



Human–Computer Interaction-Driven Analytical Framework for Determining Optimal Sustainable Agriculture Strategies

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ABSTRACT

This study develops an innovative decision-making model for prioritizing sustainable agriculture strategies using a human-computer interaction (HCI)-based approach. A fundamental problem facing sustainable agriculture today is the inability to objectively determine which strategies will yield more effective results under limited resources. In the literature, most studies addressing this issue have subjective expert assessments, ignoring or assuming equal weight in the decision-making process. This methodological shortcoming reduces decision quality and limits implementation success. To address this shortcoming, the model developed establishes a dynamic interaction process with experts, in line with human-computer interaction principles, and determines the importance weights of experts using a machine learning algorithm. This approach objectively calculates each expert's contribution to the decision-making process by analyzing the experts' demographic characteristics, experience levels, and evaluation behaviors. In the analytical phase of the model, criteria weights are determined using the SIDTE method, alternative rankings are performed using the RATGOS technique, and Gaussian fuzzy sets are used to model uncertainties. Thanks to this integrated structure, the developed model offers a strong methodological contribution that fills the gap in the literature by integrating both human expertise and artificial intelligence-supported learning within the same framework. The findings indicate that the most important criterion is renewable energy and circular economy applications (.168), followed by the development of digital agricultural technologies and control mechanisms (.156). Furthermore, the most optimal sustainable agricultural strategy was determined to be renewable energy-supported agricultural applications (.142). These results demonstrate that human-computer interaction-supported machine learning-based decision models offer significant advantages in terms of both analytical accuracy and implementation efficiency in the development of sustainable agricultural policies.

1. Introduction

Sustainable agriculture refers to the efficient and balanced use of natural resources. These practices are a production approach that aims to maintain the ecological balance and ensure the long-term economic, environmental, and social sustainability of agricultural production. This approach offers holistic solutions to global problems such as increasing global population, climate change, and the depletion of soil and water resources. Thus, it both ensures food security and supports rural development. The fundamental importance of sustainable agriculture lies in ensuring

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that agricultural activities are carried out without harming the environment, preserving natural ecosystems, and ensuring a livable environment for future generations. Various technological and application-based strategies developed within this scope make production processes more efficient and environmentally friendly [1]. Organic farming and agroecological practices naturally increase soil fertility by reducing the use of chemical fertilizers and pesticides, protect biodiversity, and strengthen ecosystem services. Renewable energy-supported agricultural practices, particularly using solar and wind energy for agricultural irrigation, greenhouse heating, or energy needs, reduce dependence on fossil fuels and significantly reduce carbon emissions. Cooperatives and green financing models facilitate farmers' access to environmentally friendly production technologies through economic collaboration, while also increasing financial resilience through low-interest loans and sustainable investment funds [2]. Climate-friendly irrigation technologies, including sensor-based systems, drip irrigation, and sprinkler systems, prevent water waste, reduce production costs, and create drought-resistant agricultural infrastructure. When all these strategies come together, sustainable agriculture becomes a holistic development model that not only ensures environmental protection but also enhances economic efficiency, social well-being, and the future sustainability of agricultural production.

Identifying the most important sustainable agriculture strategies is crucial for ensuring the effective, efficient, and targeted use of limited budgets. Because agricultural production processes are often conducted under financial, environmental, and social constraints, not knowing which strategies should be prioritized can lead to misallocation of resources, reduced investment efficiency, and policy failures. Therefore, various criteria must be considered when prioritizing sustainable agriculture strategies. Cost and financing sustainability ensure the long-term economic viability of strategies, while the development of digital agricultural technologies and audit mechanisms increases traceability and efficiency in production processes. Policies and regulations constitute the institutional framework that determines the applicability of these strategies. However, it is necessary to determine which of these criteria are most important, i.e., to systematically determine their weights [3]. Otherwise, accurately defining the most important strategies becomes quite difficult. The number of studies in the literature that simultaneously determine both the most critical sustainable agriculture strategies and the weights of the criteria to be used in prioritizing these strategies is quite limited [4]. This presents a significant gap in the literature and creates significant uncertainties for decision-makers. Lack of clarity on criteria weights leads to policymakers' inability to rationally plan resource allocation, environmental objectives conflicting with economic constraints, and strategic priorities being misaligned. In this context, a new priority analysis and a holistic assessment approach based on multi-criteria decision-making are needed. Such an analysis, by establishing a balance between the different dimensions of sustainable agriculture, will both address a gap in the academic literature and provide a more robust decision-making framework for practitioners.

The objective of this study is to develop a holistic, data-driven, decision-supporting model for identifying the most effective strategies in sustainable agriculture. The motivation for this study stems from the fact that the methods used in prioritizing sustainable agriculture strategies in the existing literature are largely based on subjective expert assessments, unclear relationships between criteria and alternatives, and insufficient consideration of fuzzy environmental conditions. The new decision-making model, developed to address these shortcomings, has an innovative structure that integrates machine learning and multi-criteria decision-making approaches. During the research process, a comprehensive literature review was conducted on the subject, and four strategy types representing different dimensions of sustainable agriculture and seven effective criteria for

evaluating these strategies were identified. Subsequently, a group of ten experts with deep expertise on the subject was formed, and the importance weights of these experts were calculated using a machine learning-based model. This phase aimed to systematically evaluate each expert's opinion and reduce the influence of bias in the decision-making process. In the analytical phase of the model, the SIDTE method was used to determine the relative importance of the criteria, and the final ranking of the strategy alternatives was achieved using the RATGOS method. In this process, Gaussian fuzzy numbers were considered to represent the uncertainties and linguistic variables in expert evaluations. Thanks to this methodological integrity, the study both fills the methodological gap in the literature theoretically and provides a practical decision support tool for policy makers, researchers, and agricultural planners. In this context, the main research questions of the study are defined as follows: (1) Which criteria play a dominant role in determining the most effective strategies in sustainable agriculture? (2) How does the integration of machine learning-based expert weighting and fuzzy multi-criteria decision-making improve decision quality in strategy ranking processes? (3) What methodological advantage does the combined use of the SIDTE and RATGOS methods provide over existing methods in the literature in prioritizing sustainable agriculture strategies? The study seeks answers to these research questions and aims to provide an innovative approach to the strategic planning of sustainable agriculture.

This study presents an innovative decision-making model that fills a methodological gap in the literature by integrating machine learning-based expert weighting with Gaussian fuzzy multi-criteria decision-making approaches for the prioritization of sustainable agriculture strategies. The developed model offers several methodological and analytical advantages over existing decision-making models in the literature for the prioritization of sustainable agriculture strategies. (1) First, the use of machine learning techniques in determining the importance weights of experts is one of the most significant innovations of the model. This approach objectively calculates expert weights by considering variables such as experts' demographic characteristics, experience levels, and domain knowledge. In many studies in the literature, expert weights are assumed equal or determined based on subjective assessments. This introduces uncertainty and bias into the decision-making process. Thanks to machine learning-based weighting, the model achieves a more realistic, reliable, and data-driven structure, thus significantly improving decision quality and methodological consistency. (2) The second advantage of the model is the development and integration of Gaussian fuzzy sets into the analysis. Gaussian fuzzy sets, thanks to the continuous and smooth structure of their membership functions, represent uncertainty more accurately and can model linguistic variables in expert judgments more precisely. Compared to triangular or trapezoidal fuzzy sets, the Gaussian approach reduces the impact of extreme values, minimizes information loss, and provides a more balanced uncertainty management in the decision-making process. In this respect, the model offers a more flexible and sensitive analysis capability than classical formulations of fuzzy logic. (3) Third, the RATGOS (Ranking Alternatives Through Gaussian Optimization System) technique used to rank strategy alternatives is another innovation that enhances the analytical power of the model. RATGOS evaluates the performance of alternatives using a geometric mean-based approach, thereby compensating for scaling differences in the data and reducing the impact of extreme values on the ranking. While numerous ranking methods such as TOPSIS, VIKOR, and COPRAS are used in the literature, RATGOS offers a more suitable solution for multidimensional and uncertain issues such as sustainable agriculture. This is because it produces a more stable and holistic ranking output by considering the interactions between criteria in a Gaussian fuzzy environment. Therefore, the developed model demonstrates a significant advantage over previous models, both theoretically and

practically, thanks to its machine learning-based expert weighting, the adaptive structure of Gaussian fuzzy sets, and the geometric mean-based computational approach of the RATGOS technique.

One of the key criteria for enhancing the effectiveness of sustainable agriculture strategies' impact on climate change and income distribution is the sustainability of costs and financing. Green finance is crucial for high-quality agricultural development. Green finance not only supports the high-quality implementation of local agriculture but also contributes to the development of agriculture on a regional basis. This situation is also influential in determining new strategies that will reduce inequality in income distribution [5]. Indeed, Saqib et al. [6] argued that new agricultural strategies need to be developed to help farmers combat climate change. The study highlights the importance of financial sustainability in the development of new technologies. In another similar study, Şimşek [7] stressed that sustainable agricultural practices are important in ensuring global food security. The study emphasized that financial support is important in developing sustainable agricultural practices against climate change. The effects of sustainable agricultural practices on climate change and income distribution are linked to the effectiveness of digital technologies and control mechanisms. In this context, Tay et al. [8] shed light on the potential of community-supported agriculture. It is emphasized that digital agricultural technologies and the control mechanisms related to these technologies will contribute to community-supported agriculture.

Rural employment creation and migration prevention measures are effective criteria for increasing the effectiveness of sustainable agricultural practices in reducing climate change and income inequality. Practices that encourage rural employment, improvements in food processing and supply chain processes, incentive mechanisms, education and youth policies, and property regulations are practices that will prevent rural migration and contribute to rural employment creation [9]. Ding et al. [10] emphasize in their study that the development of digital infrastructure will increase the quality of rural employment. It is stated that this will improve the quality of the rural workforce and prevent migration. Similarly, Lidder and Chaya [11] stated that technological developments and automation are effective in increasing rural employment. The study emphasized that technological developments play an effective role in creating rural employment. Access to education and information can also be listed among the criteria that are effective in increasing the effectiveness of sustainable agriculture strategies. Educated farmers with high access to information contribute to the development of strategies compatible with climate change [3]. They contribute to climate-resilient sustainable agriculture by developing adaptive innovation methods. For example, Hasan et al. [4] highlighted the importance of agricultural literacy in the adoption of sustainable agriculture initiatives and open innovation approaches. Finally, Chauhan and Wehrden [12] pointed out in their study that education is important in making current agricultural policies implemented in India sustainable.

Another effective criterion in mitigating the impacts of sustainable agriculture strategies on climate change adaptation and income inequality is the conservation of biodiversity. The conservation of biodiversity and the efficient use of resources are fundamental pillars of sustainable agriculture [2]. These strategies increase resilience to climate risk, while the efficient use of resources also enables the creation of policies to combat resource scarcity. Indeed, Abed et al. [13] emphasized the importance of biodiversity conservation in the global agricultural system. The study highlighted that the use of artificial intelligence-based monitoring systems would be effective in protecting biodiversity. Similarly, in another study, Nassary et al. [14] stated that biodiversity must be protected for food security and productivity in agriculture. The study also emphasized that artificial intelligence technologies must be used effectively in protecting biodiversity. In addition to protecting biodiversity, renewable energy applications are also important in increasing the effectiveness of

sustainable agriculture strategies in the process of adapting to climate change. Finally, Hahn et al. [15] indicated in their study that the use of renewable energy in agriculture will lead to increased productivity. The study also included assessments of the financial infrastructure required for renewable energy investment.

Policy and regulations are among the factors that determine the feasibility and impact of sustainable agriculture strategies. In other words, well-designed policies are effective in promoting sustainable agriculture. Policy regulations govern resource management, contribute to the development of R&D and IT infrastructure, and enable the establishment of risk and insurance systems [1, 16]. Indeed, Feng et al. [17] stated in their study that regulations on the use of land for sustainable agriculture would prevent soil pollution. They emphasized that the policies to be implemented would reduce soil pollution and control the use of agricultural pesticides by establishing a legal framework. Another study by Chen and Gao [18] suggested that green subsidies should be developed to promote green development in agriculture. It was reported that these planned subsidies would support sustainable agriculture and increase the labor force employed in agriculture. It is also stated that subsidies will eliminate the imbalance seen in income distribution in agriculture.

Sustainable agriculture is a broad concept encompassing objectives such as increasing production each year, protecting nature and the environment during production, ensuring gender equality in production and product distribution, and ensuring fair income distribution. Sustainable agriculture strategies are crucial for achieving these objectives. Failure to adapt to climate change leads to numerous negative scenarios, including negatively impacting soil health, increasing the risk of drought, and decreasing product quality. Experiencing these scenarios negatively impacts those who directly earn their income from agriculture, which in turn exacerbates income inequality in society. Therefore, this study aims to develop sustainable agriculture strategies to develop climate change-adapted agricultural practices and improve income distribution. Developing these strategies requires a number of criteria and policies. These criteria are, respectively, cost and financing sustainability, the development of digital agricultural technologies and control mechanisms, practices to create rural employment and prevent migration, access to education and information, the protection of biodiversity and the efficient use of resources, renewable energy and circular economy practices, and policies and regulations. Applying these criteria simultaneously and effectively seems unlikely due to time, human capital, and financial constraints. Even implementing each of these criteria in a single step can be quite costly for some investors and the public sector. In other words, these criteria may require a skilled workforce, a strong technological infrastructure, and may also necessitate effective time management. Therefore, a large portion of the studies in the literature do not serve investors' resources in line with sustainable agriculture strategies, representing one of the most significant gaps in the literature. New studies are needed to address this gap. A key element of these new studies should be to conduct a priority analysis among these criteria to determine which is more important. Based on this priority analysis, it will be possible to offer policy recommendations to investors regarding which strategies should be prioritized. Therefore, this study will contribute by offering strategies to improve income distribution based on climate-adapted agriculture. This study also develops a multi-criteria decision-making model to determine the importance of selected criteria. This will ultimately lead to the identification of more important criteria and contribute to filling this gap in the literature.

2. Methodology

This section includes the introduction of Gaussian fuzzy numbers as well as the formulation of dimensionality reduction based SITDE-RATGOS hybrid model for the evaluation of sustainable agriculture strategies. The flowchart of methodology is visualized in Figure 1.

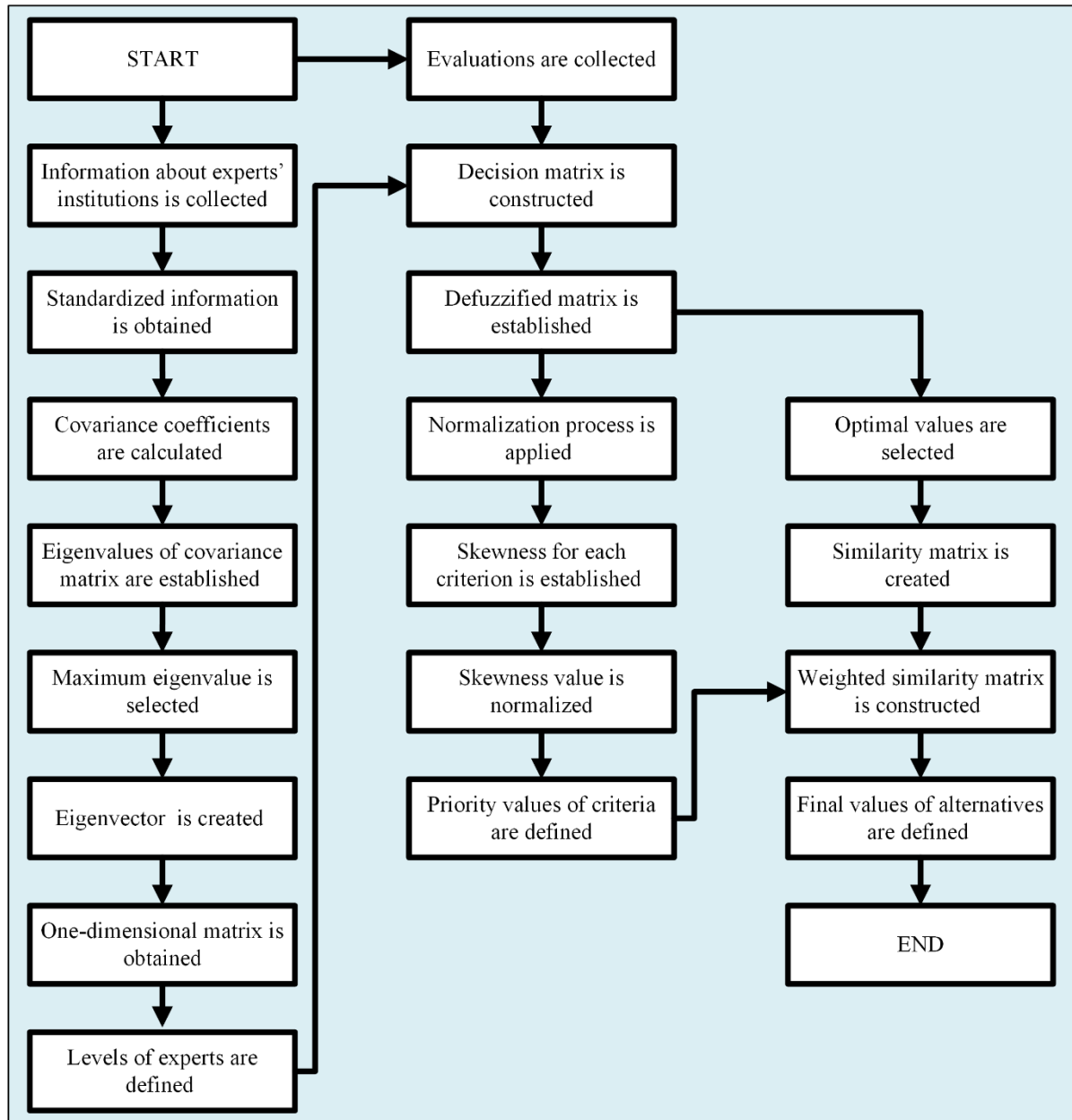


Fig. 1. Flowchart

2.1. Dimensionality Reduction Algorithm

This approach is developed as a solution to the criticism in the literature of giving equal importance to evaluations. This approach aims to use the expert level as a basis for evaluation. The expert level can be determined by the expert's status within their institution. In other words, the institution's periods of activity, the number of business partners, and the number of locations all contribute to the expert's experience. In this context, the expert level can be determined using anonymous data obtained from the websites of the institutions to which the experts are affiliated. Using this approach, the expert level is calculated using dimensionality reduction as follows [19].

By examining the websites of the experts' institutions, common variables are determined and the matrix structure shown in Equation (1) is constructed.

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1c} \\ \vdots & \ddots & \vdots \\ y_{e1} & \cdots & y_{ec} \end{bmatrix} \quad (1)$$

Where the numbers of experts' institutions and common variables are symbolized as e and c , respectively. Thus, y_{ij} means the value of j^{th} common variable for i^{th} expert's institution. Next, since the ranges of the common variables are not the same, the average ($\bar{y}$) and standard deviation (σ) values in Equations (2) and (3) are calculated to standardize the variables (z). These values are then standardized using Equation (4).

$$\bar{y}_j = \frac{1}{e} \sum_{i=1}^e y_{ij} \quad (2)$$

$$\sigma_j = \sqrt{\frac{1}{e} \sum_{i=1}^e (y_{ij} - \bar{y}_j)^2} \quad (3)$$

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1c} \\ \vdots & \ddots & \vdots \\ z_{e1} & \cdots & z_{ec} \end{bmatrix} = \begin{bmatrix} \frac{y_{11} - \bar{y}_1}{\sqrt{\sum_{i=1}^e (y_{i1} - \bar{y}_1)^2}} & \cdots & \frac{y_{1c} - \bar{y}_c}{\sqrt{\sum_{i=1}^e (y_{ic} - \bar{y}_c)^2}} \\ \vdots & \ddots & \vdots \\ \frac{y_{e1} - \bar{y}_1}{\sqrt{\sum_{i=1}^e (y_{i1} - \bar{y}_1)^2}} & \cdots & \frac{y_{ec} - \bar{y}_c}{\sqrt{\sum_{i=1}^e (y_{ic} - \bar{y}_c)^2}} \end{bmatrix} \quad (4)$$

Afterwards, the covariance coefficients (cv) between the standardized variables are calculated with Equation (5) and the covariance matrix (A) in Equation (6) is obtained.

$$cv_{jk} = \frac{1}{e} \sum_{i=1}^e (z_{ij} - \bar{z}_j)(z_{ik} - \bar{z}_k) \quad (5)$$

$$A = \begin{bmatrix} cv_{11} & \cdots & cv_{1c} \\ \vdots & \ddots & \vdots \\ cv_{c1} & \cdots & cv_{cc} \end{bmatrix} \quad (6)$$

c eigenvalues (λ) of covariance matrix are established by Equation (7). I is identity matrix.

$$\det(A - \lambda_i I) = 0 \quad (7)$$

Equation (8) selects the maximum eigenvalue.

$$\lambda^* = \max \lambda_i \quad (8)$$

The eigenvector (Ψ) corresponding to the maximum eigenvalue is created by Equation (9).

$$(A - \lambda^* I)\Psi = 0 \quad (9)$$

Finally, the matrix in Equation (1) is multiplied by the eigenvector with the matrix multiplication operator as Equation (10). Later, the levels of experts are defined as Equation (11).

$$K = Y\Psi = \begin{bmatrix} k_1 \\ \vdots \\ k_e \end{bmatrix} \quad (10)$$

$$L_i = \frac{k_i}{\sum_{i=1}^e k_i} \quad (11)$$

2.2. Gaussian Fuzzy Sets

Gaussian fuzzy sets are sets that express an object's membership using a Gaussian distribution. The greatest advantage of Gaussian sets is that they define the membership values of objects over a wide range. Furthermore, the Gaussian distribution is the most observed distribution in nature and is used in many disciplines, particularly statistics, to solve real-world problems. In GFS ($\tilde{G} = (x, \sigma)$), the membership of an object (t) is described as Equation (12) [20].

$$\mu_{\tilde{G}}(t) = e^{-\frac{(t-x)^2}{2\sigma^2}} \quad (12)$$

Where x and σ are the mean and standard deviation of Gaussian distribution, respectively. Assume that $\tilde{G}_1$ and $\tilde{G}_2$ are two GFSSs. Then, some operators are identified in Equations (13) – (15).

$$\tilde{G}_1 + \tilde{G}_2 = (x_1 + x_2, \sqrt{\sigma_1^2 + \sigma_2^2}) \quad (13)$$

$$\tilde{G}_1 - \tilde{G}_2 = (x_1 - x_2, \sqrt{\sigma_1^2 + \sigma_2^2}) \quad (14)$$

$$k\tilde{G}_1 = (kx_1, k\sigma_1) \quad (15)$$

Where k is positive number. However, in analysis operations, interval arithmetic definitions of these numbers are generally used. The interval arithmetic representation of $\tilde{G}$ is presented in Equation (16) with α -cut.

$$I_{\tilde{G}} = [L, U] = [x - \sqrt{-\ln \alpha} \sigma, x + \sqrt{-\ln \alpha} \sigma] \quad (16)$$

Where L and U are the lower and upper limits. Let I_1 and I_2 be two interval numbers. Then some operators are defined in Equations (17) - (21).

$$I_1 + I_2 = [L_1 + L_2, U_1 + U_2] \quad (17)$$

$$I_1 - I_2 = [L_1 - U_2, U_1 - L_2] \quad (18)$$

$$I_1 \times I_2 = [\min(L_1L_2, L_1U_2, U_1L_2, U_1U_2), \max(L_1L_2, L_1U_2, U_1L_2, U_1U_2)] \quad (19)$$

$$\frac{I_1}{I_2} = \left[\min\left(\frac{L_1}{L_2}, \frac{L_1}{U_2}, \frac{U_1}{L_2}, \frac{U_1}{U_2}\right), \max\left(\frac{L_1}{L_2}, \frac{L_1}{U_2}, \frac{U_1}{L_2}, \frac{U_1}{U_2}\right) \right] \quad (20)$$

$$SF(I_1) = \frac{L_1 + U_1}{2} \quad (21)$$

2.3. GF-SITDE-based GF-RATGOS

While SITDE is an objective method developed to determine the priority values of the criteria, RATGOS is based on the geometric mean of the weighted optimal similarity ratio in ranking the alternatives. The integration of the combination of these two methods with Gaussian fuzzy numbers is introduced below [21].

First, since the decision matrix needs to be constructed, after n criteria and m alternatives are determined, the evaluations from each expert are collected and converted into GFNs. Thus, evaluation matrices are constructed for each expert. The evaluation matrix for the r^{th} expert ($\tilde{D}_r$) has the structure in Equation (22).

$$\tilde{D}_r = \begin{bmatrix} \tilde{d}_{11}^r & \cdots & \tilde{d}_{1n}^r \\ \vdots & \ddots & \vdots \\ \tilde{d}_{m1}^r & \cdots & \tilde{d}_{mn}^r \end{bmatrix} \quad (22)$$

Where $\tilde{d}_{ij}^r = (x_{\tilde{d}_{ij}^r}, \sigma_{\tilde{d}_{ij}^r})$. The GFNs are transformed into interval arithmetic with α -cut using Equation (23).

$$\tilde{d}_{ij}^r = [x_{\tilde{d}_{ij}^r} - \sqrt{-\ln \alpha} \sigma_{\tilde{d}_{ij}^r}, x_{\tilde{d}_{ij}^r} + \sqrt{-\ln \alpha} \sigma_{\tilde{d}_{ij}^r}] \quad (23)$$

Afterwards, the numbers are multiplied by the levels of experts with the help of Equation (24). Next, the expert-weighted GFNs are summed by Equation (25).

$$\tilde{p}_{ij}^r = L_r \tilde{d}_{ij}^r \quad (24)$$

$$\tilde{b}_{ij} = \sum_{r=1}^e \tilde{p}_{ij}^r \quad (25)$$

In other words, Equations (15) and (17) are used. Thus, decision matrix ($\tilde{B}$) illustrated in Equation (26) is constructed.

$$\tilde{B} = \begin{bmatrix} \tilde{b}_{11} & \cdots & \tilde{b}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{b}_{m1} & \cdots & \tilde{b}_{mn} \end{bmatrix} \quad (26)$$

Next, the matrix is defuzzified via Equation (27).

$$B = SF(\tilde{B}) = \begin{bmatrix} SF(\tilde{b}_{11}) & \cdots & SF(\tilde{b}_{1n}) \\ \vdots & \ddots & \vdots \\ SF(\tilde{b}_{m1}) & \cdots & SF(\tilde{b}_{mn}) \end{bmatrix} = \begin{bmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{bmatrix} \quad (27)$$

After creating the defuzzified matrix (B), SITDE is performed. Firstly, the normalization process is applied regarding to type of criterion using Equations (28) and (29).

$$nb_{ij} = \frac{\min_i b_{ij}}{b_{ij}}; j \in B \quad (28)$$

$$nb_{ij} = \frac{b_{ij}}{\max_i b_{ij}}; j \in C \quad (29)$$

While beneficial criterion is symbolized with B , cost criterion is represented by C . Next, standard deviation (σ_j) for normalized matrix (nb) are computed using Equations (2) and (3). Later, the skewness (sv) for each criterion is established via Equation (30).

$$sv_j = \frac{m}{(m-1)(m-2)} \sum_{i=1}^m \left(\frac{nb_{ij} - \bar{nb}_j}{\sigma_j} \right)^3 \quad (30)$$

After that, the skewness value is normalized by Equation (31).

$$ns_j = \log \left(\left((sv_j + 1) + (|\min sv_j| + 1) \right) \right) \quad (31)$$

Where $(|\min sv_j| + 1)$ ensures all values inside the logarithmic function are positive by offsetting with the minimum skewness value between all criteria and then summed with one. The last step of SITDE defines the priority values (w) of criteria as Equation (32).

$$w_j = \frac{ns_j}{\sum_{j=1}^n ns_j} \quad (32)$$

Immediately after the priority values of the criteria are calculated with SITDE, the steps of RATGOS are applied. With Equations (33) and (34), optimal values (o) are determined for each criterion of the decision matrix in Equation (26) [22].

$$o_j = \max_i b_{ij}; j \in B \quad (33)$$

$$o_j = \min_i b_{ij}; j \in C \quad (34)$$

Afterwards, the similarity matrix (sm) is created using Equations (35) and (36).

$$sm_{ij} = \frac{b_{ij}}{o_j}; j \in B \quad (35)$$

$$sm_{ij} = \frac{o_j}{b_{ij}}; j \in C \quad (36)$$

The weighted similarity matrix (ws) is constructed by Equation (37).

$$ws_{ij} = w_j sm_{ij} \quad (37)$$

Finally, the final values (f) of alternatives are defined as Equation (38).

$$f_j = \sqrt[n]{\prod_{j=1}^n ws_{ij}} \quad (38)$$

3. Results

The section includes the results of evaluation of sustainable agriculture strategies. In other words, the results of the steps of Figure 1 are presented under subsections.

3.1. Defining the Levels of Experts

To determine the experts' rankings, anonymous information from the institutions they work for is reviewed. The assumption here is that experts working at reputable institutions have higher expertise. Within this framework, the websites of each expert's institution are reviewed to gather information. This information includes the number of business partners, the number of locations they operate in, the number of certifications they hold, such as ISO 9001, and their period of activity. Table 1 summarizes this information from the experts' institutions.

Table 1.
Information about Experts' Institutions

	Business Partners	Locations	Certificate (ISO)	Activity Period
Expert.1	10	5	6	18
Expert.2	22	7	7	29
Expert.3	11	6	6	27
Expert.4	16	7	6	30
Expert.5	15	7	7	33
Expert.6	15	7	6	34
Expert.7	16	7	6	38
Expert.8	14	5	5	22
Expert.9	17	6	6	27
Expert.10	15	5	5	24

Next, the average and standard deviation values in Equations (2) and (3) are calculated to standardize the variables. These statistics are presented in Table 2.

Table 2.
Average and Deviation

	Business Partners	Locations	Certificate (ISO)	Activity Period
Average	15.1	6.2	6.0	28.2
Deviation	3.113	.872	.632	5.653

As can be understood from Table 2, the institutions have been operating for an average of 28.2 years and operate from an average of six different locations. Additionally, the institutions hold an average of six certifications. Furthermore, the institutions have an average of 15.1 business partners. This information in Table 1 is then standardized using Equation (4). The standardized information is shared in Table 3.

Table 3.
Standardized Information

	Business Partners	Locations	Certificate (ISO)	Activity Period
Expert.1	-.518	-.435	.000	-.571
Expert.2	.701	.290	.500	.045
Expert.3	-.417	-.073	.000	-.067
Expert.4	.091	.290	.000	.101

Expert.5	-.010	.290	.500	.268
Expert.6	-.010	.290	.000	.324
Expert.7	.091	.290	.000	.548
Expert.8	-.112	-.435	-.500	-.347
Expert.9	.193	-.073	.000	-.067
Expert.10	-.010	-.435	-.500	-.235

Afterwards, the covariance coefficients between the standardized variables are calculated with Equation (5) and the covariance matrix in Equation (6) is obtained. The covariance matrix is illustrated in Table 4.

Table 4.
Covariance Matrix

	Business Partners	Locations	Certificate (ISO)	Activity Period
Business Partners	.100	.055	.041	.044
Locations	.055	.100	.073	.088
Certificate (ISO)	.041	.073	.100	.045
Activity Period	.044	.088	.045	.100

Four eigenvalues of covariance matrix are established by Equation (7). The eigenvalues and explained variance are displayed in Table 5. Equation (8) selects the maximum eigenvalue for loss the minimum information. The maximum eigenvalue is .275751.

Table 5.
Eigenvalues and Explained Variances

	Value	Exp. Variance
Eigenvalue.1	.275751	69%
Eigenvalue.2	.00457	1%
Eigenvalue.3	.063213	16%
Eigenvalue.4	.056466	14%

The first eigenvalue contains 69% of the variance in the matrix. In other words, it is possible to preserve a large proportion of the information by using this eigenvalue. The eigenvector corresponding to this eigenvalue is created by Equation (9). The elements of this vector are shown in Table 6.

Table 6.
Eigenvector's Elements

	Elements
1	.41739
2	.582818
3	.468544
4	.516309

Finally, the matrix in Equation (1) is multiplied by the eigenvector with the matrix multiplication operator as Equation (10). Thus, one-dimensional matrix is obtained. Later, the levels of experts are defined as Equation (11). The results are expressed in Table 7.

Table 7.

One-dimensional Matrix and Levels of Experts		
	One- dimension	Levels Experts of
Expert.1	19.193	.070
Expert.2	31.515	.115
Expert.3	24.840	.091
Expert.4	29.059	.106
Expert.5	30.659	.112
Expert.6	30.706	.113
Expert.7	33.189	.122
Expert.8	22.459	.082
Expert.9	27.344	.100
Expert.10	23.909	.088

As can be seen levels of experts in Table 7, the most important expert is Expert 7 with .122 since maximum locations and maximum activity period. The second important expert is Expert 2 with .115 since this expert has the maximum business partners, maximum location and maximum certification.

3.2. Weighting and Ranking

First, since the decision matrix needs to be constructed, 7 criteria and 4 alternatives are determined. Four alternatives for sustainable agriculture are organic agriculture and agroecological practices (OAAP), renewable energy-supported agriculture practices (RESAP), cooperatives and green financing models (CGFM), and climate-friendly irrigation technologies (CFIT). The criteria to be taken into consideration when selecting the most optimal of these strategies are determined. The criteria list is shared in Table 8 with short codes.

Table 8.
Criteria List

Definition	Short Code
Cost and Financing Sustainability	CSFN
Development of digital agricultural technologies and control mechanisms	DGTCM
Practices to create rural employment and prevent migration	RREMPM
Access to Education and Information	EDUINF
Protection of biodiversity and efficient use of resources (land and water resources)	DVSSUS
Renewable Energy and Circular Economy Applications	RWCEA
Policies and Regulations	PLCRG

Firstly, the evaluations from each expert are collected. The evaluations are described in Table 9 using linguistic scales. The linguistic scales are no (N), low (L), medium (M), high (H), and very high (VH).

Table 9.
Evaluations

	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	M	L	M	L	M	L	L
RESAP	VH	VH	H	H	H	VH	H
CGFM	M	M	M	M	L	M	L
CFIT	M	L	L	L	M	M	M
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	M	L	L	L	M	L	M
RESAP	H	VH	H	H	H	H	H
CGFM	L	M	N	L	M	M	M
CFIT	L	L	M	L	L	N	M
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	M	L	M	M	L	L	M
RESAP	H	VH	H	H	H	H	VH
CGFM	M	M	M	L	M	L	L
CFIT	M	M	M	M	L	N	L
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	M	M	M	M	L	M	L
RESAP	H	VH	H	H	H	H	VH
CGFM	M	L	N	M	L	L	L
CFIT	L	M	L	L	M	M	L
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	L	L	M	L	M	M	L
RESAP	VH	H	H	VH	H	H	H
CGFM	M	M	L	L	L	M	L
CFIT	L	L	L	L	M	N	M
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	L	M	L	L	L	M	L
RESAP	VH	VH	H	VH	H	H	VH
CGFM	L	M	H	L	M	L	M
CFIT	L	M	M	L	M	L	M
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	M	L	M	L	L	L	L
RESAP	H	H	H	VH	VH	H	VH
CGFM	M	L	VH	N	H	M	M
CFIT	L	L	H	M	M	M	L
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	L	L	N	L	L	M	L
RESAP	H	VH	H	H	H	VH	VH
CGFM	M	L	N	N	L	L	M
CFIT	M	M	M	M	M	L	M
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG

OAAP	M	L	M	M	L	L	L
RESAP	VH	H	M	H	H	VH	H
CGFM	M	L	M	M	M	L	M
CFIT	M	M	N	L	L	L	L
	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	M	L	L	L	M	M	M
RESAP	VH	H	M	H	VH	VH	H
CGFM	L	M	L	N	L	L	M
CFIT	L	M	L	N	L	M	L

The scales converted into GFNs with membership .2, .35, .5, .65, .8, respectively. The standard deviation equals to .1 for all scales. Thus, evaluation matrices are constructed for each expert. The GFNs are transformed into interval arithmetic with α -cut using Equation (23). Afterwards, the numbers are multiplied by the levels of experts with the help of Equation (24). The levels of experts in Table 7 are used for this. Next, the expert-weighted GFNs are summed by Equation (25). Decision matrix ($\alpha = .1$) are shared in Table 10.

Table 10.
Decision Matrix ($\alpha = .1$)

	CSFN	DGTCM	RREM PM	EDUINF	DVSSU S	RWCEA	PLCRG
OA	[.302,.6	[.231,.5	[.276,.	[.243,.5	[.256,.5	[.273,.5	[.242,.5
AP	06]	35]	58]	46]	6]	77]	46]
RES	[.571,.8	[.585,.8	[.47,.7	[.55,.85	[.53,.83	[.549,.8	[.575,.8
AP	74]	88]	74]	4]	3]	53]	79]
CGF	[.301,.6	[.287,.5	[.28,.5	[.196,.5	[.298,.6	[.261,.5	[.291,.5
M	04]	9]	84]	]	01]	65]	95]
CFIT	[.25,.55	[.285,.5	[.28,.5	[.229,.5	[.289,.5	[.208,.5	[.272,.5
	3]	89]	83]	33]	93]	12]	76]

Next, the matrix is defuzzified via Equation (27). Defuzzified matrix is summarized in Table 11.

Table 11.
Defuzzified Matrix

	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	.454	.383	.428	.395	.408	.425	.394
RESAP	.722	.737	.622	.702	.681	.701	.727
CGFM	.453	.438	.432	.348	.449	.413	.443
CFIT	.402	.437	.432	.381	.441	.360	.424

After creating the defuzzified matrix, SITDE is performed. Firstly, the normalization process is applied regarding to type of criterion using Equations (28) and (29). All criteria are beneficial. For this reason, the minimum value is divided by the values. The normalized matrix is displayed in Table 12.

Table 12.
Normalized Matrix

	CSFN	DGTC	RREMP	EDUIN	DVSSU	RWCE	PLCR
	M	M	F	S	A	G	
OAAP	.885	1.000	1.000	.881	1.000	.847	1.000
RESA	.556	.520	.688	.495	.599	.514	.542

P

CGFM	.887	.873	.990	1.000	.908	.872	.890
CFIT	1.00	.876	.991	.913	.925	1.000	.930
0							

Next, standard deviation for normalized matrix are computed using Equations (2) and (3). Later, the skewness for each criterion is established via Equation (30). After that, the skewness value is normalized by Equation (31). The results are summarized in Table 13.

Table 13.

Standard Deviation, Skewness and Normalized Skewness

	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
Std Dev	.166	.179	.132	.194	.154	.180	.177
sv	-	-2.299	-3.072	-2.605	-2.596	-2.087	-2.616
ns	.439	.443	.301	.392	.394	.475	.390

The last step of SITDE defines the priority values of criteria as Equation (32). The priority values are shown in Figure 2.

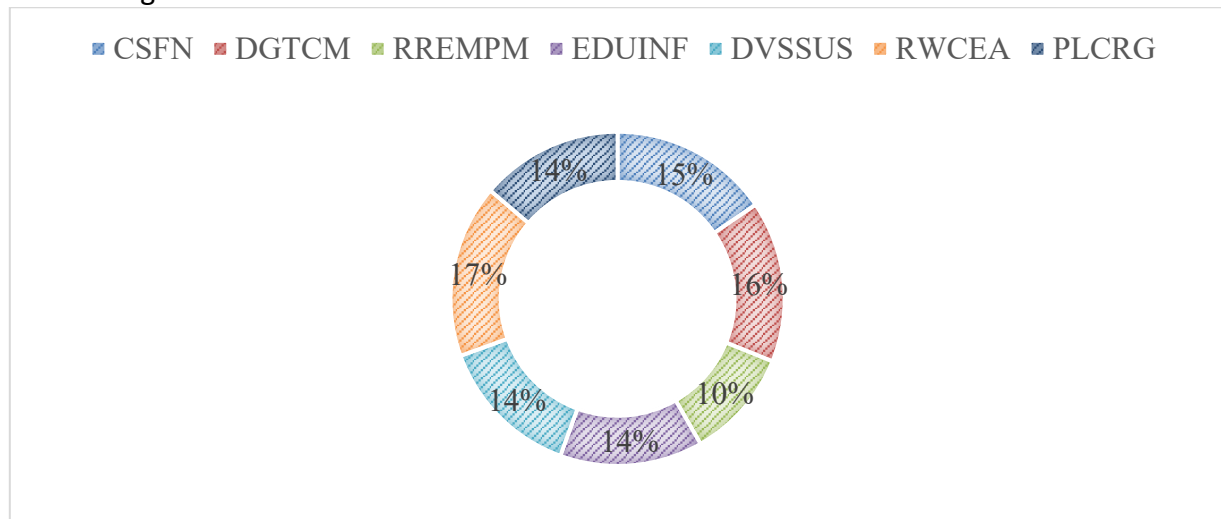


Fig. 2. Priority Values

According to priority values in Figure 2, the most important criterion is renewable energy and circular economy applications with .168. The second important criterion is development of digital agricultural technologies and control mechanisms with .156. Immediately after the priority values of the criteria are calculated with SITDE, the steps of RATGOS are applied. With Equations (33) and (34), optimal values are determined for each criterion of the decision matrix in Table 11. The optimal values are selected regarding the maximum values since all criteria are beneficial. The optimal values are presented in Figure 3.

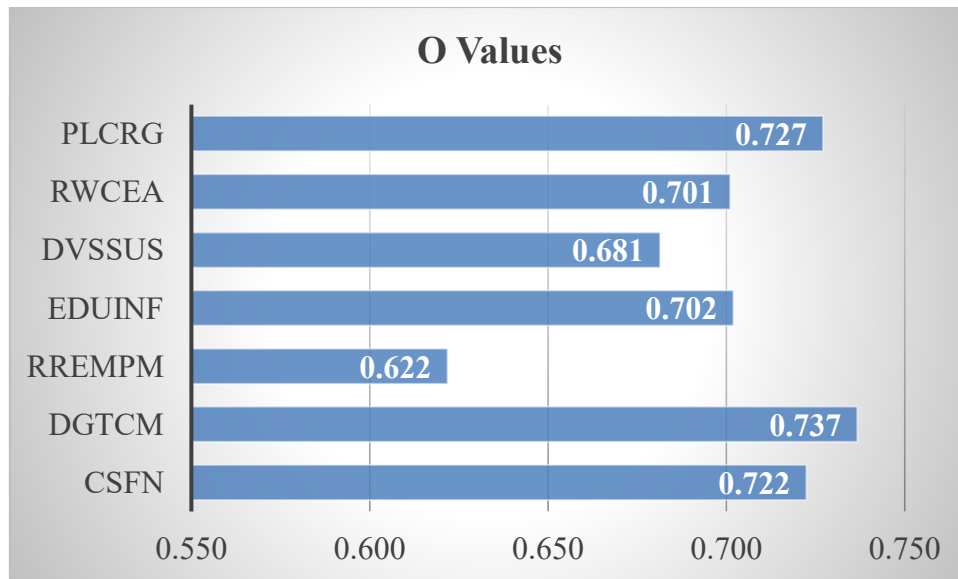


Fig. 3. Optimal Values

Afterwards, the similarity matrix is created using Equations (35) and (36). Similarity matrix is exhibited in Table 14.

Table 14.
Similarity Matrix

	CSFN	DGTC	RREMP	EDUIN	DVSSU	RWCE	PLCR
	M	M	F	S	A	G	
OAAP	.628	.520	.688	.562	.599	.606	.542
RESA	1.00	1.000	1.000	1.000	1.000	1.000	1.000
CGFM	.627	.595	.695	.495	.660	.589	.609
CFIT	.556	.593	.694	.543	.647	.514	.583

The weighted similarity matrix is constructed by Equation (37). Priority values in Figure 2 are used as weight values. The weighted similarity matrix is expressed in Table 15.

Table 15.
Weighted Similarity Matrix

	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
OAAP	.097	.081	.073	.078	.083	.102	.075
RESAP	.155	.156	.106	.138	.139	.168	.138
CGFM	.097	.093	.074	.069	.092	.099	.084
CFIT	.086	.093	.074	.075	.090	.086	.080

Finally, the final values of alternatives are defined as Equation (38). The results are visualized in Figure 4.

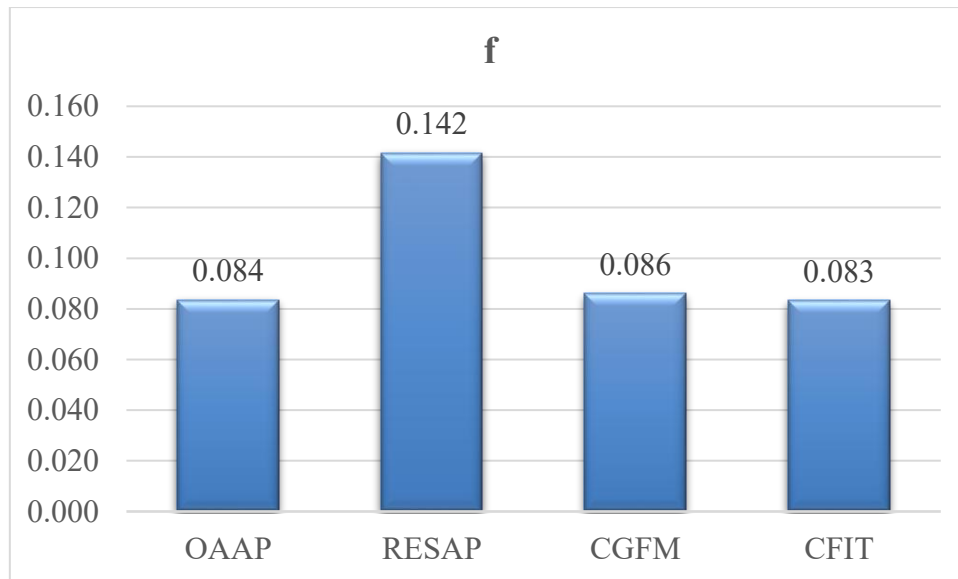


Fig. 4. Final Values of Alternatives

When Figure 4 is examined, the most optimal alternative for sustainable agriculture is renewable energy-supported agriculture practices with .142. All intermediate tables are for an alpha value of 0.1. The order of the criteria according to other alpha values is given in Table 16.

Table 16.

Order of Criteria by Alpha-cut Values

	CSFN	DGTCM	RREMPM	EDUINF	DVSSUS	RWCEA	PLCRG
$\alpha = .1$	3	2	7	5	4	1	6
$\alpha = .2$	3	2	7	5	4	1	6
$\alpha = .3$	3	2	7	5	4	1	6
$\alpha = .4$	3	2	7	5	4	1	6
$\alpha = .5$	3	2	7	5	4	1	6
$\alpha = .6$	3	2	7	5	4	1	6
$\alpha = .7$	3	2	7	5	4	1	6
$\alpha = .8$	3	2	7	5	4	1	6
$\alpha = .9$	3	2	7	5	4	1	6
$\alpha = 1$	3	2	7	5	4	1	6

As can be seen in Table 16, the results are the same for all alpha values. Similarly, the ranking of the alternatives according to other alpha values is given in Figure 5.

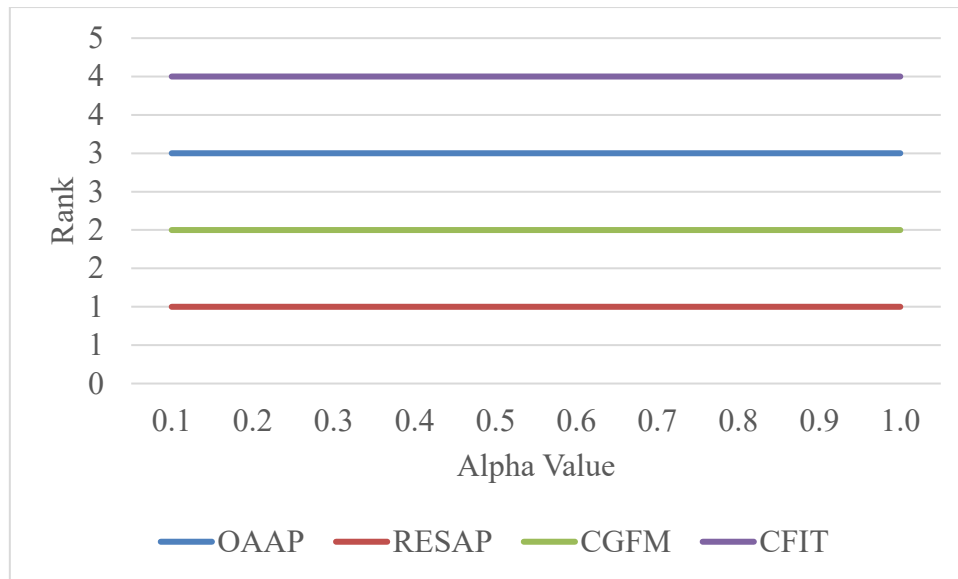


Fig. 5. Ranks of Alternatives by Alpha-cut Values

As can be seen in Figure 5, the results are the same for all alpha values. Consistency in ranking for both alternatives and criteria indicates the validity of the model. In other words, it expresses the robustness of the model.

3.3. Comparative and Sensitivity

To demonstrate the validity of the results, the criteria are weighted using LOPCOW and ranked using RATGOS. A comparison of the criteria priority values of the LOPCOW and SITDE methods is given in Figure 6.

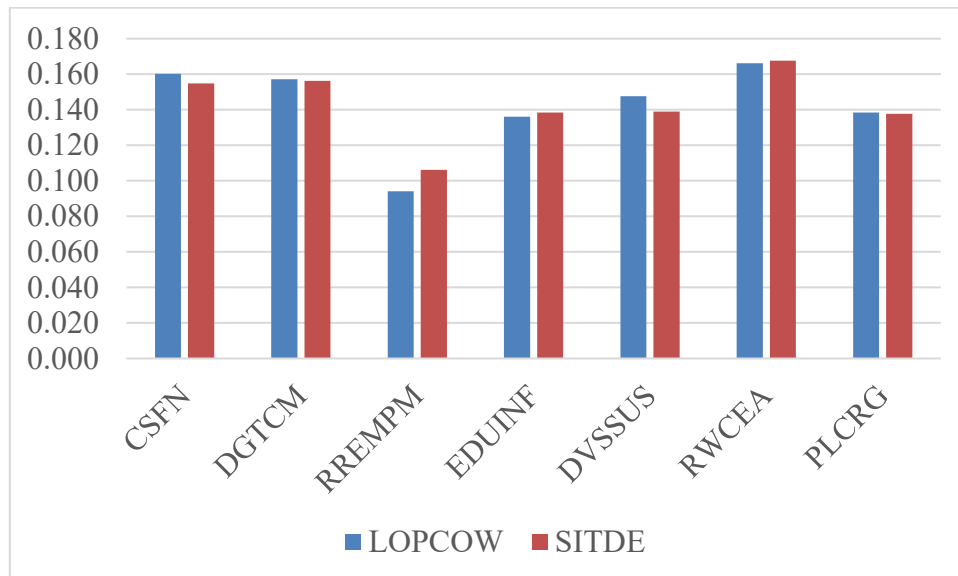


Fig. 6. Weights of LOPCOW and SITDE

The correlation coefficient between the two methods is examined to assess the reliability of the results. The correlation coefficient between the criteria obtained from the two methods is 0.929, a sufficiently high value. This high value demonstrates the reliability of the results. The results of SITDE-based RATGOS and LOPCOW-based RATGOS are presented in Table 17.

Table 17.
Comparative Results

	LOPCOW-based RATGOS	SITDE-based RATGOS
OAAP	.083	.084
RESAP	.141	.142
CGFM	.085	.086
CFIT	.083	.083

As can be seen from Table 17, the results obtained from both methods are similar and the rankings are the same. This demonstrates the validity of the results.

4. Conclusion

The main objective of this study is to develop sustainable agricultural strategies to improve income distribution through climate-adapted agriculture. Several criteria were established for the development of these strategies, and achieving these simultaneously would be quite costly and time-consuming for both the private and public sectors. For these reasons, the highest priority criterion was determined using a multi-criteria decision-making method. The most important criteria for a sustainable agricultural strategy that improves climate change-adapted agriculture and income distribution are renewable energy and circular economy practices. Renewable energy and circular economy practices are interconnected policies and targets that are increasingly important for reducing dependence on fossil fuels [23]. The primary goal of renewable energy use is to minimize greenhouse gas emissions, reduce dependence on fossil fuels, and provide clean and affordable energy for human health. Today, the main causes of climate change are the increase in greenhouse gas emissions and the disruption of the natural balance due to dependence on fossil fuels [24]. Nature has a constantly renewing cycle, and increasing the use of renewable energy regularizes rainfall, minimizes environmental degradation, and increases soil and water fertility, allowing for increased agricultural production [25]. According to Raza et al. [26], the circular economy is an umbrella concept that implements zero-waste practices based on source waste separation and encompasses many sustainable development goals. Jha and Sharma [27] studied that the core of the circular economy is zero waste, a concept derived from nature's transformative power. Therefore, circular economy practices are deeply intertwined with agriculture and are a crucial policy for sustainable agricultural strategies. Heyl et al. [28] stated that, therefore, it is beneficial to address renewable energy and circular economy policies to develop policies that are both climate-compatible and improve income distribution. The transition from fossil fuel use, which contributes to climate change, to clean and low-cost energies should be accelerated. To achieve this, the use of insulated greenhouses should be expanded, low-interest agricultural loans should be increased, and grants and incentives should be accelerated to support farmers and agricultural producers. Gopal et al. [29] demonstrated that idle agricultural land should be opened to employment for renewable energy-based agricultural production. Furthermore, energy-saving machinery should be allocated, and micro-energy networks should be established through cooperatives, where energy is generated on-site. This will not only prevent climate change, increase the productivity of renewable energy-based agriculture, but also ensure more equitable income distribution through cooperatives, incentives, and credit opportunities. Camini et al. [30] recommended implementing a circular economy as another policy option. In agricultural production, converting waste into resources is faster and less costly than other production processes. This is because plant waste is used as organic fertilizer through composting, reducing the use of chemical fertilizers. Gong et al. [31] demonstrated that this, in turn, increases soil fertility, thereby increasing agricultural productivity and achieving a more

equitable income distribution. However, for this mechanism to work, everyone involved in agriculture, especially farmers, should receive training in circular economy topics such as rainwater harvesting, food waste management, biogas production, and more. Tax exemptions and exceptions for people working in these areas should be increased within relevant legal regulations. Integrated villages based on a circular economy, where renewable energy is produced and used and zero waste is produced, should be established, and these villages should be expanded as efficiency increases.

Among the criteria that must be implemented to develop sustainable agricultural strategies that adapt to climate change and improve income distribution, the second most important criterion, according to the priority analysis, is the development of digital agricultural technologies and control mechanisms. Digitalization is developing and updating itself at a dizzying pace every day. Companies, institutions, organizations, and states that fail to keep pace with this development are doomed to extinction. Therefore, like every sector, the agricultural sector must keep pace with digitalization [32]. Digitalization in agriculture not only enables the use of renewable energy but also significantly increases productivity. Furthermore, digitalization is taking its place as a key tool in sustainable development goals. The use of early warning systems for a climate-adapted agricultural model, the use of machines and devices that conduct soil analysis and identify which crops are suitable for which soils, and the elimination of over-irrigation and drought risks through smart irrigation systems are among the key examples of digitalization in agriculture [33]. The use of digitalization in agriculture will reduce unhealthy agricultural practices and natural disasters such as frost, floods, and landslides. This will increase product diversity and quality, thereby boosting agricultural exports and increasing farmers' incomes [34]. According to Liu and Li [35], digitalization in agriculture both supports climate-resilient agriculture and has a regulating effect on income distribution. Van der Velden et al. [36] stated that for this mechanism to function effectively, rural populations must be informed, agricultural universities or vocational schools that provide applied training should be established, more resources should be allocated from the public budget to agricultural R&D, and projects in this area should be supported. Bureaucratic obstacles should be removed to accelerate implementation. Li et al. [37] also studied that while digitalization in agriculture is being implemented, active control mechanisms are crucial to prevent unhealthy agricultural practices due to a lack of sufficient knowledge and skills. For example, growing tea in orange groves, planting corn where wheat should be grown, etc. Practices should be audited, and producers should be guided appropriately. Zhang et al. [38] suggested that errors in the taxation of agricultural income should be penalized, and digital technologies should be utilized for auditing and control.

The aim of this study is to develop a comprehensive and intelligent decision-making model based on human–computer interaction to determine the most effective sustainable agriculture strategies. To achieve this objective, a hybrid methodological framework integrating machine learning, Gaussian fuzzy sets, and multi-criteria decision-making techniques has been established. The proposed model employed a systematic process: expert opinions are collected from ten specialists in the field, expert importance weights are objectively calculated using a machine learning algorithm, criterion weights are determined through the SIDTE technique, and alternative prioritization is performed using the RATGOS method. Gaussian fuzzy sets are incorporated to handle uncertainty and linguistic vagueness in expert judgments effectively. The results revealed that the most significant criterion is renewable energy and circular economy applications (0.168), followed by the development of digital agricultural technologies and control mechanisms (0.156), while the most optimal sustainable agriculture strategy is identified as renewable energy-supported agricultural practices (0.142). This study contributes to the literature by introducing a novel integration of HCI principles and machine learning-based expert weighting into a fuzzy MCDM framework, filling a critical methodological gap

in the prioritization of sustainability strategies. Moreover, the proposed model enhances analytical accuracy, reduces subjectivity, and provides policymakers and practitioners with a robust, data-driven decision support tool for sustainable agricultural development.

Despite its theoretical and methodological contributions, this study has several limitations that should be acknowledged. The analysis was conducted exclusively within the agricultural sector, which restricts the generalizability of the findings. Future research could expand the application of the proposed model to other sectors such as energy, manufacturing, or transportation to examine whether similar decision dynamics apply across different sustainability contexts. Additionally, the proposed model itself can be further enhanced. The current study employed a limited number of experts; therefore, increasing the number and diversity of experts in future studies would improve the robustness and external validity of the results. Moreover, while machine learning was successfully utilized to calculate expert importance weights, incorporating a broader set of demographic, cognitive, and behavioral variables could refine the model's accuracy in capturing expert influence. Future studies are encouraged to explore adaptive or deep learning algorithms to strengthen the learning process, and to integrate dynamic feedback loops within the HCI framework to further improve decision efficiency. Addressing these limitations will not only enhance the precision and applicability of the proposed model but also pave the way for a more generalized and intelligent decision-making architecture applicable to various sustainability domains.

Author Contributions

"Conceptualization, M.A. and A.N.Ç.; methodology, S.E.; software, S.E.; validation, H.D., S.Y. and S.E.; formal analysis, S.E.; investigation, S.Y.; resources, M.A.; data curation, A.N.Ç.; writing—original draft preparation, M.A.; writing—review and editing, S.E.; visualization, S.Y.; supervision, H.D.; project administration, S.Y.; funding acquisition, S.Y. All authors have read and agreed to the published version of the manuscript

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Data Availability Statement

Conflicts of Interest

The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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