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Strategy for accelerating the realization of climate-smart agriculture using a circular economy perspective approach

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Abstract: This research aims to accelerate the realization of Climate Smart Agriculture (CSA) with a Circular Economy Perspective Approach. The research was conducted in Kopeng Village, Getasan District, Semarang Regency, Central Java. The sampling technique used in this research was the purposive sampling method to select research personnel. The first analytical method in this research is Mactor analysis. The second data analysis method used in this research is ANP (Analytic Network Process). The research results show that the strategy to accelerate the realization of Climate Smart Agriculture (CSA) using a circular economy perspective requires strong collaboration and synergy between stakeholders/actors. The stakeholders who have the strongest role and influence are organic farmers, research institutions, and universities. Efforts to realize climate-smart agriculture based on a circular economy have the main strategic objectives of increasing agricultural productivity amidst uncertain climate change and reducing farmers' dependence on the use of chemical inputs. The strategic priorities in realizing climate-smart agriculture based on a circular economy are selecting plant varieties that are resistant to extreme weather and improving water resource management.
Keywords: *Circular Economy, Climate Smart Agriculture (CSA), Mactor, ANP.*

1. Introduction

Climate change, which is increasingly happening now, has reduced economic growth and increased income inequality, due to the potential for food insecurity, scarcity of water resources and population movement. Several nations, such as Indonesia, are confronted with the possibility of significant losses and heightened vulnerability, particularly in agriculture. Over time, this could undermine progress toward reaching the Sustainable Development Goals (SDGs) [1, 2] .

Agriculture is a sector affected by climate change, but also a contributor to global warming [3]. Empirical evidence shows that of the 70% of GHG caused by human activities, 14% is contributed by the agricultural sector. In addition, pollution from pesticide residues and heavy metals in water and agricultural land is a serious problem facing the agricultural sector. Agricultural land contaminated with pesticide residues is dangerous for human and animal health [4]. Long-term heavy metal contamination will reduce soil fertility because it inhibits soil microbial activity, as well as reducing the soil's capacity to absorb nutritional elements and inhibit mineralization. On the other hand, the contribution to increased emissions from the agricultural sector comes from the use of chemical pesticides in Indonesia, which reached 1,597 tons per year. The low efficiency of using pesticides and chemical fertilizers has caused ecological damage and waste of resources [5].

Climate change can adversely affect biodiversity, natural resources, and environmental services,

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leading to potential losses for the nation, communities, and individuals alike. Changes in the frequency and intensity of rainfall and significant increases in temperature also contribute to a decrease in agricultural productivity of between 5-20 percent [6, 7]. As in the majority of developing countries, agriculture plays an important role in the Indonesian economy. The agricultural sector in Indonesia contributes 13.28% of Gross Domestic Product (GDP) and is able to absorb a workforce of 38.7 million. In the agricultural sector, the increasing frequency of extreme events has led to the proliferation of pests and diseases. Thus, efforts to reduce and adapt to the risks of climate change are needed to maintain and increase food security in Indonesia.

Problems arising from climate change and increasing agricultural sector activity over time result in a decline in environmental quality and sustainability [8]. The right approach is needed to be able to continue to support the economic system while preserving the surrounding environment. To address the potential negative effects of climate change on agriculture, one approach is the adoption of climate-smart agriculture, commonly known as Climate Smart Agriculture (CSA) [9, 10]. The implementation of climate smart agriculture has three main pillars, namely productivity, adaptation and mitigation. By implementing climate smart agriculture, it is hoped that it can increase agricultural productivity, reduce GHG emissions and also increase environmental sustainability.

In efforts to implement Climate Smart Agriculture (CSA), a circular economy approach can be used. This approach is intended to create clean and sustainable agriculture by utilizing waste as input for environmentally friendly agricultural production. The application of a circular economy can help farmers utilize surrounding waste to produce organic agricultural inputs to replace chemicals such as fertilizers, pesticides, insecticides and others. In this way, the negative impacts of the use of chemicals can be reduced and can help accelerate the realization of climate-smart agriculture.

Kopeng Village, which is located in Semarang Regency, Central Java, has abundant agricultural potential because it is located on a mountain slope, so the agricultural land in this village is also very fertile. However, the climate change that is occurring has made farmers in Kopeng Village overwhelmed in the agricultural production process. Erratic weather and increasingly widespread pest attacks have caused agriculture in Kopeng Village to experience a decline in quality and productivity.Apart from having abundant agricultural potential, Kopeng Village also has very attractive tourism potential. There are many tourist attractions and other supporting aspects in Aini Village such as hotels, restaurants and others. This can be used as a source of waste for local farmers to support agricultural production facilities using circular economy principles.

Research on strategies to accelerate the realization of Climate Smart Agriculture (CSA) using a Circular Economy (CE) perspective approach still faces several significant gaps, indicating an urgent need for further research and practical implementation [5, 11, 12]. One of the main gaps is the lack of empirical studies that test the real implementation of CSA and CE integration in the field. Most of the existing literature still focuses on theories and conceptual models without providing practical guidance that can be applied by farmers and agribusiness actors. Additionally, there are limitations in research that adapts CSA and CE strategies to specific local conditions, including geographic variations such as differences in climate, soil type, and traditional farming practices, as well as socio-economic factors such as farming scale and access to markets. This research aims to accelerate the realization of Climate Smart Agriculture (CSA) with a Circular Economy Perspective Approach.

2. Methods

The study was carried out in Kopeng Village, located in the Getasan District of Semarang Regency, Central Java. This location was chosen due to its significant agricultural potential and the high rate of agricultural land conversion. The research is planned to take place from April 2024 to December 2024. A purposive sampling method was employed to select the research participants. The initial analysis in this study uses the Mactor method, which offers an in-depth evaluation of the strategies and actions of various actors. The Mactor method (Alliance and Conflict Matrix: Tactics, Goals, and Recommendations) is based on the analysis of inter-actor dynamics and interactions. It aims to provide a broad view of the key issues, expected actor strategies, power structures, and possible alliances or conflicts. The main goal of this method is to explore potential developments within the system under study, helping to build more organized and coherent future scenarios. In this research, the Mactor method will be used to analyze stakeholders' preferences and their level of support for specific objectives [13]. Additionally, it will assess how much support each stakeholder provides for particular goals and groups. The Mactor method will also be utilized to identify the actors involved in implementing climate-smart agriculture with a circular economy approach. Once the key actors are identified, they will be categorized according to their roles, such as primary, key, or supporting actors. Moreover, the actor analysis will be used to examine the relationships and interactions between these different stakeholders.

Godet [14] The MACTOR technique is based on three primary inputs presented in matrix form. These inputs represent the 'relationships of influence' between actors. For example, the influence of actor A on actor D can be direct (from A to D) or indirect, through intermediate actors B and C. The MACTOR model uses a position matrix, referred to as 1MAO (Matrix Actor Objective) and 2MAO, which incorporates the Salience variable representing the actor-objective relationship. The third input is the MID (Matrix of Direct Influence), which represents the influence variables. In the software, users only need to input the MID matrix, 1MAO, and 2MAO matrices, which are then processed through a mathematical algorithm. Using the MID matrix, MACTOR calculates both direct and indirect effects of one actor on another, as shown in Figure (XX). This is represented in the MIDI matrix (Matrix of Indirect and Direct Influence), where the influence from A to B is computed using a specific formula:

$$MIDI_{A\to B} = MID_{A\to B} + \sum_{C} [\min(MID_{A\to C}, MID_{C\to B})]$$

This matrix is then utilized in the subsequent stage to assess the "balance of power." To determine this balance, it is necessary to first calculate the total direct and indirect influence of each actor. If interpreted as the total direct influence of actor A on others (for example B), then:M_A

$$M_A = \sum_{B} (MIDI_{A,B}) - MIDI_{A,A}$$

If defined as the total direct and indirect influence that actor A receives from other actors, it represents actor A's level of dependency, then:D_A

$$D_A = \sum_{B} (MIDI_{B,A}) - MIDI_{A,A}$$

By incorporating these two components along with the basic power coefficient, the calculation is then performed using a specific formula:

$$r_A = \left[\frac{(M_A - MIDI_{A,A})}{\sum_A (M_A)}\right] x \left[\frac{M_A}{M_A + D_A}\right]$$

In the next step, MACTOR calculates a crucial matrix, which serves as a fundamental component in the analysis and discussion. This matrix is produced from a previous process or is a product of and or $3MAOMACTOR3MAO2MAOr_A$

$$3MAO_{A,i} = 2MAO_{A,i} \times r_A$$

By analyzing this matrix, various analytical outputs can be generated. One of these is the mobilization coefficient, which indicates how each actor responds in a given situation. This feature is generated through a formula $3MAO$

$$Mob_A = \sum |3MAO|$$

The analysis results also reveal areas of agreement and disagreement concerning a goal, which are determined through specific calculations: $3MAO$

$$Ag_A = \sum_{a} (3MAO_{A,i}(3MAO > 0))$$

$$DisAg_A = \sum_{a} (3MAI_{Ai}(3MAO < 0))$$

Another key feature derived from the matrix is the convergence matrix, which indicates the extent to which actors agree on a particular issue, while divergence represents the optimal scenario. The convergence matrix is calculated using a specific equation:$3MAO(3CCA)(3DDA)$

$$3CAA = \frac{1}{2}\sum_{i}(|3MAO_{A,i}| + |3MAO_{B,i}|)(3MAO_{A,i} \times 3MAO_{B,i} > 0)$$

While the divergence matrix is written:

$$3DAA = \frac{1}{2}\sum_{i}(|3MAO_{A,i}| + |3MAO_{B,i}|)(3MAO_{A,i} \times 3MAO_{B,i} < 0)$$

The calculation of convergence and divergence between actors ultimately leads to the determination of the final indicator, known as the ambivalent coefficient for each actor, which is derived using a specific formula $MACTOR$

$$3EQ_i = 1 - \left[\frac{(\sum_k ||3CAA_{i,k} - 3DAA_{i,k}||)}{\sum_k ||3CAA_{i,k} + 3DAA_{i,k}||}\right]$$

These formulas outline the analytical framework. In practice, the analysis is guided by the following principles:$MACTORMACTOR$

1. Create a table outlining the "strategies of actors."
2. Identify the strategic issues and objectives.
3. Map the actors' positions concerning the advantages and disadvantages of the objectives.
4. Determine the priority goals for each actor.
5. Analyze the balance of power for each actor.
6. Integrate the balance of power into the analysis of convergence and divergence.
7. Formulate key questions for the reconstruction process.

The second approach utilized for data analysis in this research is the Analytic Network Process (ANP), a mathematical model created to support decision-making when multiple interrelated factors (dependencies) and feedback loops are involved. The ANP method considers both internal interactions and feedback within a particular cluster (internal dependence) and external interactions between different clusters (external dependence). Within ANP, comparisons are made among the elements of each cluster to evaluate the interactions across the entire network. This method relies on three core principles that form the theoretical basis of the technique. These principles are considered valid based on common understanding, without needing empirical validation. According to these principles:

2.1. Reciprocal

If activity X is deemed six times more significant than activity Y, then the importance of activity Y is one-sixth that of activity X.

2.2. Homogeneity

This principle indicates that when the elements being compared have only a slight difference, the likelihood of making judgment errors increases substantially. Unlike the typical Likert scales, which usually range from 1 to 5, the scales used in the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) are distinct. Specifically, the ANP scale has a broader range, stretching from 1 to 9. The following section details the scale employed in the ANP.

Table 1.
Scales in ANP.

Description	**Level of Importance**	**Explanation**
Very much greater influence/level of influence	9	There is compelling evidence that strongly favors one element over the other, with a high likelihood of confirmation
Between grades 7-9	8	A middle value that represents two neighboring values
Very much greater influence/level of importance	7	One element is clearly superior to the others, as evidenced in practice
Between 5-7	6	A middle value that represents two neighboring values
Greater influence/level of importance	5	Experience and judgment clearly favor one element over the other
Between 3-5	4	A middle value between two neighboring values
Slightly greater influence/level of importance	3	Experience and judgment somewhat favor one element over the other
Between 1-3	2	A middle value that represents two closely related values
The same magnitude of influence/level of importance	1	The two elements being compared have an equal contribution to the goal

The procedure for performing an analysis with the Analytic Network Process (ANP) is illustrated in the image below:

Step 1: Formation of the ANP Network

The formation of the Analytic Network Process (ANP) network involves structuring a decision problem into interconnected elements and clusters, allowing for dependencies and feedback loops. The process begins by identifying key elements and grouping them into clusters, followed by establishing relationships between them.

Step 2: Pairwise Comparisons

Pairwise comparisons involve evaluating two elements at a time to determine their relative importance or preference based on a specific criterion. Experts or decision-makers assign numerical values using a predefined scale, such as the Saaty scale, to quantify the strength of one element over another. These comparisons are then used to construct a matrix, which helps derive priority weights through normalization and consistency analysis.

For an $n \times n$ pairwise comparison matrix, the number of comparisons needed is determined using the formula $n \times (n-1)/2$, where n represents the total number of elements being assessed. Furthermore, reciprocal values can be automatically calculated and assigned for reverse comparisons within the matrix. The pairwise comparison value aij must satisfy the following equation:

$aij \times aji = 1$

Here, aij represents the value of the pairwise comparison, which is determined using the fundamental scale.

Step 3: Consistency Check

By evaluating the resulting comparison matrices, eigenvectors are extracted, which represent the weights of the elements. The local priority vector is then computed as shown in the following equation:

$Aw = \lambda max$

where A represents the matrix of pairwise comparison values; w is the priority vector, also known as the principal eigenvector; and λmax is the maximum or principal eigenvalue of matrix A.

Consistency check in pairwise comparisons ensures that the judgments made by decision-makers are logically consistent. It involves calculating the consistency ratio (CR), which compares the consistency index (CI) of the judgment matrix with a random index (RI). A CR value below 0.1 indicates acceptable consistency, while higher values suggest the need for adjustments in the comparisons to improve reliability. The CI and CR are calculated using the equation shown below:

$CR = CI/RI$

with CI = (λmax−n)/(n−1) (3) where CR represents the consistency ratio; CI represents the consistency index; RI represents the random index; and n is the size of matrix A.

Step 4: Supermatrix and Global Priority Calculation

Relative importance is established through pairwise comparisons. However, this alone does not completely capture the differences between clusters and elements. To overcome this, the supermatrix is utilized, as demonstrated in the equation below:

$$W = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} & \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix} \end{array}$$

(ANP) is a structured matrix that represents the n network. It is formed by arranging the local nto a weighted supermatrix, which accounts for o derive the global priority, the supermatrix is onverges to a stable state, ensuring consistent priority values for final decision-making.

3. Results and Discussion

In the strategy to accelerate the implementation of Climate Smart Agriculture (CSA) with a circular economy approach, collaboration and synergy among various relevant stakeholders are essential. These stakeholders include regional government groups, village governments, communities, entrepreneurs, farmer organizations, and non-profit organizations. Their involvement considers the following factors:

1. These stakeholders/actors hold the authority to implement Climate Smart Agriculture in Kopeng Village.
2. These stakeholders/actors will be affected by the implementation of Climate Smart Agriculture.
3. The participation of these stakeholders/actors is critical for the success of Climate Smart Agriculture in Kopeng Village.
4. These stakeholders/actors possess the necessary competence to implement Climate Smart Agriculture.

Considering these factors, the stakeholders/actors who serve as the data sources for this research are as follows:

Table 2.
Stakeholder/Actor Mapping.

No	Stakeholders/Actors	Issue	Objectives/Goals
1	Organic farmer	Strategy for Accelerating the Realization of Climate Smart Agriculture (CSA) with a circular economy perspective approach	Economic aspect: Increased production Increasing farming efficiency Increase in farmer income Social aspect: Economic equality Increased welfare Poverty reduction Environmental Aspects: Reducing the use of chemical agricultural inputs Biodiversity conservation
2	Conventional farmers		
3	Public		
4	Research institutions		
5	Agriculture-based business and industry world		
6	College		
7	Trader		
8	Department of agriculture		
9	Financial institutions		

Based on Table 2, the mapping of actors involved and interested in the Acceleration Strategy for the Realization of Climate Smart Agriculture (CSA) with a circular economy approach includes 9 actors. The composition of these actors demonstrates a diverse set of characteristics, reflecting involvement across various sectors, government levels, and non-governmental institutions. These actors are entities that have an interest in, and a role in mobilizing resources to influence the realization of smart agriculture in Kopeng Village. Understanding the relationships between these actors is crucial to advancing efforts to accelerate the implementation of Climate Smart Agriculture (CSA) from a circular economy perspective. To analyze these relationships, the researchers employed Mactor software (Matrix of Alliance Conflict Tactics Operations and Responses). The following section outlines the relationships between the actors in the smart agriculture climate model for Kopeng Village.

Table 3.
Influence and dependency matrix between actors.

MDII	Organic farmer	Conventional farmers	Public	Research institutions	Business world and industrial world	College	Trader	Department of agriculture	Financial institutions	II
Organic farmer	24	21	22	22	24	23	23	12	24	195
Conventional farmers	11	24	21	20	20	15	13	20	14	158
Public	23	19	13	21	18	17	14	15	14	154
Research institutions	24	18	21	20	24	16	17	12	18	170
Business world and industrial world	16	19	20	17	21	17	22	11	17	160
College	24	20	17	18	24	18	20	14	19	174
Trader	20	21	19	19	14	20	16	21	13	163
Department of agriculture	12	22	20	12	21	12	24	23	18	164
Financial institutions	21	17	21	11	14	14	24	16	22	160
In	175	181	174	160	180	152	173	144	159	1498

Table 3 indicates that stakeholders with the highest influence in the Acceleration Strategy for the Realization of Climate Smart Agriculture (CSA) include the Department of Agriculture (score of 194), Organic Farmers (score of 195), Universities (score of 174), and Research Institutions (score of 170). On the other hand, the stakeholder with the lowest influence is the consumer community, with a score of 154. Additionally, stakeholders with a higher tendency to be dependent are conventional farmers (score of 181) and the business and industrial sectors (score of 180). In contrast, the stakeholder with the lowest dependency is the Department of Agriculture, with a score of 144.

The actor preference matrix for goals illustrates the preferences of the stakeholders involved concerning the desired goals or targets for implementing Climate Smart Agriculture (CSA) in Kopeng Village. These goals are divided into three categories: economic, social, and environmental. The economic category includes goals such as boosting production, enhancing farming efficiency, and increasing farmer income. The social category focuses on promoting economic equality, improving welfare, and alleviating poverty. The environmental category aims at reducing the use of chemical agricultural inputs and preserving biodiversity. The level of actor mobilization and objectives are outlined in the following table:

Table 4.
Degree of actor mobilization and goals.

2MAO	**Increased Productivity**	**Increasing farming efficiency**	**Increasing Farmer Income**	**Economic equality**	**Increased welfare**	**Poverty Reduction**	**Reducing the use of chemical agricultural inputs**	**Biodiversity conservation**	**Absolute Sum**
Organic farmer	2	3	4	2	2	3	4	2	22
Conventional farmers	4	3	2	3	3	4	-2	4	21
Public	2	3	0	2	3	2	3	2	17
Research institutions	2	0	2	1	1	0	2	2	10
Business world and industrial world	4	1	3	2	3	3	3	2	21
College	4	2	0	2	1	1	4	3	17
Trader	3	4	0	2	0	-4	2	2	9
Department of agriculture	3	2	3	1	2	3	2	1	17
Financial institutions	1	2	0	2	3	2	4	2	16
Number of agreements	25	20	14	17	18	14	22	20	
Number of disagreements	0	0	0	0	0	-1	-1	0	
Number of positions	25	20	14	17	18	13	21	20	

Table 4 shows the position of each actor on each target/goal (objective), considering the level of each actor's opinion regarding the competitiveness target and the hierarchy of the targets. The output of this matrix serves two purposes. First, it determines the degree of mobilization, which highlights the target/objective that most engages the actors. Second, it identifies the actors who are most active in mobilizing their resources to achieve these goals or objectives.

The degree of mobilization (shown in the bottom row) reveals which goals are expected to become the primary issues that provoke stakeholder reactions. In the efforts to realize a smart agriculture climate, the most pressing issues are increasing productivity (score of 25) and reducing the use of chemical agricultural inputs (score of 22). The actors most mobilized to address these issues are organic farmers (score of 22), conventional farmers (score of 21), and the industrial sector (score of 21). These actors are the most actively engaged in responding to challenges in realizing a smart agriculture climate in Kopeng Village.

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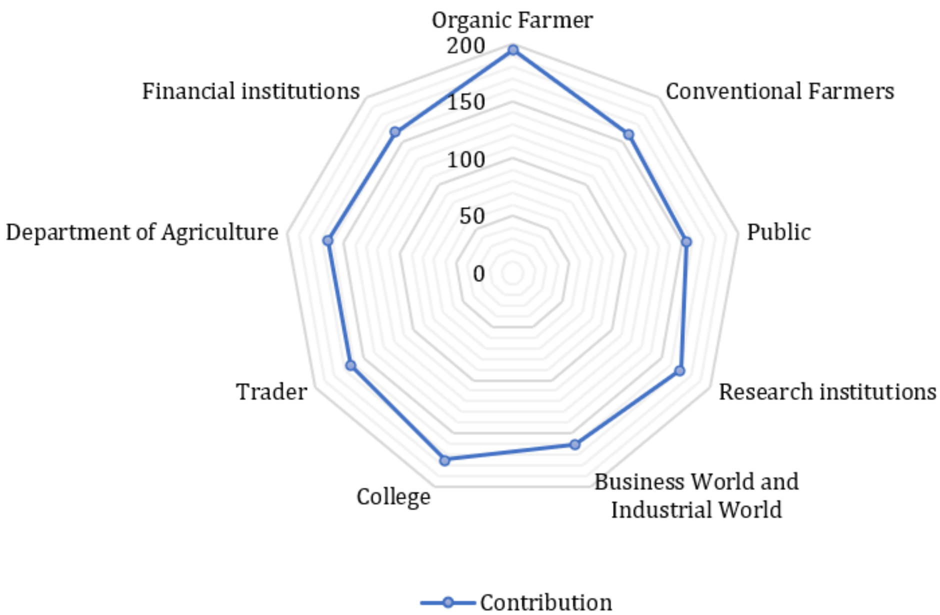

Figure 1.
Actor role patterns in realizing climate smart agriculture.

Figure 1 shows that the level of convergence (agreement and alignment) among actors in implementing Climate Smart Agriculture in Kopeng Village is generally moderate. By examining the objectives/goals and their roles in mobilizing resources, we can identify the actors with the "strongest convergences," who play the most important role in realizing Climate Smart Agriculture. These key actors include organic farmers, research institutions, and universities. Organic farmers must act as influencers, encouraging conventional farmers who still rely on inorganic methods to transition to CSA farming based on a circular economy approach. Currently, most farmers in Kopeng continue to depend on inorganic farming practices. The critical role of these key actors will be supported by those in the "strong convergences" category, including organic farmers, research institutions, and universities.

The results from the ANP (Analytic Network Process) analysis show that the pairwise comparison matrix between criteria/groups was created based on questionnaires filled out by key individuals. This matrix uses values ranging from 1 to 9. After completing the assessments, the average value from the questionnaires is calculated to derive a relative value. This relative value is then used as input for the ANP, specifically in the super decision application developed by M. Saaty. Below are the results of group comparisons between the criteria:

Table 5.
Results comparative analysis between criteria.

Criteria	Weight
Reducing chemical inputs	0.3121
Efficient irrigation management	0.1251
Sustainable soil conservation	0.2373
Climate change adaptation and mitigation	0.1032
Increasing the social and economic welfare of farmers	0.1437
Efficient farming management	0.2132

Table 5 shows the priority strategy for realizing a circular economy-based smart agriculture climate, based on the priority value (eigenvector). The criterion for reducing chemical inputs ranks first

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with a value of 31.21%. In second place is sustainable soil conservation with a value of 23.73%. Meanwhile, efficient farming management takes third place with a value of 21.32%.

3.1. Priority Order Based on Criteria

The final priority in the ANP model is determined through absolute weighting using an interval scale (1.0), which also serves as an indicator of relative dominance. The priority value is calculated by normalizing the matrix vector. In the final priority, there are limiting weights that are normalized by cluster and ranked accordingly. The final priority value, shown in the table below, reflects the weight of all elements, including those with limiting weights and those normalized by cluster. The limiting weight comes from the limit supermatrix, while the normalized by cluster refers to the division of limiting element weights by the total sum of those weights within a component. The final priority is used to identify the best alternative, which is the one with the highest final value. Below are the final priorities for selecting a strategy to implement circular economy-based smart agriculture:

Table 6.
Results of comparative analysis of all criteria and sub-criteria.

No	Criteria	Sub criteria	Normalized by cluster	Limiting
1	Sustainable soil conservation	Use of land cover	0.2364	0.0564
		No-till land management	0.1257	0.0346
		Crop rotation	0.3386	0.0766
2	Efficient irrigation management	Prevention of water pollution	0.1421	0.0289
		Improved water resources management	0.3464	0.0956
		Water saving irrigation	0.3114	0.0561
3	Efficient farming management	Plant various types of plants	0.1593	0.0131
		Maintain wild vegetation	0.2247	0.0187
		Implement intercropping	0.3162	0.0271
4	Reducing chemical inputs	Use of organic pesticides	0.0764	0.0187
		Use of biological fertilizer	0.1563	0.0317
		Integrated pest management	0.1077	0.0238
		Reduction of chemical fertilizers and pesticides	0.2598	0.0485
5	Increasing the social and economic welfare of farmers	Promote fair trade	0.1217	0.0298
		Improving decent working conditions	0.2193	0.0188
		Increased access to education and technology	0.3592	0.0311
6	Climate change adaptation and mitigation	Weather forecast when planting	0.0301	0.0292
		Crop diversification	0.0488	0.0348
		Reduce greenhouse gas emissions	0.1257	0.0579
		Choose plant varieties that are resistant to extreme weather	0.3957	0.1391

From Table 6, the strategic priorities for realizing a circular economy-based smart agriculture climate are presented. The priorities chosen above reflect strategies that have been determined by the key person—an individual with expertise in the field—and processed through the Super Decision application to derive a strategy for realizing a smart agriculture climate based on a circular economy. These priorities are based on all sub-criteria elements, with the most prioritized strategy being the selection of extreme weather-resistant plant varieties, which has a limiting value of 13.91%. The second priority is improving water resources management, with a limiting value of 9.5%. Lastly, the final priority is planting a variety of plant types, which has a limiting value of 1.3%.

4. Discussion

Cimate Smart Agriculture (CSA) focuses on three main pillars, namely increasing agricultural productivity in a sustainable manner, building resilience to climate change, and reducing greenhouse gas emissions. On the other hand, Circular Economy (CE) aims to minimize waste and maximize resource reuse through closed cycles in production and consumption systems. The integration of these two approaches can create an agricultural system that is not only productive and resilient to climate change, but also efficient and environmentally friendly [3].

To accelerate the realization of CSA with a CE approach, strategies need to be developed that include technological innovation, local adaptation, supportive policies, and increasing farmer capacity [2]. Technological innovations such as the use of climate sensors, drones and artificial intelligence can help farmers optimize the use of water, fertilizer and pesticides, as well as predict extreme weather conditions. This technology can also be used to monitor plant health in real-time, thereby reducing crop losses and increasing production efficiency. Additionally, agricultural practices such as agroforestry, crop rotation, and the use of organic fertilizers can be integrated within the CE framework to support environmental and economic sustainability [8].

Adaptation of CSA and CE strategies to local contexts is also critical. Each region has different climatic conditions, soil types and traditional agricultural practices, so a one-size-fits-all approach will not be effective [9]. In-depth local research is needed to adapt these strategies to specific conditions, as well as to identify and exploit existing local potential. In addition, socio-economic factors such as the scale of the farming business, access to markets, and the farmer's education level must also be considered in developing this strategy [10].

Supportive policies are another key element in accelerating the realization of CSA with a CE approach. Governments need to develop policies that provide economic incentives for sustainable agricultural practices, such as subsidies for green technologies, microcredit for small farmers, and training programs. These policies should be supported by regulations that reduce barriers to the adoption of CSA and CE practices, as well as promote research and development in these areas 9 [15].

Increasing farmer capacity through education and training is also very important. Farmers need to be provided with the knowledge and skills necessary to implement CSA and CE practices. Training programs can cover how to use new technologies, sustainable farming practices and climate risk management. Collaboration between government, the private sector, academia and local communities is also needed to create an ecosystem that supports the adoption of CSA and CE [16]. The role of organic farmers and research institutions is very crucial in the strategy to accelerate the realization of Climate Smart Agriculture (CSA) with a Circular Economy (CE) perspective approach. Organic farmers, with their commitment to sustainable agricultural practices, already apply many principles in line with CSA and CE [6]. They avoid the use of synthetic chemicals, exploit natural cycles to increase soil fertility, and often use crop diversification techniques that can increase resilience to climate change. These practices not only reduce negative environmental impacts but also support the long-term sustainability of agricultural systems [7]. By adopting and promoting innovative technologies such as compost from organic waste, rainwater harvesting, and renewable energy, organic farmers can become a model for the integration of CSA and CE, demonstrating that resource efficiency and climate resilience can be achieved without sacrificing productivity.

Research institutions play an equally important role in accelerating the realization of CSA with a CE approach. Through research and development, the institute can explore and develop new technologies, best practices and innovative farming systems. Research on climate-resilient crop varieties, soil management techniques that increase carbon sequestration, and efficient methods of water management are critical to supporting CSA. Additionally, research institutions can help identify and measure the environmental and economic impacts of CSA and CE practices, providing the empirical data needed to shape effective policies and support decisions at the field level.

Climate change adaptation and mitigation play a central role in the strategy to accelerate the realization of Climate Smart Agriculture (CSA) with a Circular Economy (CE) perspective approach. Adaptation in this context refers to the ability of agricultural systems to adapt to changing climatic conditions and reduce the resulting negative impacts. This includes using plant varieties that are resistant to drought, flooding, and temperature extremes, as well as implementing efficient water management practices, such as drip irrigation and rainwater harvesting [11]. Adaptation also involves

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diversifying crops and planting patterns to reduce the risk of crop failure due to uncertain climatic conditions. By integrating CE principles, such as reusing crop residues as compost and managing organic waste to improve soil fertility, farmers can increase the resilience of their farming systems to climate change while minimizing waste and maximizing resource utilization.

On the other hand, climate change mitigation within the CSA framework focuses on reducing greenhouse gas emissions produced by agricultural activities. This involves practices such as efficient fertilizer management to reduce nitrogen oxide emissions, use of organic fertilizers that reduce dependence on synthetic chemicals, and tree planting and agroforestry that serve as carbon sinks [12]. Better livestock management, including efficient feeding and manure management, also contributes to reduced methane emissions. The CE approach strengthens these mitigation efforts by ensuring that every input in the agricultural system is used as efficiently as possible and converted into value-added products or reprocessed into resources, reducing the need for external inputs that often contribute to greenhouse gas emissions [17].

Collaboration between adaptation and mitigation creates synergies that strengthen the agricultural system as a whole. For example, conservation farming techniques that reduce tillage not only help in carbon sequestration but also increase soil water retention, making crops more resistant to drought [18]. Likewise, agroforestry systems not only sequester carbon but also provide shade and wind protection for plants, as well as increasing biodiversity which can help control pests naturally. The implementation of CE principles in adaptation and mitigation ensures that every step taken to reduce the impacts of climate change also contributes to resource efficiency and long-term sustainability.

5. Conclusion

Based on the results and discussion, it can be concluded that in strategic effortsAccelerating the Realization of Climate Smart Agriculture (CSA) with a Circular Economy Perspective Approach requires strong collaboration and synergy between stakeholders/actors. The stakeholders who have the strongest role and influence are organic farmers, research institutions and universities. Efforts to realize climate smart agriculture based on a circular economy have the main strategic objectives of increasing agricultural productivity amidst uncertain climate change, and reducing farmers' dependence on the use of chemical inputs. The strategic priorities in realizing a smart agriculture climate based on a circular economy are selecting plant varieties that are resistant to extreme weather and improving water resource management.

The results of this research provide practical implications, namely increasing resource efficiency in the agricultural sector. By integrating CE principles, such as reusing agricultural waste as compost or bioenergy, farmers can reduce dependence on expensive and potentially environmentally damaging external inputs. This not only lowers production costs but also increases environmental sustainability by reducing greenhouse gas emissions and minimizing waste.

Additionally, adoption of CSA technologies and practices developed through this research can help farmers overcome the challenges of climate change. For example, the use of crop varieties that are resistant to extreme climate conditions, efficient irrigation practices, and soil management techniques that increase water retention and carbon sequestration can increase agricultural resilience and productivity. In this way, farmers can be better prepared to deal with extreme weather events such as drought or floods, which are becoming more frequent due to climate change. This also has implications for increasing food security, because a more resilient agricultural system can guarantee stable food availability even in the midst of climate challenges.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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