

Original article

Sustainable Agricultural Supply Chains and Green Logistics: The TFN-Based LOPCOW-RAM Multi-Criteria Evaluation Framework

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Abstract

The transition to sustainable agricultural supply chains requires adopting innovative, eco-friendly logistics solutions that balance cost-effectiveness, operational performance, and ecological responsibility. In this study, a comprehensive decision-making framework was developed to evaluate and prioritize green logistics alternatives in sustainable agricultural product supply chains. Seven alternatives, such as multimodal transportation, electric vehicle-based distribution, renewable energy-supported cold chain systems, and reverse logistics, were examined in line with twelve realistic criteria covering cost, environmental, technological, and operational dimensions. Triangular Fuzzy Numbers (TFNs) have been used to address uncertainty and imprecision in expert opinions. The LOPCOW method was applied to objectively determine the relative importance of the criteria, followed by the RAM method to rank the logistic alternatives according to their integrated performance. The board, comprised of four experts from diverse academic and professional backgrounds, contributed to the evaluations to ensure credibility and inclusiveness. The findings indicate that low-emission, technology-integrated solutions are key to sustainability in agricultural logistics. This research contributes to the literature by applying TFN-based LOPCOW and RAM integration in a unique context. It provides policymakers, logistics providers, and supply chain stakeholders with valuable insights for developing greener, more resilient agricultural systems.

Keywords: Sustainable Agriculture, Agricultural Supply Chains, Green Logistics, Multi-Criteria Decision Making, LOPCOW, RAM, Triangle Fuzzy Numbers, Logistics Alternatives, Sustainability Assessment

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INTRODUCTION

The rapid globalization of agri-food markets and the increasing demand for sustainable food production have made logistics a critical determinant of supply chain resilience. Agricultural products supply chains are inherently complex due to seasonality, perishability, and dependence on external factors such as climate, energy costs, and international trade regulations. In this context, logistical decisions not only impact operational efficiency and cost but also shape the environmental and social footprint of agricultural systems. However, selecting the most suitable logistics alternatives for sustainable agriculture supply chains remains a challenging problem due to the large number of criteria, conflicting stakeholder interests, and high uncertainty about future market and environmental conditions.

The significance of this problem lies in its direct impact on food security, farmer profitability, consumer well-being, and ecological sustainability. Inefficient or unsustainable logistics practices lead to excessive greenhouse gas emissions, post-harvest losses, high operational costs, and reduced market competitiveness. For policymakers, such inefficiencies result in food import dependencies, increased trade vulnerabilities, and pressure on natural resources. For manufacturers and logistics providers, cost increases, reputational risks, and compliance challenges with international sustainability standards arise. If left unaddressed, these problems could jeopardize not only agricultural development but also economic and environmental goals at the national and global levels.

Despite its critical importance, this problem has not been adequately addressed in the literature. Current studies mostly focus on cost minimization or single-criteria optimization, ignoring the multidimensional nature of sustainability in agricultural logistics. In addition, the decision-making approaches used in previous research have limitations, including oversimplification, a lack of integration between objective and subjective assessments, and an inability to address ambiguity in expert opinions adequately. It highlights a clear research gap and highlights the need for advanced multi-criteria decision-making (MCDM) frameworks that can manage uncertainty and complexity.

To fill this gap, this study proposes a hybrid evaluation framework that combines LOPCOW and RAM methods in a Triangular Fuzzy Numbers (TFN) environment. While the LOPCOW method allows reliable determination of the objective weights of the criteria, the RAM method enables flexible, transparent sorting of the alternatives. The use of TFNs enables effective modeling of linguistic ambiguities in expert evaluations. This integrated approach guarantees a balanced, realistic, and comprehensive evaluation of logistics alternatives in sustainable agricultural supply chains.

The study's contributions stand out in three dimensions. First, it makes an original methodological contribution by integrating TFN-based LOPCOW and RAM for the first time in the field of agricultural logistics. The second evaluates realistic logistics alternatives, including green and technology-based solutions, against 12 cost- and benefit-oriented criteria. Third, it provides strategic directions for

policymakers, logistics managers, and agricultural stakeholders for designing more sustainable, resilient, and competitive supply chains. The expected impact of this research extends beyond the academic literature, supporting managerial and policy decision-making processes aligned with global sustainability goals.

The rest of the article is structured as follows: The second part examines the literature on sustainable agricultural logistics and multi-criteria decision-making approaches. In the third part, the proposed research methodology and TFN-based LOPCOW-RAM integration are introduced. In the fourth part, alternatives, criteria, and a panel of experts are presented; In the fifth chapter, analysis and findings are given. In the sixth chapter, findings, theoretical contributions, and managerial implications are discussed; In the seventh chapter, the main results, limitations, and future research directions are conveyed.

Research Background

In recent years, the concept of sustainability has reshaped all production and supply chain systems on a global scale. This transformation is directly related to the goals of reducing environmental impacts, using natural resources efficiently, and increasing social welfare. The agricultural sector plays a strategic role in sustainability efforts, as it underpins both economic growth and ecosystem balance. Although agriculture is the second-largest source of greenhouse gas emissions globally (IPCC, 2014), it is also a staple of livelihoods, food security, and employment for billions of people (Thompson & Amoroso, 2010). Therefore, aligning agricultural production and supply chains with sustainability principles is imperative not only for environmental but also for ensuring social and economic sustainability (Hassini et al., 2012; Nematollahi & Tajbakhsh, 2020).

The growing global population and changing consumption patterns are placing significant pressure on food production systems. It is predicted that the world population will reach 10 billion by 2050, suggesting that existing agricultural supply chains may be insufficient to meet food demand (Searchinger et al., 2018). On the other hand, increasing production and distribution increases the environmental burden; It leads to problems such as deforestation, soil erosion, water pollution, and carbon emissions (Chianese et al., 2016; Pretty et al., 2011). This dilemma has made the creation of sustainable agricultural supply chains (SASC) inevitable. The concept of SASC is defined as a management approach that aims to integrate environmental and social dimensions while maintaining the economic efficiency goals of traditional supply chains (Carter & Rogers, 2008).

Although studies on sustainable agricultural supply chains have gained momentum since the 1990s, comprehensive content analysis by Nematollahi and Tajbakhsh (2020) revealed that quantitative methods are applied to a limited extent in this field. The researchers systematically examined 247 articles published between 1987 and 2019 and classified the literature into four main research axes: agricultural planning, supply chain management, sustainable development, and modeling methodology. This

analysis emphasizes that sustainability-based decisions should encompass not only environmental but also social welfare, energy efficiency, green technologies, and policy dimensions.

A significant part of previous studies has focused both exclusively on agricultural production processes (Ahumada & Villalobos, 2009; Behzadi et al., 2020) and general sustainable supply chain management (Pires Ribeiro & Barbosa-Povoa, 2018; Rajeev et al., 2017). However, the lack of comprehensive studies at the intersection of these two fields, that is, those that systematically address agriculture-oriented sustainable supply chains, draws attention. Although Syahrudin and Kalchschmidt (2012) were the first to recognize this gap, their studies fall short of current standards due to methodological limitations and limited sample coverage. In this regard, Nematollahi and Tajbakhsh (2020) conducted the largest-scale quantitative review in the literature, enabling analysis of sustainable agricultural supply chains through a comprehensive database encompassing both crop and animal production.

Studies show that the success of sustainable agricultural supply chains is possible not only with green transformations in production processes, but also in logistics and distribution systems. Green logistics aims to reduce the carbon footprint, develop energy-efficient transportation systems, and minimize environmental impact through waste management and reverse logistics applications (Hasani et al., 2012; Rentizelas et al., 2019; Soysal, 2016). Closed-loop supply chains provide both economic and environmental sustainability by reusing agricultural waste and reintroducing it into the value chain (Bortolini et al., 2018; Prive et al., 2018). In addition to reducing food losses, these approaches also play a critical role in the production of renewable energy sources such as biomass and biogas (De Menna et al., 2018). In parallel, recent studies have proposed fuzzy multi-criteria decision-support frameworks to help logistics enterprises operationalize green marketing and environmental compliance strategies, further underlining the strategic importance of green transformation in the logistics sector (Görçün et al., 2025).

Since decision-making processes in sustainable agricultural supply chains require the evaluation of multiple economic, environmental, and social criteria simultaneously, multi-criteria decision-making (MCDM) methods are an important tool in this field. In recent years, fuzzy-logic-based models have been widely used to reduce uncertainty in agricultural decision-making environments (Behzadi et al., 2020). The Triangle Fuzzy Number (TFN)-based LOPCOW-RAM evaluation approach developed in this direction allows for the analysis of sustainability criteria in a numerical, weight-based manner. The LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting) method objectively determines criterion weights (Korucuk et al., 2024), while the Root Assessment Method (RAM) model produces more consistent results by normalizing performance differences between alternatives (Sotoudeh-Anvari, 2023). The LOPCOW method has recently gained wide application in transportation and urban mobility decision problems, including the sustainability assessment of micro-mobility solutions (Ecer et al., 2023), the selection of transportation demand management strategies (Aytekin et

al., 2024), and the evaluation of public transportation systems (Kundu et al., 2024), reflecting its adaptability to green and sustainable logistics contexts. This integrated approach provides a powerful analytical framework for evaluating green logistics performance in agricultural supply chains from both quantitative and qualitative perspectives.

Thus, the TFN-based LOPCOW-RAM model proposed in this study aims to fill the methodological gap in the literature in the assessment of sustainable agricultural supply chains. The model examines the performance of green logistics practices holistically, encompassing environmental impacts, social benefits, and economic efficiency, aligning with the four-dimensional SASC research paradigm proposed by Nematollahi and Tajbakhsh (2020). In this respect, the research provides a methodological contribution to the academic literature. It provides an applicable roadmap for decision-makers in the agricultural sector to develop sustainability-oriented strategies.

To further clarify the originality of the proposed integration relative to closely related fuzzy LOPCOW- and RAM-based studies, Table 1 positions the present study against representative recent applications in terms of application context, fuzzy/uncertainty modelling approach, weighting method, ranking method, and the sustainability dimensions considered.

Table 1. Positioning of the proposed TFN-LOPCOW-RAM framework relative to closely related recent studies

Study	Application Context	Fuzzy / Uncertainty Approach	Weighting Method	Ranking Method	Sustainability Dimensions Considered
This study	Green logistics alternatives in sustainable agricultural supply chains	Triangular Fuzzy Numbers (TFN)	TFN-LOPCOW	TFN-RAM	Economic, environmental, technological, operational, and social (12 criteria)
Ecer et al. (2023)	Sustainability of micro-mobility solutions in urban transportation	Interval-Valued Fermatean Neutrosophic Sets + Delphi	LOPCOW	CoCoSo	Environmental and technological
Korucuk et al. (2024)	Warehouse site selection for humanitarian relief organizations	Interval-Valued Fermatean Fuzzy Sets	LOPCOW	RAFSI	Operational and logistical resilience
Gopisetty et al. (2025)	Sustainable electric-vehicle selection	Crisp (double-normalization framework)	LOPCOW	RAM	Environmental and technological
Kundu et al. (2024)	Public transportation systems for sustainable cities	Fuzzy multi-criteria group decision-making	Not LOPCOW-based	Not RAM-based	Environmental and social

MATERIALS and METHODS

To address the decision-making problem in evaluating and selecting green logistics practices in the context of sustainable agriculture, this study developed an integrated fuzzy multi-criteria decision-making (MCDM) model comprising four stages. In the first stage of the model, a committee of experts was formed (Table 2), and the alternatives and evaluation criteria to be considered in the selection process were determined jointly. Then, both numerical and fuzzy data were collected. In the second stage, the weights of the determined criteria were calculated using the fuzzy LOPCOW method. In the third stage, the choice of alternatives' preferability levels was determined using the fuzzy RAM method. In the final stage, a comprehensive sensitivity analysis was conducted to test the reliability and robustness of the proposed fuzzy model. The general structure and algorithmic functioning of the proposed model are summarized in This sensitivity analysis followed a systematic criterion-weight perturbation procedure: the weight of each of the three highest-weighted criteria (C3, C1, and C2) was, in turn, increased and decreased by 10% and 25% while the weights of the remaining criteria were rescaled proportionally so that all weights continued to sum to one; the RAM procedure was then re-executed for each of the resulting scenarios, and the stability of the alternative ranking, particularly the position of the top-ranked alternative, was evaluated across scenarios. To further probe the robustness of the results, the final alternative ranking obtained from the proposed TFN-LOPCOW-RAM framework was additionally compared with the rankings produced by applying the same TFN-based weights within two others widely used MCDM ranking methods, namely TOPSIS and MARCOS (Figure 1).

Table 2. Profiles of experts

Expert	Graduation Degree	Age	Department Graduated	Area of Expertise	Experience (Years)
U1	Ph.D.	52	Logistics and Supply Chain Management	International logistics corridors, green logistics, multimodal transportation	25
U2	Ph.D.	45	Agricultural Economics	Agribusiness, export marketing, agricultural product supply chains	20
U3	Master's Degree	38	Industrial Engineering	Multi-criteria decision making, optimization, sustainability analysis	15
U4	Undergraduate	34	Food Engineering	Cold chain management, food safety, quality control	10

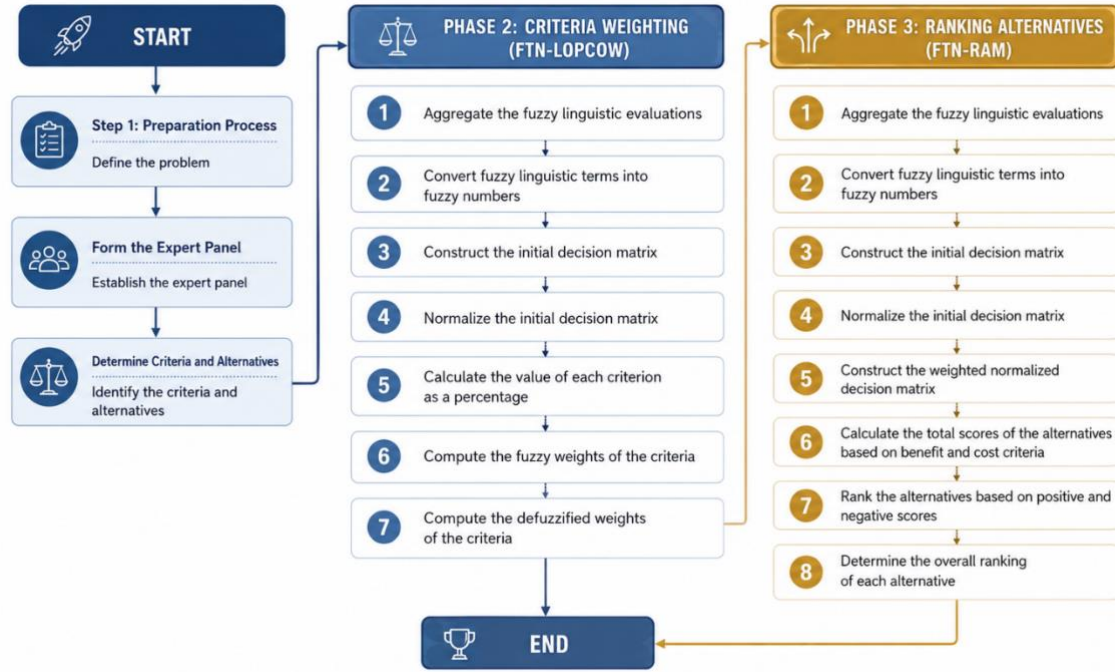


Figure 1. Basic algorithm and implementation steps of the proposed decision-making model

During the preparation phase, evaluation criteria and decision alternatives were jointly defined with the experts shown in Table 1. These criteria and alternatives are presented in Table 2.

The initial pool of candidate criteria and alternatives was first compiled from a review of the recent fuzzy MCDM and sustainable-logistics literature (e.g., Ecer et al., 2023; Korucuk et al., 2024; Kundu et al., 2024). This preliminary list was then presented to the four-member expert panel described in Table 1 in a structured evaluation session, in which each item was discussed individually and retained, revised, or eliminated on the basis of expert consensus regarding its relevance to sustainable agricultural green-logistics decisions. Criteria and alternatives that received unanimous or near-unanimous support after this discussion were adopted for the final decision model summarized in Table 3.

Table 3. Selection criteria and decision options

Criteria of choice				Decision Options	
Code	Criteria	Code	Criteria	Code	Alternatives
C1	Investment Cost	C8	Long-Term Sustainability and Scalability	A1	Electric Road Transport
C2	Operational Cost	C9	Trade Ease and Logistics Compliance	A2	Hydrogen / LNG Fueled Transport Vehicles
C3	Infrastructure Requirement	C10	Product Safety and Traceability	A3	Rail-Based Transportation
C4	Carbon Emission	C11	Compliance with Environmental Regulations	A4	Sea (Reefer Container) Transportation
C5	Delivery Speed	C12	Social Acceptance and Image Contribution	A5	Solar Refrigerated Containers
C6	Reducing Food Loss / Preserving Freshness			A6	IoT-Based Cold Chain Monitoring Systems
C7	Energy Efficiency			A7	Energy-Efficient Cooling Technologies

Experts then made linguistic evaluations for both criteria and decision alternatives. These evaluations were converted into triangular fuzzy numbers according to the fuzzy comparison scale in Table 4.

Table 4. Linguistic comparison scales for criteria and options

Criteria					Alternatives				
Linguistic terms	Code	TFNs			Linguistic terms	Code	TFNs		
Very Low	VL	0,1	0,2	0,3	Very Weak	VW	1,00	2,00	3,00
Low	L	0,2	0,3	0,4	Weak	W	2,00	3,00	4,00
A little low	SL	0,3	0,4	0,5	Medium Underweight	MW	3,00	4,00	5,00
Medium	M	0,4	0,5	0,6	Medium	M	4,00	5,00	6,00
A little high	SH	0,5	0,6	0,7	High	MH	5,00	6,00	7,00
High	H	0,6	0,7	0,8	Very High	VH	7,00	8,00	9,00
Very High	VH	0,7	0,8	0,9	Absolute High	AH	8,00	9,00	10,00

Preliminary Information on Triangular Fuzzy Sets

Fuzzy set theory (Zadeh, 1965) is frequently used to express uncertainties, especially in the field of multi-criteria decision-making. In this approach, TFNs, a special form of fuzzy sets, are widely applied in decision processes (Zavadskas et al., 2021). The following section briefly describes the mathematical representation of fuzzy sets and triangle fuzzy numbers.

If a fuzzy number $\tilde{A}$ membership function $\mu_{\tilde{A}}: R \rightarrow [0,1]$ defined on the real number set R , satisfies the condition given in Eq. (1), this number is considered a triangular fuzzy number (TFN) (Zadeh, 1965).

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{u-x}{u-m} & m \leq x \leq u \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

The l and u values in Eq. (1) represent the lower and upper bounds of the fuzzy number A , respectively, while the m value indicates the peak or most likely value (Kundu et al., 2021). The operation rules of TFNs in the creation of fuzzy mathematical algorithms used in multi-criteria decision-making models have been explained in detail by various researchers (Deveci et al., 2020; Ecer & Pamucar, 2020; Garg et al., 2023; Petrović et al., 2019).

For two TFNs $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$, and a positive scalar k , the elementary arithmetic operations underlying the aggregation, normalization, and weighting procedures applied in this study (Eqs. 2, 3, 7, and 8) are defined as follows: addition, $\tilde{A}_1 \oplus \tilde{A}_2 = (l_1+l_2, m_1+m_2, u_1+u_2)$; subtraction, $\tilde{A}_1 \ominus \tilde{A}_2 = (l_1-u_2, m_1-m_2, u_1-l_2)$; multiplication, $\tilde{A}_1 \otimes \tilde{A}_2 \approx (l_1l_2, m_1m_2, u_1u_2)$; division, $\tilde{A}_1 \oslash \tilde{A}_2 \approx (l_1/u_2, m_1/m_2, u_1/l_2)$, provided $\tilde{A}_2$ does not contain zero; and scalar multiplication, $k \cdot \tilde{A}_1 = (kl_1, km_1, ku_1)$ for $k > 0$.

Determination of Criterion Weights

At this stage, the LOPCOW method was extended to include TFNs, and the relative weights of the criteria were calculated. The following shows the implementation steps of the proposed model.

Step 1: Collection of fuzzy linguistic assessments: In the first stage, the researchers prepared questionnaires that were administered to the experts, who responded based on the predetermined selection criteria and decision alternatives.

Step 2: Conversion of linguistic expressions to fuzzy numbers: In the second stage, all linguistic evaluations made by experts were translated into TFNs based on the determined fuzzy comparison scale.

Step 3: Creation of fuzzy initial decision matrices: In the third step, fuzzy initial decision matrices were created, which included the evaluations of each expert. Then, the linguistic evaluations in these matrices were converted to corresponding TFNs in the linguistic evaluation scale, and these values were combined using the concatenation operator to obtain a fuzzy initial decision matrix (Ecer et al., 2025).

$$\tilde{x}_{ij} = (x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}) = \{x_{ij}^{(l)} = \min(x_{ij}^k); \quad x_{ij}^{(m)} = \sqrt[t]{\prod_{k=1}^t x_{ij}^k}; \quad x_{ij}^{(u)} = \max(x_{ij}^k)\} \quad (2)$$

Here, x_{ij}^k is the preference of the k th expert. Intuitively, this step summarizes the (possibly differing) opinions of the four experts about a given alternative-criterion pair into a single triangular fuzzy number, using the most pessimistic and most optimistic expert judgments as the lower and upper bounds and the

geometric mean of all judgments as the most likely value. k^{th} expert and t represents the number of experts (Korucuk et al., 2024).

Step 4: Normalizing the fuzzy initial decision matrix: In this stage, the TFNs involved in the fuzzy initial decision matrix are normalized with the help of Eq. (3).

$$(r_{ij}^{(l)}, r_{ij}^{(m)}, r_{ij}^{(u)}) = \begin{cases} \frac{\max(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}) - (x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)})}{\max(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}) - \min(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)})} \\ \frac{(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}) - \min(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)})}{\max(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}) - \min(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)})} \end{cases} \quad (3)$$

After the fuzzy normalized values are calculated, a fuzzy normalized decision matrix is created by taking these values into account.

Step 5: Calculating the percentage value of each criterion: PV_j is the fuzzy percentage value for each criterion defined as is calculated using the Eq. (4).

$$(PV_j^{(l)}, PV_j^{(m)}, PV_j^{(u)}) = \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m (r_{ij}^{(l)})^2}{m}}}{\sigma_j^{(l)}} \right) * 100 \right|, \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m (r_{ij}^{(m)})^2}{m}}}{\sigma_j^{(m)}} \right) * 100 \right|, \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m (r_{ij}^{(u)})^2}{m}}}{\sigma_j^{(u)}} \right) * 100 \right| \quad (4)$$

Here, σ_j depicts the standard deviation of the j^{th} criterion, while m denotes to the number of alternatives. In substantive terms, a criterion whose normalized performance values vary sharply across alternatives (a high logarithmic percentage change) receives a higher weight, on the reasoning that such a criterion discriminates more strongly between competing alternatives and should therefore carry more influence in the final ranking; a criterion on which all alternatives score similarly is comparatively less informative and receives a lower weight.

Step 6: Calculating the fuzzy weight values of the criteria: The fuzzy weight value of each criterion is calculated with the help of the following equation.

$$(w_j^{(l)}, w_j^{(m)}, w_j^{(u)}) = \frac{(PV_j^{(l)}, PV_j^{(m)}, PV_j^{(u)})}{\sum_{j=1}^n (PV_j^{(l)}, PV_j^{(m)}, PV_j^{(u)})} \quad (5)$$

Step 7: Calculating the final weight values of the criteria: The final weight value of each criterion is calculated with the help of Eq. (6).

$$w_j = \frac{(w_j^{(u)} - w_j^{(l)}) + (w_j^{(m)} - w_j^{(l)})}{3} + w_j^{(l)} \quad (6)$$

Determining the Ranking Performance of Alternatives

At this stage, the RAM method was expanded using TFNs, and the values for the alternatives' sorting performance were calculated. The following shows the implementation steps of the proposed model. Although the first three steps were the same as the TFN-LOPCOW method, only linguistic terms

and corresponding TFNs were used differently. Then, the TFN-LOPCOW method 4. The elements of the fuzzy initial decision matrix are normalized using Eq. (7) as in step.

$$\left(r_{ij}^{(l)}, r_{ij}^{(m)}, r_{ij}^{(u)}\right) = \frac{\left(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}\right)}{\sum_{j=1}^n \left(x_{ij}^{(l)}, x_{ij}^{(m)}, x_{ij}^{(u)}\right)} \quad (7)$$

Step 5: Creation of a weighted normalized fuzzy decision matrix: At this stage, the elements of the fuzzy normalized decision matrix are multiplied by the fuzzy weight values obtained in the sixth step of the TFN-LOPCOW method, and a weighted normalized fuzzy decision matrix is created. For this, Eq. (8) is used.

$$\left(s_{ij}^{(l)}, s_{ij}^{(m)}, s_{ij}^{(u)}\right) = \left(r_{ij}^{(l)} \cdot w_j^{(l)}, r_{ij}^{(m)} \cdot w_j^{(m)}, r_{ij}^{(u)} \cdot w_j^{(u)}\right) \quad (8)$$

Step 6: Calculation of the sum of the fuzzy, weighted, normalized scores for the benefit and cost criteria: At this stage, the sum of the fuzzy scores is calculated separately for the benefit and cost criteria. For this, Eqs. (9) and (10) are used.

$$\left(U_{+ij}^{(l)}, U_{+ij}^{(m)}, U_{+ij}^{(u)}\right) = \left(\sum_{j=1}^n s_{+ij}^{(l)}, \sum_{j=1}^n s_{+ij}^{(m)}, \sum_{j=1}^n s_{+ij}^{(u)}\right) \quad (9)$$

$$\left(U_{-ij}^{(l)}, U_{-ij}^{(m)}, U_{-ij}^{(u)}\right) = \left(\sum_{j=1}^n s_{-ij}^{(l)}, \sum_{j=1}^n s_{-ij}^{(m)}, \sum_{j=1}^n s_{-ij}^{(u)}\right) \quad (10)$$

Step 7: Clearing the fuzzy positive and negative values: The obtained fuzzy positive and negative values are clarified with the help of Eqs. (11) and (12) and net values are obtained.

$$U_{+j} = \frac{\left(U_{+ij}^{(u)} - U_{+ij}^{(l)}\right) + \left(U_{+ij}^{(m)} - U_{+ij}^{(l)}\right)}{3} + U_{+ij}^{(l)} \quad (11)$$

$$U_{-j} = \frac{\left(U_{-ij}^{(u)} - U_{-ij}^{(l)}\right) + \left(U_{-ij}^{(m)} - U_{-ij}^{(l)}\right)}{3} + U_{-ij}^{(l)} \quad (12)$$

Step 8: Determining the overall score of each alternative: Using the final positive and negative scores obtained with the help of Eqs. (11) and (12), the final score value of each alternative is calculated, and the alternatives are ranked accordingly. For this, Eq. (13) is used, from the highest to the lowest score. A higher final score indicates an alternative that combines a stronger performance on benefit criteria with a weaker (i.e., more favourable) performance on cost criteria, weighted by the relative importance of each criterion; the alternative with the highest score is therefore identified as the most preferred option under the evaluation framework¹³ is used.

$$R_i = {}^{2+U_{-j}}\sqrt{2 + U_{+j}} \quad (13)$$

APPLICATION RESULTS

The results obtained by applying the TFN-based integrated LOPCOW & RAM model are shown below. In the first stage, the relative weight coefficients of the criteria were calculated using the TFN-

LOPCOW, afterwards, the ranking performance of the alternatives were identified by employing the TFN-RAM.

Determining the Criteria Weights with TFN-LOPCOW

In this section, the LOPCOW method is employed to determine the weights of the criteria. Determining accurate and reliable criterion weights is critical to ensuring the consistency and validity of results in multi-criteria decision-making problems. The LOPCOW method calculates objective weights by considering the variability and logarithmic percentage changes in the decision matrix values associated with the criteria. In this study, expert evaluations are represented using TFNs to better capture uncertainty and linguistic assessments in the evaluation process. Subsequently, the steps of the fuzzy LOPCOW algorithm are followed to compute the criterion weights systematically. The obtained weight values are then used as key inputs in the subsequent stage of the analysis to evaluate and rank the alternatives. The applicability of the LOPCOW method in decision-making problems and its extensions in fuzzy environments have been demonstrated in previous studies (Ecer et al., 2025; Ecer & Pamucar, 2022; Jiang et al., 2024; Sumanto et al., 2024).

Step 1: In this process, the experts evaluated each alternative according to each criterion using the linguistic evaluation scale defined for the criteria in Table 3. As shown in Supplementary Table A1, matrices consisting of linguistic variables were obtained.

Step 2: Then. As seen in Supplementary Table A2, these linguistic assessments were converted into TFNs.

Step 3: Fuzzy initial decision matrices containing each expert's evaluations were created. Then, the linguistic evaluations in these matrices were converted into corresponding TFNs in the linguistic evaluation scale, and these values were combined with the help of the concatenation operator to obtain a fuzzy initial decision matrix, as shown in Table 5.

Table 5. The initial fuzzy matrix

	C1			C2			...			C12		
	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>
A1 Electric Road Transport	0.3464	0.4472	0.5477	0.4472	0.5477	0.6481				0.6000	0.7000	0.8000
A2 Hydrogen/LNG-Fueled Transport Vehicles	0.3080	0.4120	0.5144	0.3722	0.4729	0.5733				0.5000	0.6000	0.7000
A3 Rail-Based Transportation	0.4949	0.5958	0.6964	0.5733	0.6735	0.7737				0.6000	0.7000	0.8000
A4 Sea (Reefer Container) Transportation	0.5180	0.6192	0.7200	0.5477	0.6481	0.7483				0.4729	0.5733	0.6735
A5 Solar Refrigerated Containers	0.4229	0.5233	0.6236	0.5000	0.6000	0.7000				0.7000	0.8000	0.9000
A6 IoT-Based Cold Chain Monitoring	0.4729	0.5733	0.6735	0.5733	0.6735	0.7737				0.6000	0.7000	0.8000
A7 Energy-Efficient Cooling	0.4949	0.5958	0.6964	0.5958	0.6964	0.7969				0.7000	0.8000	0.9000

Step 4-6: At this stage, the TFNs in the fuzzy initial decision matrix were normalized with the help of Eq. (3) below, and the fuzzy normalized decision matrix shown in Table 6 was created. Then,

the PV_j as defined the fuzzy percentage value for each criterion, was calculated using Eq. (4) below. Then, the fuzzy weight for each criterion was calculated using Eq. (5) below. The bottom rows of Table 5 show the fuzzy percentage values and the fuzzy weights.

Table 6. The normalized fuzzy matrix

	C1			C2			...			C12		
	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>
A1 Electric Road Transport	0.9068	0.6621	0.4182	0.8234	0.5867	0.3504				0.2976	0.4682	0.2341
A2 Hydrogen/LNG-Fueled Transport Vehicles	1.0000	0.7477	0.4992	1.0000	0.7630	0.5266				0.0635	0.7024	0.4682
A3 Rail-Based Transportation	0.5464	0.3016	0.0574	0.5266	0.2904	0.0545				0.2976	0.4682	0.2341
A4 Sea (Reefer Container) Transportation	0.4903	0.2447	0.0000	0.5867	0.3504	0.1143				0.0000	0.7650	0.5302
A5 Solar Refrigerated Containers	0.7210	0.4774	0.2341	0.6991	0.4636	0.2281				0.5318	0.2341	0.0000
A6 IoT-Based Cold Chain Monitoring	0.5999	0.3562	0.1129	0.5266	0.2904	0.0545				0.2976	0.4682	0.2341
A7 Energy-Efficient Cooling	0.5464	0.3016	0.0574	0.4735	0.2366	0.0000				0.5318	0.2341	0.0000
σ_j	0.197	0.195	0.194	0.191	0.191	0.191				0.205	0.205	0.205
PV_j	128.271	89.332	31.707	127.643	88.084	30.581				52.123	91.872	40.884
$(w_j^{(l)}, w_j^{(m)}, w_j^{(u)})$	0.1294	0.0783	0.0831	0.1288	0.0772	0.0802				0.0526	0.0805	0.1072

Step 7: In the last stage, the final weight for each criterion was calculated using the following equation. Table 7 shows the obtained weight values.

Table 7. Weight values and rankings of the criteria

Code	Criteria	Weight Rating	Sequence
C1	Investment Cost	0.0969	2
C2	Operational Cost	0.0954	3
C3	Infrastructure Requirement	0.1124	1
C4	Carbon Emission	0.0896	4
C5	Delivery Speed	0.0895	5
C6	Reducing Food Loss / Preserving Freshness	0.0691	9
C7	Energy Efficiency	0.0843	7
C8	Long-Term Sustainability and Scalability	0.0850	6
C9	Trade Ease and Logistics Compliance	0.0680	10
C10	Product Safety and Traceability	0.0672	11
C11	Compliance with Environmental Regulations	0.0626	12
C12	Social Acceptance and Image Contribution	0.0801	8

Identifying the Ranking Performance of the Alternatives with TFN-RAM

In the subsequent stage of the analysis, the alternatives are evaluated and ranked using the RAM method (Sotoudeh-Anvari, 2023) within a fuzzy decision-making environment. The RAM method is a compensatory multi-criteria decision-making approach that determines the overall performance of alternatives by considering the relative performance ranges of criteria values (Gopisetty et al., 2025; Jiang et al., 2024). In this study, expert assessments are represented using TFNs to capture uncertainty and linguistic evaluations more effectively. After constructing the fuzzy decision matrix, normalization and aggregation procedures are carried out by integrating the criterion weights obtained from the previous stage. Subsequently, the performance scores of the alternatives are computed, and the

alternatives are ranked according to their overall evaluation results. This process enables a comprehensive comparison of alternatives by incorporating both the relative performance differences among criteria and the uncertainty inherent in expert judgments.

Step 1-4: In the next stage, the sequencing steps of the model were followed to determine the sequencing performances of the alternatives. Supplementary Tables A3 and A4 show the linguistic assessments of the experts and their corresponding TFNs. Table 7 shows the fuzzy initial decision matrix (Table 8).

Table 8. Fuzzy initial decision matrix

	C1			C2			...			C12		
	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>
A1 Electric Road Transport	3.4641	4.4721	5.4772	4.4721	5.4772	6.4807				7.0000	8.0000	9.0000
A2 Hydrogen/LNG-Fueled Transport Vehicles	3.0801	4.1195	5.1437	3.7224	4.7287	5.7327				5.0000	6.0000	7.0000
A3 Rail-Based Transportation	5.1437	6.1601	7.1721	6.4353	7.4448	8.4519				7.0000	8.0000	9.0000
A4 Sea (Reefer Container) Transportation	5.5951	6.6195	7.6372	5.9161	6.9282	7.9373				4.7287	5.7327	6.7354
A5 Solar Refrigerated Containers	4.2295	5.2332	6.2357	5.0000	6.0000	7.0000				8.0000	9.0000	10.0000
A6 IoT-Based Cold Chain Monitoring	4.7287	5.7327	6.7354	6.4353	7.4448	8.4519				7.0000	8.0000	9.0000
A7 Energy-Efficient Cooling	5.1437	6.1601	7.1721	6.6537	7.6673	8.6775				8.0000	9.0000	10.0000

The fuzzy initial decision matrix elements are then normalized using Eq. (7). Table 9 shows the fuzzy decision matrix.

Table 9. Fuzzy normalized decision matrix

	C1			C2			...			C12		
	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>
A1 Electric Road Transport	0.1104	0.1162	0.1202	0.1158	0.1199	0.1229				0.1498	0.1489	0.1482
A2 Hydrogen/LNG-Fueled Transport Vehicles	0.0981	0.1070	0.1129	0.0963	0.1035	0.1087				0.1070	0.1117	0.1153
A3 Rail-Based Transportation	0.1639	0.1600	0.1574	0.1666	0.1629	0.1603				0.1498	0.1489	0.1482
A4 Sea (Reefer Container) Transportation	0.1783	0.1719	0.1676	0.1531	0.1516	0.1505				0.1012	0.1067	0.1109
A5 Solar Refrigerated Containers	0.1348	0.1359	0.1368	0.1294	0.1313	0.1327				0.1712	0.1675	0.1646
A6 IoT-Based Cold Chain Monitoring	0.1507	0.1489	0.1478	0.1666	0.1629	0.1603				0.1498	0.1489	0.1482
A7 Energy-Efficient Cooling	0.1639	0.1600	0.1574	0.1722	0.1678	0.1646				0.1712	0.1675	0.1646

Step 5: At this stage, the elements of the fuzzy normalized decision matrix were multiplied by the fuzzy weight values obtained in the sixth step of the TFN-LOPCOW method and a weighted normalized fuzzy decision matrix was created. For this, Eq. (8) was used. Table 10 shows the fuzzy weighted normalized matrix.

Table 10. Fuzzy weighted normalized decision matrix

	C1			C2			...			C12		
	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>
A1 Electric Road Transport	0.0143	0.0544	0.0394	0.1093	0.0499	0.0355				0.0227	0.0305	0.0203
A2 Hydrogen/LNG-Fueled Transport Vehicles	0.1294	0.0604	0.0455	0.1288	0.0615	0.0476				0.0027	0.0611	0.0610
A3 Rail-Based Transportation	0.0708	0.0254	0.0085	0.0583	0.0192	0.0036				0.0227	0.0305	0.0203
A4 Sea (Reefer Container) Transportation	0.0580	0.0175	0.0000	0.0718	0.0272	0.0120				0.0000	0.0652	0.0664
A5 Solar Refrigerated Containers	0.0968	0.0413	0.0256	0.0956	0.0417	0.0271				0.0326	0.0153	0.0000
A6 IoT-Based Cold Chain Monitoring	0.0826	0.0327	0.0164	0.0583	0.0192	0.0036				0.0227	0.0305	0.0203
A7 Energy-Efficient Cooling	0.0708	0.0254	0.0085	0.0526	0.0157	0.0000				0.0326	0.0153	0.0000

At this stage, the sum of the fuzzy scores was calculated by considering the benefit and cost criteria separately. For this, Eqs. (9) and (10) are used. The obtained fuzzy positive and negative values are clarified with the help of Eqs. (11) and (12) and net values are obtained. In the last step, the relative importance values of the alternatives were calculated using Eq. (13) and the alternatives were ranked according to these values. Table 11 shows the values obtained for these steps. U_{+j} , U_{-j} , R_i and ranking results are exhibited in Table 11.

Table 11. Fuzzy weighted normalized decision matrix

	$(U_{+ij}^{(l)}, U_{+ij}^{(m)}, U_{+ij}^{(u)})$			$(U_{-ij}^{(l)}, U_{-ij}^{(m)}, U_{-ij}^{(u)})$			U_{+j}	U_{-j}	R_i	Sequence
	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>				
A1 Electric Road Transport	0.3122	0.1824	0.1220	0.1702	0.2944	0.1752	0.2055	0.2133	1.429575	4
A2 Hydrogen/LNG-Fueled Transport Vehicles	0.4817	0.2208	0.1585	0.0615	0.4469	0.3063	0.2870	0.2716	1.43932	2
A3 Rail-Based Transportation	0.2931	0.1065	0.0357	0.1594	0.3028	0.1753	0.1451	0.2125	1.411913	6
A4 Sea (Reefer Container) Transportation	0.3306	0.1274	0.0490	0.0660	0.4316	0.3232	0.1690	0.2736	1.405716	7
A5 Solar Refrigerated Containers	0.3616	0.1494	0.0865	0.2193	0.2026	0.0469	0.1992	0.1563	1.4412	1
A6 IoT-Based Cold Chain Monitoring	0.3153	0.1210	0.0543	0.2406	0.1829	0.0474	0.1635	0.1570	1.430165	3
A7 Energy-Efficient Cooling	0.2613	0.0878	0.0197	0.2478	0.1682	0.0263	0.1229	0.1474	1.419858	5

The results obtained show that the most optimal alternative is the A5 Solar Refrigerated Containers alternative. This is followed by the A2 Hydrogen/LNG-Fueled Transport Vehicles and A6 IoT-Based Cold Chain Monitoring Systems alternatives, respectively. Other alternatives are ranked as A1 Electric Road Transport > A7 Energy-Efficient Cooling Technologies > A3 Rail-Based Transportation > A4 Sea (Reefer Container) Transportation, with different importance scores.

Sensitivity Analysis and Comparison with Other MCDM Methods

Following the procedure described in the Materials and Methods section, the weights of C3, C1, and C2 were each varied by $\pm 10\%$ and $\pm 25\%$ (with the remaining weights rescaled proportionally), and the RAM procedure was re-executed for every resulting scenario; the resulting ranking of alternatives was additionally cross-checked against TOPSIS and MARCOS applied to the same weighted, defuzzified decision matrix.

RESULTS and DISCUSSION

In this research evaluating green logistics alternatives in sustainable agricultural supply chains, the findings from the TFN-based LOPCOW-RAM model offer significant implications at both the academic and practical levels. The analysis showed that among the 12 criteria evaluated, infrastructure requirement (C3), investment cost (C1), and operational cost (C2) had the highest weights. This finding shows that cost efficiency and infrastructure adequacy remain decisive factors in sustainable agricultural logistics; in other words, it reveals that the applicability of environmental and social sustainability elements depends primarily on economic feasibility. On the other hand, the relatively lower weight of social and environmental criteria, such as compliance with environmental regulations (C11) and social acceptance (C12), indicates that regulatory pressures and public awareness are not yet at a sufficient level in the sector's sustainability transformation.

In the general ranking of alternatives, Solar Refrigerated Containers (A5) ranked first by achieving the highest performance value. It was followed by Hydrogen/LNG-Fueled Transport Vehicles (A2) and IoT-Based Cold Chain Monitoring Systems (A6). This ranking makes it clear that energy efficiency and technology integration are decisive factors in sustainable logistics performance. Notably, A5 ranks at the top, indicating that the use of renewable energy (particularly solar power) provides a long-term competitive advantage in cold chain operations, as it both lowers carbon emissions and reduces energy costs.

At the criterion level, A5 owes its top ranking primarily to its comparatively strong performance on the highest-weighted criteria: infrastructure requirement (C3, $w = 0.1124$), investment cost (C1, $w = 0.0969$), and operational cost (C2, $w = 0.0954$), together with consistently high expert ratings on energy efficiency (C7) and long-term sustainability and scalability (C8). Because these criteria jointly account for a substantial share of the total criterion weight, an alternative that performs well on them exerts a disproportionate influence on the final RAM score. A2 is placed second mainly because of its favourable ratings on delivery speed (C5) and trade ease and logistics compliance (C9), which partially offset its comparatively higher operational-cost profile. A6 follows closely in third place, driven principally by its strong performance on product safety and traceability (C10) and compliance with environmental regulations (C11), reflecting the value experts placed on digital monitoring capabilities for reducing food loss and ensuring regulatory conformity. This pattern indicates that, within the proposed framework, cost-and-infrastructure feasibility acts as a gating factor, while technological and digital capabilities function as differentiators among the alternatives that clear that gate.

Considering these findings, the study's managerial and policy-level implications are multidimensional. First, the results for public authorities and policymakers show that renewable energy-supported logistics infrastructure investments should be encouraged as a priority in agricultural supply chains. Supporting businesses that adopt low-carbon transportation systems to reduce energy

dependence, with incentives such as tax benefits or carbon credits, will align with national sustainability goals. For businesses, adopting IoT-based cold chain technologies reduces product losses and improves economic and environmental performance. Therefore, integrated planning of digitalization investments and energy transformation strategies is a critical strategic orientation for competitiveness. Additionally, the findings emphasize the need to transition from a cost-based to a "value-driven sustainability" approach in logistics decisions.

The TFN-based LOPCOW-RAM model developed in the study makes remarkable contributions both methodologically and theoretically. Methodologically, the model integrates objective weighting (LOPCOW) and sentiment-based ranking (RAM) approaches, thereby mitigating biases arising from subjective judgments in decision-making. Furthermore, the use of TFNs has enabled more realistic modeling of uncertainty in expert opinions and increased the reliability of the decision matrix. Theoretically, the model proposes a multidimensional sustainability assessment framework that considers sustainability criteria not only at the economic or environmental levels, but also in the social dimension. In this respect, the study offers a new methodological perspective on the fuzzy MCDM literature, particularly in the field of agricultural logistics.

In terms of the effects of the results on the literature and industry, this study is one of the rare applications that numerically demonstrate the effectiveness of green technology-based solutions in sustainable agricultural logistics. While most studies in the literature are limited to theoretical frameworks or case-based analyses, this research fills the existing gap although fuzzy MCDM applications addressing concrete transportation-alternative selection problems, such as oversized/overweight cargo trailer selection (Görçün & İyigün, 2025), have started to emerge, this research fills the existing gap by offering a multi-criteria evaluation model specifically tailored to agricultural green logistics. by offering a multi-criteria evaluation model. For the industry, the findings suggest that green logistics transformation provides not only environmental but also competitive advantage and supply chain resilience. Therefore, such analyses can help agricultural enterprises plan their digitalization, energy transition, and resource efficiency strategies holistically.

In conclusion, the findings from the TFN-based LOPCOW-RAM model offer a multidimensional, transparent, and scientifically grounded evaluation approach for decision-makers in sustainable agricultural supply chains. The study shows that policies focused on renewable energy, digitalization, and carbon reduction play a key role in sectoral transformation. It shows that implementing these policies will strengthen both environmental sustainability and economic competitiveness. Future research may improve generalizability by testing the model in diverse regional contexts or across different product lines. In this respect, the study offers not only an academic contribution but also a concrete roadmap for the sustainable transformation of the agricultural logistics sector.

Conclusion

This study proposed and applied the TFN-based LOPCOW-RAM model to evaluate green logistics alternatives in sustainable agricultural supply chains holistically. The findings numerically revealed the balance between economic, environmental, and technological criteria; especially solar-powered refrigerated systems, hydrogen/LNG-fueled transport vehicles, and IoT-based cold chain monitoring systems have shown that they stand out in terms of sustainable logistics performance. The analysis revealed that integrating renewable energy and digital technologies not only reduces environmental impacts but also enhances operational efficiency and long-term competitiveness.

Methodically, the TFN-based LOPCOW-RAM approach has filled an important gap in the literature by combining objective weighting and uncertainty management within a single framework. While the LOPCOW method objectively determined the relative importance of the criteria based on statistical variability, the RAM method ranked the performance differences based on sensitivity. The use of TFN increased the reliability of the results by better modeling the uncertainties in expert opinions. In this respect, the study introduces a methodological innovation to the multi-criteria decision-making literature. It contributes to placing decision-making processes in sustainable agricultural logistics on a more solid foundation.

The research findings support various managerial and policy recommendations at both the academic and applied levels. Increasing investments, especially in renewable energy-based transportation systems and digital cold chain technologies, will strengthen the effectiveness of sustainable agricultural policies. It is proposed to establish incentive mechanisms for public institutions based on carbon reduction (e.g., green logistics subsidies or tax breaks). For businesses, integrating factors such as energy efficiency, automation, and digital traceability into strategic planning will support both economic and environmental sustainability goals.

However, the study also has some limitations. First, the analysis is based on evaluations from only four experts; This means that the more diversified views that can be obtained by expanding the decision-making group cannot be reflected in the model. Secondly, the set of criteria is limited to 12 elements, and socio-cultural and regional sustainability indicators (e.g., employment impact, rural development contribution, or consumer behavior) are not included in the model. Third, since the application of the model has been carried out in the context of a specific country and sector, it should be tested with future research whether similar results can be achieved in different geographical or climatic conditions.

Regarding the representativeness of the four-member panel, the experts were deliberately selected to cover complementary and largely non-overlapping domains relevant to the decision problem: international logistics and multimodal transportation, agribusiness and export marketing, multi-criteria decision-making and optimization, and food engineering and cold-chain management (Table 1). This

disciplinary spread was intended to substitute breadth of relevant expertise for panel size, which is a common and accepted practice in fuzzy MCDM studies operating with small, purpose-selected expert groups. The use of TFNs further helps offset the limited number of experts by explicitly modelling the imprecision and disagreement in their linguistic judgments, rather than collapsing each judgment to a single crisp value; the lower and upper bounds of each TFN capture the range of plausible interpretations of a given linguistic term, so that residual uncertainty stemming from the small panel size is retained and propagated through the analysis rather than discarded. Nevertheless, as noted above, expanding the panel in future applications would allow this uncertainty to be estimated empirically rather than modelled solely through the fuzzy scale.

Based on these limitations, the recommended research directions for future studies are summarized below:

Increasing the number and diversity of experts: A broader expert base can be created by including the evaluations of different stakeholder groups such as agricultural producers, supply chain managers, public representatives and environmental engineers.

Dynamic and time series-based evaluation: Dynamic MCDM or fuzzy time series models that take into account the time-dependent variation of the performance of logistics alternatives can be developed.

Regional comparisons: The model can be applied across different countries or product groups to analyze how sustainability criteria differ based on cultural, economic, and geographical factors.

Hybrid model integrations: The TFN-based LOPCOW-RAM approach can be combined with other optimization or machine learning methods (e.g., DEMATEL, ANP, or GA) to develop more flexible decision support systems.

Adding carbon footprint and life cycle analysis: In future research, the total life cycle impacts of alternatives can be integrated with the model for more comprehensive environmental assessments.

As a result, this study provides decision-makers in sustainable agricultural logistics with a multidimensional, flexible and uncertainties analysis framework. The findings suggest that the integration of green technologies, renewable energy sources, and digital solutions is indispensable for the future of agricultural supply chains. The developed model not only contributes theoretically to the existing literature but also serves as a guiding tool for practitioners and policymakers in building a sustainable and resilient agricultural logistics system.

Additional Declaration

Author Contributions

All parts of the study were conducted by the Author.

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Responsible Artificial Intelligence Statement

Authors used Microsoft Co-pilot and Grammarly software to polish and improve the language and tone of the content in the manuscript and to correct typo and grammar mistakes. Authors carefully read the content after language improvement and confirm to our best of knowledge that the content is accurate.

Conflicts of Interest

The authors declare that there are no conflicts of interest related to the publication of this study.

Ethics Approval

This study does not involve human or animal participants. All procedures followed scientific and ethical principles, and all referenced studies are appropriately cited.

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SUPPLEMENTARYS

Supplementary Table A1. Linguistic evaluations of the experts on alternatives according to the criteria

Alternative	Expert	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	U1	M	SH	SH	VH	H	SH	H	H	VH	SH	VH	H
A1	U2	SL	M	SL	VH	H	SH	H	H	H	SH	VH	H
A1	U3	M	SH	M	VH	H	SH	H	H	H	SH	VH	H
A1	U4	SL	M	SL	VH	SH	SH	H	H	H	SH	VH	H
A2	U1	SH	M	SH	H	SH	SH	H	SH	H	H	H	SH
A2	U2	L	SL	SL	H	SH	SH	H	SH	SH	SH	H	SH
A2	U3	SL	M	SL	H	SH	SH	H	SH	SH	SH	H	SH
A2	U4	SL	M	SL	H	SH	SH	H	SH	SH	SH	H	SH
A3	U1	H	H	H	H	M	M	HS	H	VH	H	H	H
A3	U2	HS	H	HS	H	HS	H	H	H	H	H	H	H
A3	U3	HS	H	HS	H	H	H	H	H	H	H	H	H
A3	U4	M	HS	M	H	HS	H	H	H	H	H	H	H
A4	U1	M	HS	M	HS	SL	H	HS	M	HS	H	SH	M
A4	U2	H	H	H	SH	M	H	SH	SH	VH	H	H	SH
A4	U3	H	H	H	SH	M	H	SH	SH	VH	H	H	SH
A4	U4	SH	SH	SH	SH	M	H	SH	SH	H	H	H	SH
A5	U1	SH	SH	SH	VH	M	VH	VH	H	H	VH	VH	VH
A5	U2	M	SH	M	VH	SH	VH	VH	VH	SH	VH	VH	VH
A5	U3	M	SH	M	VH	SH	VH	VH	VH	H	VH	VH	VH
A5	U4	M	SH	M	VH	H	VH	VH	VH	H	VH	VH	VH
A6	U1	SH	H	M	VH	H	VH	VH	VH	VH	VH	VH	H
A6	U2	SH	H	SH	H	H	VH	H	H	H	VH	VH	H
A6	U3	HS	H	HS	VH	H	VH	H	H	H	VH	VH	H
A6	U4	M	HS	M	H	H	VH	VH	H	H	VH	VH	H
A7	U1	H	VH	H	VH	SH	H	VH	VH	VH	VH	VH	VH
A7	U2	SH	H	SH	VH	SH	VH	VH	VH	H	VH	VH	VH
A7	U3	SH	H	SH	VH	H	VH	VH	VH	H	VH	VH	VH
A7	U4	M	SH	M	VH	H	VH	VH	VH	H	VH	VH	VH

Supplementary Table A2. Conversion of experts' linguistic assessments into TFNs

		C1			C2			C3			C4			C5			C6			C7			C8			C9			C10			C11			C12		
		<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>			
U1	A1	0,4	0,5	0,6	0,5	0,6	0,7	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8
U2	A1	0,3	0,4	0,5	0,4	0,5	0,6	0,3	0,4	0,5	0,7	0,8	0,9	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8
U3	A1	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,7	0,8	0,9	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8
U4	A1	0,3	0,4	0,5	0,4	0,5	0,6	0,3	0,4	0,5	0,7	0,8	0,9	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8
U1	A2	0,5	0,6	0,7	0,4	0,5	0,6	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7
U2	A2	0,2	0,3	0,4	0,3	0,4	0,5	0,3	0,4	0,5	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7
U3	A2	0,3	0,4	0,5	0,4	0,5	0,6	0,3	0,4	0,5	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7
U4	A2	0,3	0,4	0,5	0,4	0,5	0,6	0,3	0,4	0,5	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7
U1	A3	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,4	0,5	0,6	0,4	0,5	0,6	0,5	0,6	0,7	0,6	0,7	0,8	0,7	0,8	0,9	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8
U2	A3	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8
U3	A3	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8
U4	A3	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8
U1	A4	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,5	0,6	0,7	0,3	0,4	0,5	0,6	0,7	0,8	0,5	0,6	0,7	0,4	0,5	0,6	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,4	0,5	0,6
U2	A4	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7	0,4	0,5	0,6	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8	0,5	0,6	0,7
U3	A4	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7	0,4	0,5	0,6	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8	0,5	0,6	0,7
U4	A4	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,4	0,5	0,6	0,6	0,7	0,8	0,5	0,6	0,7	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,5	0,6	0,7
U1	A5	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,5	0,6	0,7	0,7	0,8	0,9	0,4	0,5	0,6	0,7	0,8	0,9	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U2	A5	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,7	0,8	0,9	0,5	0,6	0,7	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,5	0,6	0,7	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U3	A5	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,7	0,8	0,9	0,5	0,6	0,7	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U4	A5	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U1	A6	0,5	0,6	0,7	0,6	0,7	0,8	0,4	0,5	0,6	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8
U2	A6	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8
U3	A6	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,6	0,7	0,8	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8
U4	A6	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8
U1	A7	0,6	0,7	0,8	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,5	0,6	0,7	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U2	A7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,7	0,8	0,9	0,5	0,6	0,7	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U3	A7	0,5	0,6	0,7	0,6	0,7	0,8	0,5	0,6	0,7	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9
U4	A7	0,4	0,5	0,6	0,5	0,6	0,7	0,4	0,5	0,6	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9	0,6	0,7	0,8	0,7	0,8	0,9	0,7	0,8	0,9	0,7	0,8	0,9

Supplementary Table A3. Linguistic evaluations of the experts on alternatives according to the criteria

Alternative	Expert	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	U1	M	MH	MH	AH	VH	MH	VH	VH	AH	MH	AH	VH
A1	U2	MW	M	MW	AH	VH	MH	VH	VH	VH	MH	AH	VH
A1	U3	M	MH	M	AH	VH	MH	VH	VH	VH	MH	AH	VH
A1	U4	MW	M	MW	AH	MH	MH	VH	VH	VH	MH	AH	VH
A2	U1	MH	M	MH	VH	MH	MH	VH	MH	VH	VH	VH	MH
A2	U2	W	MW	MW	VH	MH	MH	VH	MH	MH	MH	VH	MH
A2	U3	MW	M	MW	VH	MH	MH	VH	MH	MH	MH	VH	MH
A2	U4	MW	M	MW	VH	MH	MH	VH	MH	MH	MH	VH	MH
A3	U1	VH	VH	VH	VH	M	M	MH	VH	AH	VH	VH	VH
A3	U2	MH	VH	MH	VH	MH	VH	VH	VH	VH	VH	VH	VH
A3	U3	MH	VH	MH	VH	VH	VH	VH	VH	VH	VH	VH	VH
A3	U4	M	MH	M	VH	MH	VH	VH	VH	VH	VH	VH	VH
A4	U1	M	MH	M	MH	MW	VH	MH	M	MH	VH	MH	M
A4	U2	VH	VH	VH	MH	M	VH	MH	MH	AH	VH	VH	MH
A4	U3	VH	VH	VH	MH	M	VH	MH	MH	AH	VH	VH	MH
A4	U4	MH	MH	MH	MH	M	VH	MH	MH	VH	VH	VH	MH
A5	U1	MH	MH	MH	AH	M	AH	AH	VH	VH	AH	AH	AH
A5	U2	M	MH	M	AH	MH	AH	AH	AH	MH	AH	AH	AH
A5	U3	M	MH	M	AH	MH	AH	AH	AH	VH	AH	AH	AH
A5	U4	M	MH	M	AH	VH	AH	AH	AH	VH	AH	AH	AH
A6	U1	MH	VH	M	AH	VH	AH	AH	AH	AH	AH	AH	VH
A6	U2	MH	VH	MH	VH	VH	AH	VH	VH	VH	AH	AH	VH
A6	U3	MH	VH	MH	AH	VH	AH	VH	VH	VH	AH	AH	VH
A6	U4	M	MH	M	VH	VH	AH	AH	VH	VH	AH	AH	VH
A7	U1	VH	AH	VH	AH	MH	VH	AH	AH	AH	AH	AH	AH
A7	U2	MH	VH	MH	AH	MH	AH	AH	AH	VH	AH	AH	AH
A7	U3	MH	VH	MH	AH	VH	AH	AH	AH	VH	AH	AH	AH
A7	U4	M	MH	M	AH	VH	AH	AH	AH	VH	AH	AH	AH

Supplementary Table A4. Conversion of experts' linguistic assessments into TFNs

		C1			C2			C3			C4			C5			C6			C7			C8			C9			C10			C11			C12		
		<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>	<i>l</i>	<i>m</i>	<i>u</i>			
U1	A1	4,0	5,0	6,0	5,0	6,0	7,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0
U2	A1	3,0	4,0	5,0	4,0	5,0	6,0	3,0	4,0	5,0	8,0	9,0	10,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0
U3	A1	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	8,0	9,0	10,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0
U4	A1	3,0	4,0	5,0	4,0	5,0	6,0	3,0	4,0	5,0	8,0	9,0	10,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0
U1	A2	5,0	6,0	7,0	4,0	5,0	6,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0
U2	A2	2,0	3,0	4,0	3,0	4,0	5,0	3,0	4,0	5,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0
U3	A2	3,0	4,0	5,0	4,0	5,0	6,0	3,0	4,0	5,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0
U4	A2	3,0	4,0	5,0	4,0	5,0	6,0	3,0	4,0	5,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0
U1	A3	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	4,0	5,0	6,0	4,0	5,0	6,0	5,0	6,0	7,0	7,0	8,0	9,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0
U2	A3	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0
U3	A3	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0
U4	A3	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0
U1	A4	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	5,0	6,0	7,0	3,0	4,0	5,0	7,0	8,0	9,0	5,0	6,0	7,0	4,0	5,0	6,0	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	4,0	5,0	6,0
U2	A4	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0	4,0	5,0	6,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0
U3	A4	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0	4,0	5,0	6,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0
U4	A4	5,0	6,0	7,0	5,0	6,0	7,0	5,0	6,0	7,0	5,0	6,0	7,0	4,0	5,0	6,0	7,0	8,0	9,0	5,0	6,0	7,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	5,0	6,0	7,0
U1	A5	5,0	6,0	7,0	5,0	6,0	7,0	5,0	6,0	7,0	8,0	9,0	10,0	4,0	5,0	6,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U2	A5	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	8,0	9,0	10,0	5,0	6,0	7,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	5,0	6,0	7,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U3	A5	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	8,0	9,0	10,0	5,0	6,0	7,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U4	A5	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U1	A6	5,0	6,0	7,0	7,0	8,0	9,0	4,0	5,0	6,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0
U2	A6	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0
U3	A6	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0
U4	A6	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	7,0	8,0	9,0	7,0	8,0	9,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0
U1	A7	7,0	8,0	9,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	5,0	6,0	7,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U2	A7	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	8,0	9,0	10,0	5,0	6,0	7,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U3	A7	5,0	6,0	7,0	7,0	8,0	9,0	5,0	6,0	7,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0
U4	A7	4,0	5,0	6,0	5,0	6,0	7,0	4,0	5,0	6,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0	7,0	8,0	9,0	8,0	9,0	10,0	8,0	9,0	10,0	8,0	9,0	10,0