), and increased land productivity (E1). This sequence ensures a solid foundation for achieving subsequent objectives in a systematic and stable manner.

The Interpretive Structural Modeling (ISM) analysis of the system needs sub-elements reveals a six-level hierarchical structure, illustrating the influence and dependency relationships among elements. At the base (level 6), Increasing Farmers' Human Resource Capacity (E6) serves as a key driver affecting higher-level elements. Elements at the top, such as Strong Farmer Group Institutions (E7) at level 2, are highly dependent, while sub-elements like Low Farming Costs (E2), Guaranteed Fair Raw Material Prices (E8), and Local Agrarian Development (E10) at level 1 are largely influenced by the foundational elements below. This hierarchy provides a clear, systematic view of how each sub-element contributes to and depends on others.

Figure 9. The Formulation of Key Sub-Elements on Each Element of Need is Based on (A) the Structure of the Objective Element and (B) the Matrix of the Objective Element

Based on Figure 9, the power-dependence matrix analysis groups the sub-elements into four quadrants. Elements with high influence and low dependency, such as Modern Cultivation Technology (E5) and E9, are classified in the Linkage quadrant, alongside Quality Superior Seed Availability (E1) and Production Capital Availability (E4). These linkage elements strongly affect the system but are also influenced by changes in other elements, making them potentially unstable. No elements fall into the autonomous quadrant, indicating that all sub-elements are interconnected.

Strategically, system development should begin with high-influence, low-dependency elements, particularly the enhancement of human resources since interventions here generate significant cascading effects. Dependent elements, including Low Farming Costs (E2), Fair Raw Material Price Guarantees (E8), and Local Agrarian Industry Development (E10), require coordinated action alongside their driving elements to ensure effective implementation.

The Interpretive Structural Modeling (ISM) analysis, reflected in the hierarchical structure and propulsion-dependency matrix, shows that obstacles in the agricultural sector are organized into five hierarchical levels with varying dependency and influence dynamics. The sub-elements are distributed across four quadrants based on their driver power and dependency, highlighting their strategic roles. Limited Quality Seed Availability (E8) and Unpredictable Climate Change (E11) fall into the Independent quadrant, characterized by high influence and low dependence. Positioned at the top of the hierarchy (Levels 5 and 4), these elements act as key drivers, requiring priority attention to prevent cascading effects on other constraints.

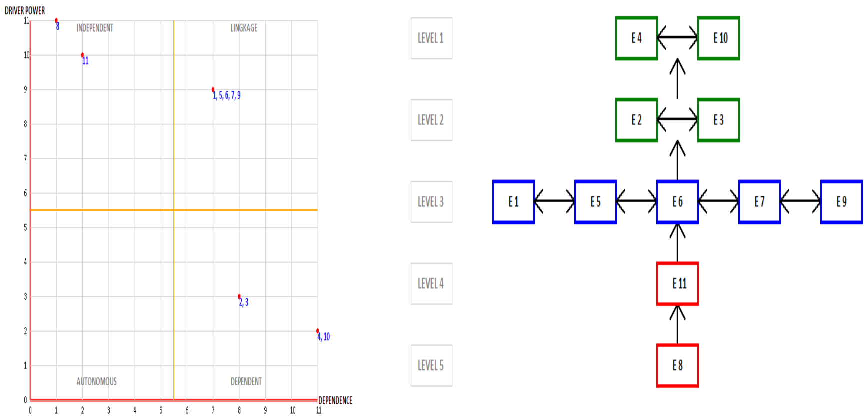

Figure 10. The Formulation of Key Sub-Elements in Each Constraint Element is Based on (A) the Structure of the Constraint Element and (B) the Constraint Element Matrix

Based on Figure 10, Sub-elements such as Difficult Access to Capital (E1), Incompatible Government Policies (E5), Limited Modern Cultivation Technology (E6), Weak Agricultural Institutions (E7), and Poor Coordination of Supporting Institutions (E9) fall into the Linkage quadrant, exhibiting high influence and high dependence. These elements are unstable, as changes affect other elements and are themselves affected, occupying Level 2 as key links between drivers and surface-level constraints. Meanwhile, Pest and Disease Attacks (E2), Lack of Post-Harvest Infrastructure (E3), Inefficient Supply Chains (E4), and Weak Farmer-Industry Partnerships (E10) are in the Dependent quadrant, with low influence but high dependence, at Levels 1–2, representing surface-level constraints arising from other factors. These findings suggest that addressing agricultural constraints should begin with the Independent elements (E8 and E11) as root causes, followed by Linkage elements as leverage points for strategic interventions.

The ISM analysis of potato agribusiness strengthening activities reveals a complex eight-level hierarchy and a thrust-dependence distribution reflecting inter-activity influence. Activities are grouped into three strategic quadrants. Commodity-Specific Policy Alignment for Production and Market Protection (E9) at Level 8 is a key driver with very high influence and low dependence, critically shaping the system while being relatively unaffected by other activities. Other independent quadrant activities, including Increasing Investment and Capital Facilities (E6), Expanding Infrastructure and Public Facilities (E11), Establishing Standardized Potato Seed Houses (E7), and Developing Integrated Potato Farmer Groups (E8), occupy intermediate levels (6–7), serving as foundational drivers for subsequent activities.

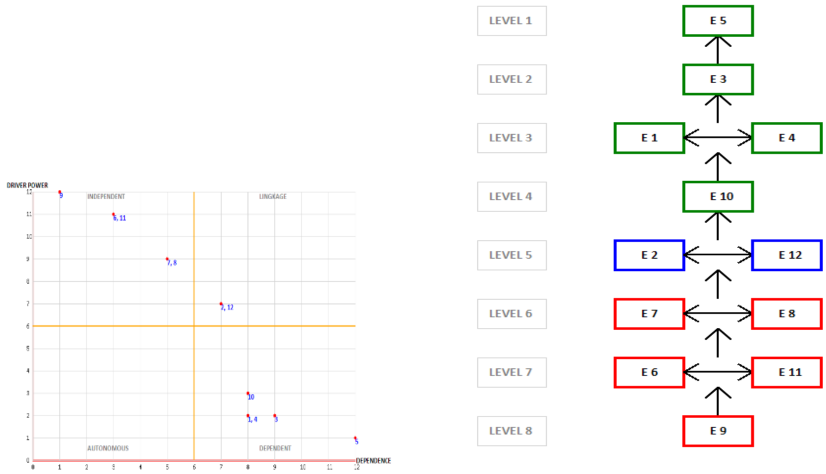

Figure 11. The Formulation of Key Sub-Elements on Each Activity Element is Based on (A) the Structure of the Activity Element and (B) the Matrix of the Activity Element

Based on Figure 11, Precision Cultivation Technical Training (E2) and Comparative Studies between Agricultural Institutions (E12) are in the Linkage quadrant at Level 5, with balanced medium-to-high thrust and dependency. These dynamic and unstable elements act as strategic links, where changes can significantly impact other activities and are themselves influenced by them. Dependent quadrant activities, Identifying Prospective Potato Agroindustry Products (E10), GIS-Based Potential Land Mapping (E1), and Establishing a Production and Logistics Center (E4) have low influence but high dependence, occupying Levels 4–3. Other dependent activities, including Farmer-Industry Partnership Contracts (E3) and Potato Processing Agroindustry Development (E5), are at Levels 2–1, representing output-level activities resulting from the implementation of lower-level initiatives.

These findings suggest that strengthening potato agribusiness should begin with independent activities (E9, E6, E11, E7, and E8) as the system's foundation, followed by reinforcing linkage activities (E2 and E12) to ensure effective connections between levels. Dependent activities (E10, E1, E4, E3, and E5) represent end goals that will be achieved organically once the driving activities are successfully implemented. This hierarchical approach enables structured action planning, minimizes resource overlap, and maximizes development impact by addressing root causes sequentially.

Similarly, the ISM analysis of actors in the potato agribusiness system reveals a four-level hierarchy and thrust-dependence distribution, highlighting strategic roles. Potato Farmers (E1), Farmer Groups (E2), Banking (E6), and Agricultural Input Suppliers (E9) fall into the Independent quadrant, indicating high influence and low dependency. These actors serve as key movers in the system, able to shape outcomes without being significantly affected by other actors.

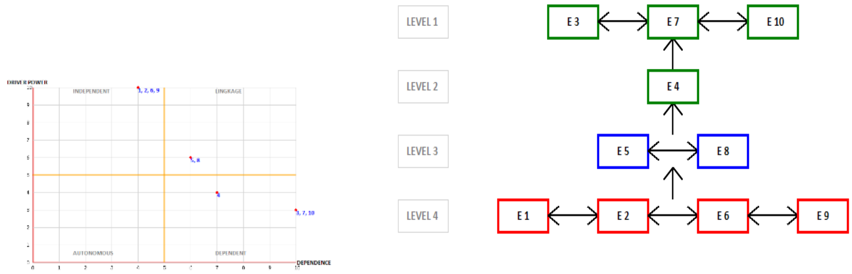

Figure 12. The Formulation of Key Sub-Elements on Each Actor Element is Based on (A) the Structure of the Actor Element and (B) the Matrix of the Actor Element

Based on Figure 12, Actors such as the Department of Plantations, Food Crops, and Horticulture (E5) and Universities/Researchers (E8) are in the linkage quadrant, with balanced thrust and dependency at intermediate levels. These dynamic and unstable actors can significantly influence other stakeholders while being sensitive to changes themselves, occupying Level 3 as strategic links between independent and dependent actors. Merchants (E4) fall into the dependent quadrant, with low influence and high dependency, indicating that their actions are largely shaped by independent and linkage actors.

Although not explicitly plotted in the power-dependence matrix, the Collector (E3), Agricultural Cooperative (E7), and Potato Processing Company (E10) occupy the highest hierarchy level (Level 1), suggesting they act as autonomous drivers with broad system impact. These findings imply that collaborative governance in potato agribusiness should prioritize independent and linkage actors as leverage points, while supporting dependent actors such as wholesalers through strengthened supply chains and inclusive policies. This structured, multi-actor approach enhances synergies and reduces friction, improving system efficiency.

4. Conclusion

The research was conducted in Solok Regency, West Sumatra, from January to December 2025, using a quantitative approach involving 300 farmers and 7 experts. Employing Structural Equation Modeling (SEM), Interpretive Structural Modeling (ISM), and ARIMA forecasting methods, the study analyzed relationships among key factors influencing agricultural decision-making. The SARIMAX model accurately predicted potato production and prices, while ISM analysis identified hierarchical relationships among objectives, needs, constraints, activities, and actors. The findings revealed that seed independence, superior variety development, and cluster-based agroindustry serve as foundational drivers of agricultural efficiency and sustainability. Integrating these quantitative and qualitative approaches provides a comprehensive framework that supports strategic decision-making, minimizes crop failure risks, and reduces market uncertainty within the agricultural sector.

The study concludes that combining forecasting-based decision-making systems with technopreneurship principles significantly enhances agricultural supply chain performance by aligning technology adoption, institutional capacity, and stakeholder collaboration. This integration not only strengthens farmers' adaptive capabilities but also promotes sustainable and inclusive growth across the agricultural ecosystem. The implications suggest that policymakers should prioritize seed independence, superior variety development, and agroindustrial clustering, while farmers and associations should leverage forecasting insights for optimized planting schedules and price maximization. Future research should focus on integrating machine learning, IoT-based data systems, and real-time analytics to enhance forecasting accuracy. It is also recommended to expand the study to other regions and commodities and to evaluate the model's long-term effectiveness in supporting sustainable and adaptive agricultural practices.

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