

Application of Fuzzy Cognitive Map for Policy Simulation in the Agricultural Sector

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ABSTRACT

Agricultural socio-economic research, such as Rural Rapid Appraisal (RRA) or Participatory Rural Appraisal (PRA), often requires quick results while dealing with subjective data. RRA systematically collects rural information, while PRA emphasizes community participation and engagement. In this context, Fuzzy Cognitive Mapping (FCM) assists in managing subjective, ill-defined, and fuzzy variables. FCM creates a network of concepts within systems through positive and negative connections, integrating diverse stakeholder perspectives to support decision-making. This research presents a preliminary model using Large Language Models (LLM) to develop FCM for oil-palm farming, specifically examining the role of middlemen. The FCM is built on subjective variables gathered through open interviews with two palm-oil farmers in Central Kalimantan. Hebbian learning enhances the accuracy of relationships between variables. Results show that FCM effectively simulates policy impacts and their outcomes across different scenarios by adjusting the learning rate and the slope of squashing function. Future research should incorporate more stakeholders to enhance LLM's capability in mapping diverse perspectives.

Keywords: FCM, Hebbian Learning, LLM, PRA, RRA.

1. INTRODUCTION

Agricultural programs use Rural Rapid Appraisal (RRA) and Participatory Rural Appraisal (PRA) for problem mapping based on qualitative data. RRA systematically gathers rural information, while PRA engages communities in identifying problems and solutions (Preece, 2006). Both methods help understand farming communities and design effective interventions (Chambers, 1994). RRA relies on expert teams, whereas PRA emphasizes community involvement. Successful programs integrate participatory approaches to represent community aspirations (Brata et al., 2022).

However, rapid PRA adoption without understanding its principles can lead to shallow applications that fail to achieve results (Chambers, 1994). The challenge of effectively integrating participatory approaches like RRA/PRA with conventional quantitative research methods restricts comprehensive data analysis (Campbell, 2002; Campbell, 2001). Bridging this methodological divide would enhance both data richness and validity, helping researchers overcome the inherent limitations of either approach used in isolation (Koutra, 2010; Catley, 1997). Studies examining PRA implementation in Indonesian villages reveal both advantages and disadvantages. Research shows that PRA facilitates stakeholder collaboration more effectively than traditional top-down approaches. However, cultural and institutional contexts significantly influence PRA's effectiveness (Barat & Yusof, 2012). Further assessment of PRA's impact on poverty alleviation indicates that it becomes less effective when implemented without adequate supportive local structures (Putri, 2007).

1.1. Simulation Models in Indonesian Agriculture

Various simulation models have been employed in Indonesian agriculture. The Oryza model simulates rice production in West Java by integrating weather, soil, and agricultural data, showing strong correlation between estimated and observed solar radiation for biomass production simulation (Sulistyowati, 2015). In Yogyakarta, Soft System Methodology evaluates organic farming business strategies through focus groups and interviews, identifying key strategies: operational evaluation, managerial improvement, and sustainability indicators (Prasetyaningtyas et al., 2019). System dynamics models successfully increased organic corn production in East Java by simulating land expansion scenarios, where smart agriculture practices enhanced productivity and provided favorable investment returns (Rosa, 2022). Decision Support Systems were developed for Central Java's soybean self-sufficiency, integrating supply, demand, and distribution dynamics to allow policymakers to test scenarios and prioritize improvements (Hisjam et al., 2020). Additionally, an agent-based model analyzed Indonesia's corn food security system, addressing weather and land use dynamics for policy analysis (Ayu et al., 2014). While beneficial, these models face data availability and complex challenges. Climate forecast integration and data generators help overcome limitations, as shown in the Pusaka Negara case, where they improved drought strategies during El Niño years (Boer et al., 2007). These models require careful calibration for real-world effectiveness. Moreover, these simulations use either qualitative or quantitative methods, but not both simultaneously.

1.2. Simulation Incorporating Qualitative and Subjective Variables

Simulations incorporating qualitative (soft) variables have seldom been undertaken in Indonesia. Fuzzy Cognitive Mapping (FCM) serves as an intermediary between RRA and PRA methodologies by integrating systematic data collection with participatory community engagement through visual representations of systems. This technique captures both expert knowledge and local perspectives in one framework, showing causal relationships between factors affecting farming communities. By converting qualitative insights into semi-quantitative models, FCM (Fuzzy Cognitive Mapping) maintains participatory knowledge while enabling structured analysis for program design. This integration creates agricultural interventions that are technically sound and representative of community concerns, resulting in more sustainable, context-appropriate solutions.

FCM supports participatory modeling by helping stakeholders visualize and organize relationships in complex socio-ecological systems, facilitating knowledge sharing and better communication (Gray et al., 2015). Adaptive FCM uses machine learning to refine these connections and incorporates feedback loops to represent dynamic interactions among variables, making it well-suited for modeling systems with complex dependencies (Obiedat & Samarasinghe, 2016).

LLMs (Large Language Models) have become advanced models capable of reasoning and natural language understanding (Weber, 2024; Matarazzo & Torlone, 2025), meeting the demand for AI systems aligned with human values (Torkamaan et al., 2024; Kaye et al., 2024). Research shows that LLMs support problem definition, human-in-the-loop collaboration, and

socio-technical design (Wray et al., 2024; Passerini et al., 2025; Bryl, 2009), making them suitable for extracting stakeholder information to build FCM.

1.3. Problem Statements

Agricultural and rural development programs struggle to accurately map complex community problems. Traditional RRA and PRA methods often fail to capture subjective stakeholder perspectives effectively. Current approaches lack robust integration between advanced computational tools and participatory methodologies, leading to incomplete problem representations and potentially ineffective interventions. This limitation reduces the capacity to simulate policy impacts and perform scenario planning in agricultural contexts. This research examines whether integrating LLMs with FCM can support problem mapping and facilitate stakeholder engagement; address subjective and narrative-based conceptual variables; and inform agricultural decision-making processes.

1.4. Research Objectives

The main objectives of this research are: first, to integrate LLMs with FCM to facilitate problem mapping in agricultural programs and assist in preparing PRA/RRAs; second, to use adaptive FCM to enable clearer articulation of issues by agricultural stakeholders through its ability to process subjective, narrative-based conceptual variables; and third, to create policy simulations and "What-If" scenarios for assessing the impacts of interventions and supporting decision-making processes.

2. LITERATURE REVIEW

2.1. Large Language Model (LLM)

Constructing FCMs using LLMs derived from interview leverages LLMs' advanced capabilities to extract meaningful insights from unstructured text. LLMs enhance the extraction of structured propositions from interviews, which form the nodes and edges of FCMs. The widespread use of LLM has shown potential in enhancing understanding and collaboration in data collection. By leveraging LLM, the FCM development process can become more efficient and inclusive, thus reducing weaknesses in manual approaches (Chin et al., 2024). This approach resembles automated concept map generation, where LLMs extract and structure the information (Perin et al., 2023).

LLMs' proficiency in understanding and generating coherent text helps identify and articulate the causal relationships essential for FCM construction (Binz & Schulz, 2023). Research by Bhaduri et al. (2024) shows that LLM can significantly accelerate the process of topic modeling and thematic analysis. LLM quickly identifies and summarizes the main topics from interview transcripts, reducing the time and effort required for manual analysis, making qualitative research more efficient. In other research, LLM has been used to analyze transcripts from semi-structured interviews, identify themes, and automatically group respondent perceptions. This approach has proven to save time and improve consistency in qualitative data analysis (Paoli, 2023).

For interview analysis, LLMs can also be used to identify key themes and sentiments that inform causal links within FCMs (Liu & Sun, 2023). Human expertise can refine this process, ensuring accuracy and relevance of extracted information, thereby enhancing the interpretability and predictive power of the resulting FCM (Liu & Sun, 2023). Additionally, LLMs can address data sparsity by generating synthetic data, creating more robust and comprehensive FCMs (Mandal & O'Connor, 2024). Hence, the synergy between LLMs and FCMs offers a promising approach for transforming qualitative interview data into actionable cognitive models, improving decision-making and understanding of complex systems.

Fine-tuning LLMs on specific datasets, such as interview transcripts, can yield cognitive models that accurately represent human decision-making processes, thereby enriching the FCMs with more nuanced insights into human behavior (Binz & Schulz, 2023). This approach not only automates the construction of FCMs but also ensures that they are grounded in real-world data, enhancing their applicability in complex system modeling (Mandal & O'Connor, 2024; Perin et al., 2023).

2.2. Fuzzy Cognitive Map (FCM)

Zadeh introduced fuzzy logic in 1965 to address uncertainty beyond binary logic (Berenji, 1992). Initially, it met with skepticism, but it gained traction in fuzzy logic control, combining conventional control with AI (Schwartz et al., 1994). In the 1990s, it evolved from uncertainty management to function approximation (Yen, 1999). Applications spread to consumer electronics and intelligent systems (Schwartz et al., 1994). Type-2 fuzzy logic later emerged with advanced uncertainty modeling (John & Coupland, 2007). Over time, fuzzy logic integrated with neural networks and expanded into robotics and decision support systems (Saatchi, 2024), proving effective across domains (Bergmann, 2008).

Type-1 and Type-2 fuzzy systems differ in uncertainty handling. Type-1 uses crisp membership functions with precise grades, limiting ambiguity management. Type-2 adds a third dimension, capturing membership function uncertainties, using value ranges for better handling of uncertainties and linguistic ambiguities (Castillo and Melin, 2007; Mendel, 2015). They excel with imprecise data by modeling both individual and group (Mendel, 2001). Interval Type-2 fuzzy systems are a practical Type-2 subset using interval-valued membership functions, simplifying computations compared to general Type-2 systems (Mendel, 2001). Despite computational complexity limiting widespread implementation, they offer advantages in uncertainty processing, yielding smoother outputs in uncertain environments (Karnik and Mendel, 1998; Tan and Chua, 2007).

The FCM development process is generally carried out in several stages. FCM development begins with individual mapping, where each stakeholder creates their fuzzy cognitive map. This allows them to independently express their perceptions about factors that influence the system. After that, group mapping is conducted where stakeholders gather to build a shared fuzzy cognitive map. This collaborative effort aims to combine their insights and create a more comprehensive understanding of the system (Pisanelli et al., 2023). Therefore, FCMs excel in group decision support by integrating expert domain knowledge into collective knowledge bases (Khan & Quaddus, 2004).

FCM consists of nodes (nodes) and connections (edges). Nodes represent concepts or variables related to the problem being studied. Connections between nodes indicate relationships between variables, either positive (supporting relationships) or negative (inhibiting relationships). One of the main features of FCM is its ability to handle uncertain relationships (fuzzy). This is important considering that many real-world problems involve factors that are difficult to quantify (Obiedat & Samarasinghe, 2016).

Mathematically, FCMs are graph-based models that represent complex systems through nodes and causal relationships, which are particularly useful for modeling and prediction tasks in various domains (Tyrovolas et al., 2023). Thus, FCMs can model complex social systems by representing interrelated concepts graphically and calculating implications through matrix algebra (Craig & Coover, 1994). Fuzziness indicates they model causal relationship uncertainty, supporting business decisions where precise values are unavailable (Hajek & Prochazka, 2016). FCMs analyze causal systems across multiple domains (Papageorgiou, 2011), with dynamic properties facilitating modeling, analysis, and decision-making (Papageorgiou & Salmeron, 2013; Papageorgiou, 2011).

FCMs capture complex relationships across domains while visualizing causal relationships in group decision-making. They integrate diverse knowledge types—stakeholder expertise, literature reviews, and survey data (Sarmiento et al., 2024)—making them suitable for participatory research (Gray et al., 2013). Their flexibility spans context and skill levels, working with both simple and sophisticated techniques (Sarmiento et al., 2024). As a comprehensive modeling method, FCMs incorporate multiple knowledge sources, visualize causality, and support scenario analysis (Khan & Quaddus, 2004). They integrate expert knowledge into collective bases, helping decision-makers navigate uncertainty. This approach has proven valuable across healthcare, environmental management, and social sciences (Apostolopoulos et al., 2024; Gray et al., 2013; Sarmiento et al., 2024).

FCMs are a form of soft computing that allows the modeling of complex systems through the representation of dynamic causal relationships between concepts. Traditionally, these maps are developed through expert input, but growing interest in automated methods has led to the exploration of deriving FCMs from textual data such as interviews. Finally, by combining fuzzy logic and neural networks, they excel in representing knowledge in ambiguous systems (Nápoles et al., 2017).

2.3. Hebbian Learning

Despite their strengths, traditionally, FCMs face limitations including dependence on potentially biased human expertise and possible convergence to undesired states (Papageorgiou et al., 2003). To alleviate these weaknesses, researchers have developed various learning methods, including Hebbian-based, population-based, and hybrid algorithms (Papageorgiou, 2012). For example, unsupervised Hebbian algorithms enable FCMs to dynamically modify their causal web as patterns evolve (Papageorgiou et al., 2003).

Hebbian learning improves FCM performance and adaptability by strengthening connections between frequently co-activated neurons. In FCMs, it updates the weight matrix representing causal relationships between concepts. The Nonlinear Hebbian Learning

algorithm uses Hebbian law and output concept conditions to adjust weights (Stach et al., 2008). Its data-driven extension utilizes historical input concept data to enhance learned FCM quality (Stach et al., 2008).

Hebbian learning in FCMs updates weights based on co-activated concepts. This enhances FCMs through: Nonlinear Hebbian Learning (NHL) adjusting weights based on input-output correlations, with Data-Driven NHL using historical data (Stach et al., 2008); Differential Hebbian Learning analyzing causal pattern changes (Salmeron & Palos-Sanchez, 2017); Unsupervised Hebbian Algorithms enabling self-tuning (Papageorgiou et al., 2003); and Adaptive FCMs with Differential Hebbian Learning for continuous adjustment (Dickerson & Kosko, 1993). These techniques enhance FCMs' adaptability to uncertainties across domains.

NHL offers advantages over traditional FCM methods: improved uncertainty propagation enhancing reliability (Salmeron & Palos-Sanchez, 2017), enhanced data learning through data-driven NHL (Stach et al., 2008), flexibility in adapting cause-effect relationships (Papageorgiou & Groumpos, 2005), reduced dependence on expert knowledge (Papageorgiou et al., 2003), and efficient performance with noisy data (Feng et al., 2019). These features make NHL valuable for developing robust FCMs.

2.4. Learning Rate and Slope of Activation Function

Two parameters significantly influence FCM performance: learning rate affects learning speed and stability, while the activation function slope determines sensitivity and non-linearity. Learning rate and activation function slope critically influence FCM performance in pattern classification and system modeling. Higher learning rates enable faster convergence but risk instability, while lower rates provide stability but require more iterations, whilst the activation function slope affects model sensitivity and non-linearity. Research has addressed these through innovations: Nápoles et al. (2016) developed a population-based algorithm with sigmoid stability features, while Napoles et al. (2018) proposed a slope estimation algorithm preserving causal weights and introducing stability conditions for accuracy-convergence assessment. Proper parameter tuning improves convergence, stability, and classification performance, with ongoing optimization research continuing (Papageorgiou & Froelich, 2011).

As a white box model, the FCM structure facilitates visualization of cause-effect relationships that are essential for scenario analysis. Scenarios developed from FCMs are used to simulate various possible outcomes by changing specific variables or conditions to observe potential system states resulting from a policy. The insights gained from these scenarios are crucial in formulating strategies for effective system intervention and management (Edwards & Kok, 2021).

3. METHODS

3.1. Data Collection

Open interviews were held with two palm oil farmers, representing small and medium-scale operations in Lamandau Regency, Central Kalimantan. The selection was not random.

The research focused on testing the model and simulation across respondent groups, using the simulation results to create scenarios.

3.2. Integrating LLMs with FCM

In this research, Large Language Models (LLMs) such as Google NotebookLM and Notion AI are used to construct the FCM structure. LLMs are utilized in this research for their ability to comprehend natural language and identify causal relationships. They do not necessitate standardized formats, such as questionnaires, which makes them appropriate for bottom-up exploration like participatory research. Additionally, LLMs can consolidate diverse agents' perceptions regarding the direction and magnitude of relationships between two concepts (nodes) in the FCM. In this research, respondents don't need to explicitly state whether relationships between concepts are positive or negative since LLM will extract this from the interview results. The use of LLMs also helps reduce bias and the risk of missed causal relationships by respondents.

Since there are two informants, the first step is to create two transcription files. NotebookLM is used to extract variables that will become concepts from each respondent. Based on these extraction results, an FCM diagram is constructed using Mermaid while also determining whether relationships are positive or negative. Subsequently, pruning is performed by combining identical concepts. The weights of relationships between concepts are further refined using Hybrid Hebbian learning and Delta Rule. The LLM results are then used to construct an Adjacency Matrix showing relationships between concepts, which is subsequently converted into an FCM diagram.

3.3. Fuzzy Cognitive Mapping

FCM in this research uses fuzzy weights (degree 1) to express the strength and direction of relationships between nodes, thus enabling a visual representation of knowledge. This consideration is particularly important in agricultural contexts, where decision-making is shaped by complex ecological, economic, and social feedback mechanisms.

To begin the calculation, the activation is determined in the form of a vector that indicates the initial conditions or policy taken. In the FCM context, the concept value at the beginning of the simulation is also called initial activation or initial concept value. This value describes how active or strong a concept is to simulate a policy or initial condition. This value typically ranges from [0, 1] for the sigmoid squashing function or in the range [-1,1] for tanh. If the concept (node) represents positive/negative influence (pros-cons) then tanh is more appropriate. If the node only represents activation between inactive and active, then sigmoid might be more suitable. The concept value will change over time through iterations. Subsequently, the value of each node is the "sum" of the weighted inputs to that concept, with the formula:

$$A_i(t + 1) = f \left(\sum_{j=1}^n w_{ji} \cdot A_j(t) \right)$$

where:

- $A_j(t)$: value of concept j at time t
- w_{ji} : weight of relationship from concept j to concept i
- f : sigmoid or tanh function

Following is the mathematical equation form of the tanh function, the squashing function used in this paper, that has been modified with the lambda parameter (λ), and used in the context of weight updates using learning rate alpha (α) to keep the concept values within the specified range $[-1,1]$. The standard version of tanh function commonly used is:

$$\tanh(\lambda x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}}$$

where

- x : input value (result of weight propagation in FCM or input to the neuron).
- λ : multiplier parameter (usually) that controls the *slope of the curve*.
- $\lambda > 1$: curve is steeper $\rightarrow$ small changes will result in large changes in output.
- $\lambda < 1$: curve is flatter $\rightarrow$ system is more stable, but adaptation is slower.

A steeper function represents that a policy is implemented quickly, whereas a flatter function indicates a slower policy implementation. By changing various steepness values, we can simulate whether policies should be implemented quickly or more gradually to keep the system stable. Note that changes that are too fast can lead to chaotic conditions (Gao et al., 2024; Papageorgiou & Groumpos, 2005; Papageorgiou & Iakovidis, 2013).

FCM can be extended using Hebbian learning principles to update the weights of connections between concepts based on the activity of the concepts themselves (Papageorgiou et al., 2004). This approach enables modeling that is more adaptive and responsive to the complexity of relationships in social-ecological-economic systems, thereby expected to improve accuracy in representing stakeholder knowledge. In the context of FCM, the classical Hebbian rule (linear):

$$\Delta w_{ij} = \alpha * c_i * c_j$$

In FCM, it is adapted as

$$W(t+1) = W(t) + \alpha * (c(t) \otimes c(t))$$

with $\otimes$ as the outer product, α representing the learning rate, and $c(t)$ denoting the concept value vector at time t . The basic principle of Hebbian Learning is:

$$\Delta W_{ij} = \eta \times x_i \times x_j$$

If two neurons (or concepts in FCM) are active together (both are large), then the connecting weight is strengthened. If one is small, the reinforcement is smaller. In this paper, the Hybrid Hebbian-Delta rule update is used:

$$\Delta W = \alpha(C_t \otimes (C_{t+1} - C_t))$$

3.4. Scenario Generation

Scenarios are conducted by changing the slope value for the activation function and the learning rate α in Hebbian learning to determine the behavior of a node (concepts) whether it will be stable, or chaotic, if a certain policy is implemented.

In FCM analysis, system behavior can be classified into four distinct attractor types. A fixed-point attractor represents a stable system that converges to a single equilibrium point and remains unchanged, while a limit cycle attractor exhibits a predictable cyclic pattern where the system moves in a closed orbit, periodically returning to its initial conditions. These patterns indicate relatively stable and predictable system behavior. More complex behaviors include the strange attractor, where the system appears chaotic but remains confined within certain boundaries, reflecting structured irregularity characteristic of complex adaptive systems. At the end is the unstable system, characterized by diverging paths where values increase without bounds or move progressively further from their starting points, signaling fundamental instability that may lead to system failure or radical transformation. Understanding these patterns helps predict how agricultural policy interventions might affect system stability. This behavior will be presented using a combination of 3 variables (*triplet*) in the 3D format.

4. RESULT AND DISCUSSION

4.1. Development and Diagramming FCM

Interviews with informants were conducted from October to November 2024 with two palm oil farmers in Lamandau, Central Kalimantan. Each of the interview results were transcribed and uploaded to Google's NotebookLM as two separate files. Several questions about the interview results were then asked through NotebookLM, yielding narratives that were later converted into Mermaid diagrams. These diagrams were created using Notion AI based on the NotebookLM input.

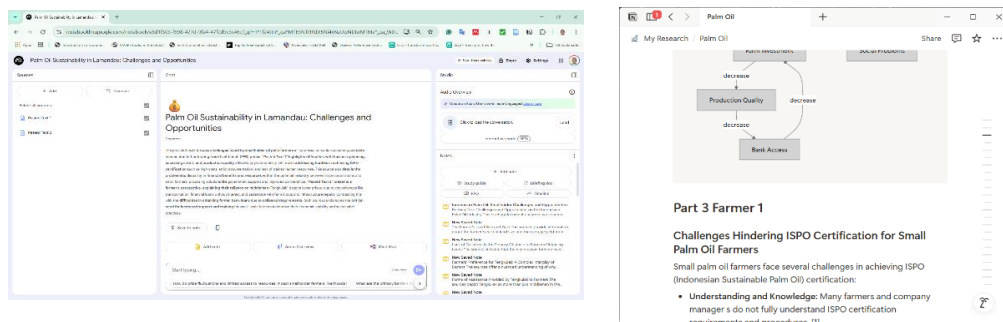


Figure 1. NotebookLM (Left) and Mermaid Diagram and LLM Filtering (Right)

The next step is merging the inputs from NotebookLM and simplify them to construct the Adjacency Matrix and FCM. Calculations were performed with several scenarios of λ (slope) values and α learning rates. The resulting FCM is presented in Figure 2 below:

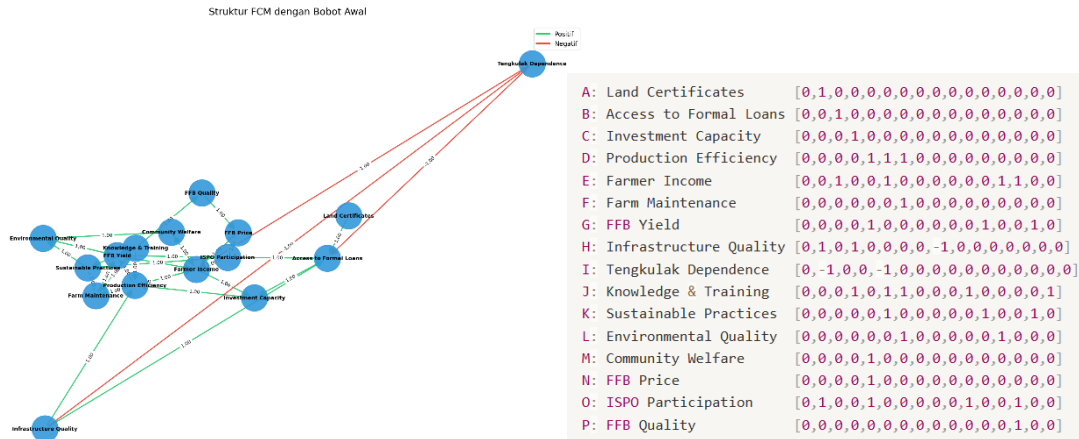


Figure 2. Fuzzy Cognitive Map and Adjacency Matrix

4.2. FCM Representation Derived from LLM (Simplified)

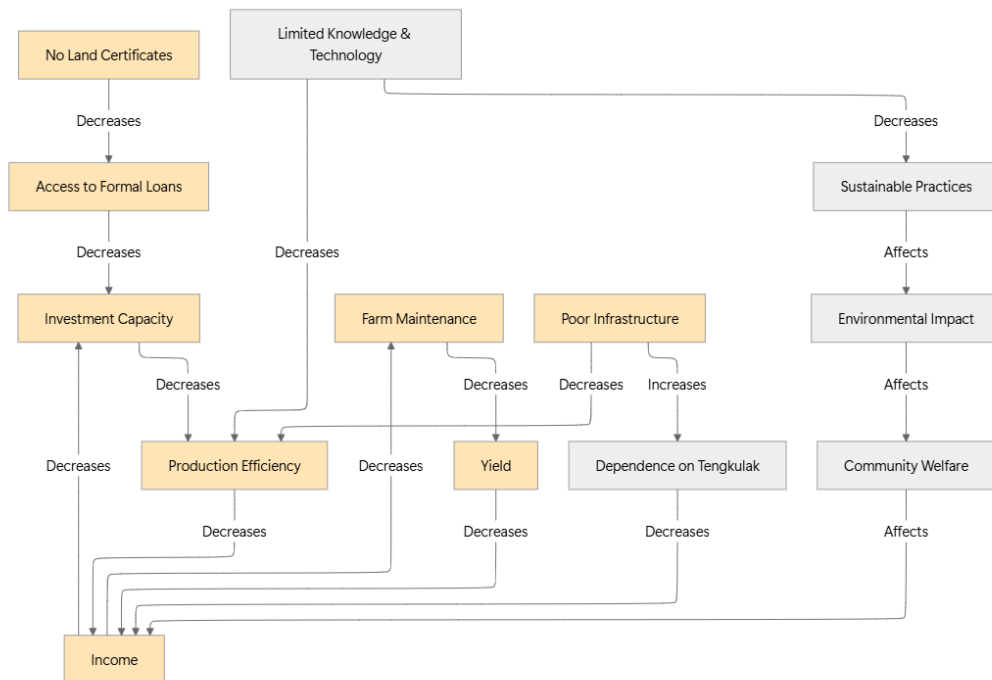


Figure 3. Challenges Encountered by Farmers

4.2.1. Funding Gap and Its Implications from the Interviews

Despite the palm oil industry's vast profits, smallholder farmers in Indonesia face persistent funding gaps, lacking the access to technology, training, and financial support that large companies enjoy. Government funds tend to favor established companies and regions, leaving smallholders at a disadvantage both economically and in terms of human resource development. This disparity also extends to environmental and social impacts, with communities shouldering the negative effects of production while profits concentrate among larger stakeholders. Bridging this financial and knowledge gap is crucial for smallholders to adopt sustainable practices, secure certifications like ISPO, and improve both their welfare and the industry's overall sustainability.

4.2.2. Credit, Technology Access, and Price Volatility Challenges

Smallholder palm oil farmers in Lamandau face intertwined challenges related to credit access, technology adoption, and the volatility of palm oil prices. Limited collateral, such as land certificates, and unstable incomes—caused by fluctuating Fresh Fruit Bunch (FFB) prices—make banks view these farmers as high-risk borrowers and often lead to loan rejections. Unable to secure formal loans, many farmers turn to informal lenders or middlemen, creating cycles of debt and dependency. Financial limitations also prevent smallholders from investing in modern technologies or infrastructure improvements, further widening the gap between them and large companies. Inadequate access to technical training and unreliable rural infrastructure make adopting new technologies even more difficult, hampering productivity and sustainability.

Volatile palm oil prices make long-term planning nearly impossible for smallholders, often forcing them to cut production costs at the expense of FFB quality and profitability. These combined issues trap farmers in a cycle of economic vulnerability and hinder their ability to achieve independence or sustainable improvements to their livelihoods.

4.3. Scenario Generation: Space Graph Representation

Simulation outcomes in FCM are influenced by the activation slope (λ) and learning rate (α), which impact node value convergence and oscillation. Table 1 summarizes how varying these parameters affect FCM dynamics.

Table 1. Effects of Different Activation Slope (λ) and Learning Rate (α)

Parameter Configuration	System Behavior	Key Characteristics
High λ ($\lambda = 1.0$) with low α ($\alpha = 0.01-0.05$)	Quick stabilization	Clear convergence of economic variables

High λ ($\lambda = 1.0$) with medium-high α ($\alpha = 0.1-0.4$)	Significant oscillations and divergence	Instability in Environmental Quality, Community Welfare, and ISPO Participation; risk of over-adjustment
Moderate λ ($\lambda = 0.5$) with all α values	Stable convergence	Smoother trajectories, reduced volatility, realistic equilibrium values even at higher learning rates
Optimal Configuration	Balanced stability and adaptability	$\alpha = 0.05-0.1$ with $\lambda = 0.5-1.0$

The effects of activation slope (λ) and learning rate (α) on Fuzzy Cognitive Map dynamics reveal distinct patterns. With high λ (1.0) and low α (0.01-0.05), the system quickly stabilizes with clear convergence of economic variables. However, when using medium to high α (0.1-0.4) with high λ , significant oscillations and divergence occur in complex concepts like Environmental Quality, Community Welfare, and ISPO Participation, indicating risk of over-adjustment from rapid weight adaptation. In contrast, moderate λ (0.5) produces more stable convergence with smoother trajectories across all α values. Even at higher learning rates ($\alpha = 0.4$), most concepts reach realistic equilibrium values, demonstrating greater resilience and robustness with lower λ values. This stability is especially valuable for long-term policy simulations or systems with uncertain dynamics.

One of the problems faced by palm oil farmers is their dependence on *Tengkulak* (middlemen). Limited funding, price fluctuations, low palm oil prices, and low production result in farmers being unable to obtain formal financing loans. Increasing farmers' production and income can reduce dependence on middlemen. This is also shown by the simulation results.

3D Phase Space: FFB Yield vs Farmer Income vs Tengkulak Dependence
 $\alpha = 0.05, \lambda = 0.5$

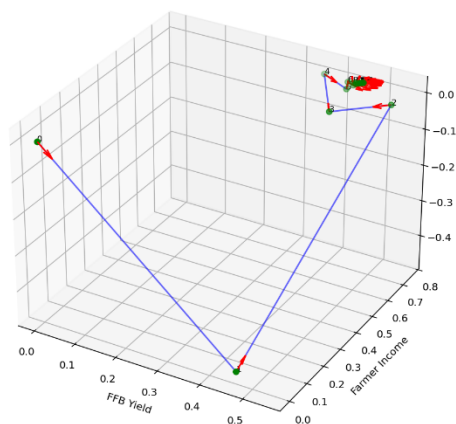


Figure 4. FFB Yield vs Farmer Income vs Middleman “Tengkulak” Dependence

From the 3D Phase Space graph with variables (Concepts) FFB Yield vs Farmer Income vs *Tengkulak* Dependence (with $\alpha = 0.05$ and $\lambda = 0.5$), it's evident that the system experiences

dynamics that eventually stabilize at a certain point. The value of Tengkulak Dependence decreases significantly from the starting point toward zero or even negative (if interpreted using tanh). The graph points show that after several iterations ($t=3$ to $t=20$), the system no longer fluctuates wildly, indicating stabilization.

The analysis reveals two positive trends: First, both FFB Yield and Farmer Income increase, demonstrating that within the existing causal relationship structure, increased productivity (FFB Yield) drives higher farmer income. Second, *Tengkulak* Dependence (middlemen) decreases, which is a positive signal indicating weakened dependence on middlemen. This reduction likely results from either more formal distribution channels becoming available or from farmers' increased income and bargaining position.

Suppose financial intervention is implemented. Strengthening access to formal financing, such as KUR (People's Business Credit) for smallholder palm oil farmers, so they can increase production capacity without dependence on middlemen. However, providing access to formal financing must be done carefully, as can be seen in the following explanation:

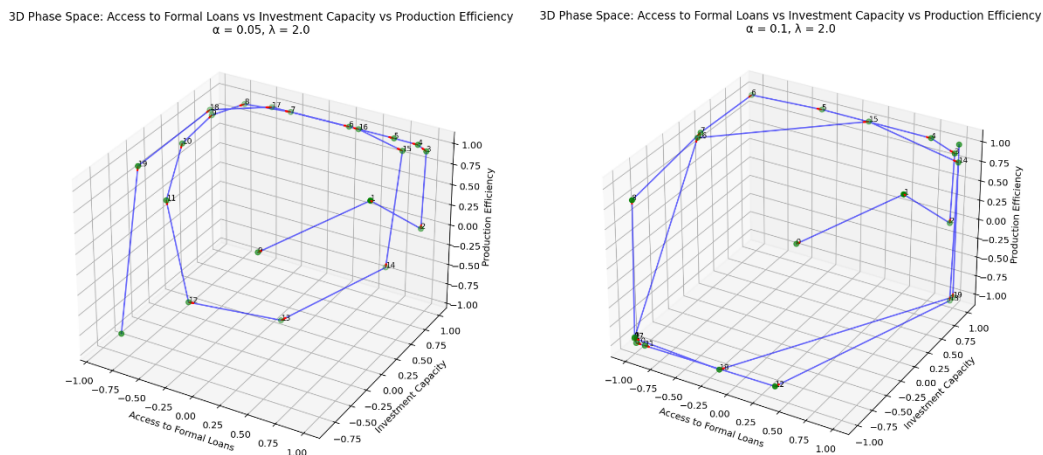


Figure 5. Simulation A ($\alpha = 0.05, \lambda = 2.0$) and B ($\alpha = 0.1, \lambda = 2.0$)

Based on the simulations provided, we can observe two distinct system behaviors under different parameter configurations. In Simulation A ($\alpha = 0.05, \lambda = 2.0$) on the left, the system exhibits large and somewhat wild oscillations before eventually stabilizing in a limit cycle pattern. This behavior indicates that the system requires more time to converge and tends to be less responsive to changes. From a policy perspective, interventions under these parameters would be characterized as conservative and stable, but with slow-acting impacts.

In contrast, Simulation B ($\alpha = 0.1, \lambda = 2.0$) on the right demonstrates sharper fluctuations with the system becoming notably more aggressive, approaching unstable conditions with significant overshooting. This indicates that the system is highly sensitive to small changes, exhibiting behavior similar to an over-adaptive system. Policy interventions under these parameters would be considered aggressive and rapid, but they carry substantial risks of social and economic instability if not accompanied by appropriate risk mitigation measures.

These findings highlight the importance of parameter selection when designing interventions in complex socio-economic systems like those involving smallholder palm oil farmers. The learning rate (α) and activation slope (λ) significantly influence how the system responds to policy changes, with higher values potentially leading to more rapid but potentially destabilizing effects. For policymakers, this suggests that careful calibration of intervention intensity is crucial to achieve desired outcomes while minimizing unintended consequences in vulnerable agricultural communities.

3D Phase Space: Access to Formal Loans vs Investment Capacity vs Production Efficiency
 $\alpha = 0.1, \lambda = 1.0$

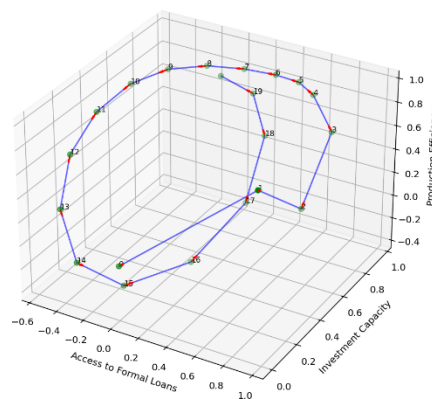


Figure 6. Balanced System $\alpha = 0.1$ and $\lambda = 1.0$ (Simulation C)

Simulation C demonstrates a more balanced system behavior with parameters $\alpha = 0.1$ and $\lambda = 1.0$. This configuration produces faster and smoother convergence, with data points gradually moving toward a stable state. The system exhibits adaptive yet stable characteristics, making it suitable for scenarios requiring gradual development and implementation. From a policy perspective, this configuration represents an incremental progressive approach that remains responsive to changes while maintaining controlled stability. This balanced configuration offers policymakers a framework for implementing interventions that can adapt to emerging circumstances without risking the system's overall stability. Access to Formal Loans consistently plays a catalytic role in enhancing Investment Capacity and subsequently Production Efficiency, supporting the policy of expanding inclusive credit mechanisms for smallholders.

5. CONCLUSION

5.1. Conclusion

Fuzzy Cognitive Mapping (FCM) has proven to be a powerful tool for understanding complex socio-economic systems, particularly in the agricultural sector. The analysis demonstrates FCM's ability to capture and simulate the dynamic relationships between various factors affecting smallholder palm oil farmers, from production efficiency to market access and environmental sustainability. Through parameter sensitivity testing (learning rate α and activation slope λ), the research reveals that optimal configurations ($\alpha = 0.05-0.1, \lambda = 0.5-1.0$)

can produce stable yet responsive system models that accurately reflect real-world conditions while avoiding chaotic behaviors.

The adaptive FCM implementing Hebbian Learning allows stakeholders to visualize interconnected challenges, test potential interventions, and identify optimal policy pathways before implementation. This participatory modeling approach bridges the gap between expert knowledge and community perspectives, creating a more holistic understanding of system dynamics. By incorporating feedback mechanisms inspired by reinforcement learning, FCM models can continuously evolve to reflect changing conditions, making them valuable tools for long-term policy planning in complex agricultural ecosystems. The simulation results provide clear direction for targeted interventions across four key areas: productivity improvement, market access strengthening, microfinance support, and price regulation—all calibrated to achieve maximum positive impact with minimal system disruption.

The development of Fuzzy Cognitive Maps (FCM) using Large Language Models (LLMs) represents a modern embodiment of Participatory Rural Appraisal (PRA), enabling inclusive community engagement in problem identification and knowledge representation through accessible, dialogue-based technology. Conversely, policy recommendations derived from FCM simulations and scenario generation exemplify Rural Rapid Appraisal (RRA) implementation, providing systematic expert analysis of complex agricultural systems. FCM effectively synergizes these complementary approaches by creating a unified framework where community knowledge (captured through LLM-facilitated participatory mapping) directly informs expert policy formulation (through simulation analysis). This integration bridges the traditional gap between bottom-up participation and top-down expertise, ensuring policy interventions are both technically sound and authentically representative of stakeholder perspectives, ultimately leading to more effective and sustainable agricultural development programs.

5.2. Recommendation

Results show productivity improvement should be prioritized through oil palm intensification programs focusing on efficiency and technology. Alternative market access via cooperatives and industry partnerships can reduce middleman dependence. Microfinance services, especially KUR, would help smallholders increase production independently. Minimum price regulations for FFB would limit middlemen's influence and ensure fair compensation. These interventions collectively address the economic and structural challenges facing Indonesian smallholder palm oil farmers.

Policy implementation should proceed cautiously. Middlemen are important and often benefit farmers, so rapid changes may disrupt the social system. Further policy simulations examining government intervention and formal finance could help create a balanced approach, giving farmers more options.

The model's analysis is limited by a small and homogenous PRA participant group. Future RRA or PRA studies should include more participants from diverse backgrounds to improve validity and applicability.

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