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Location Quotient and Fuzzy ARAS in Determining Superior Commodities in the Food Crops Subsector

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Abstract

The selection of superior food crop commodities at the regional level is very important to sup-port agricultural development policies, but it is often carried out without comprehensive strategic analysis, risking less accurate decisions. The objective of this research is to establish the superior commodities of the food crop subsector in Langkat Regency based on regional contributions and a number of strategic criteria categorized into economic, production, and environmental aspects. The methods used include Location Quotient (LQ) to measure the region's comparative advantage based on production contribution, as well as Fuzzy ARAS to evaluate seven commodities based on ten strategic criteria with expert assessment using triangular fuzzy numbers. The results show that rice is the base commodity in 13 districts and has the highest contribution distribution. However, soybeans have become the superior commodity with the highest relative utility value (1.029), followed by cassava (1.015) and rice (0.983). The LQ and Fuzzy ARAS methods have proven effective in supporting the de-termination of superior commodities based on local potential.

Keywords: Superior Commodities, Location Quotient, Fuzzy ARAS, Food Crops

1. Introduction

Indonesia is an agrarian country with favorable geographical conditions and fertile soil, so most of the population relies on the agricultural sector for their livelihood. However, this sector faces various challenges such as land conversion, soil degradation, and climate change, which lead to production uncertainty (Faoziyah et al., 2024). In such conditions, the food crop subsector becomes extremely vital in maintaining national food security. Inaccuracies in identifying leading commodities still occur frequently and can trigger inefficiencies, regional development disparities, and weak policy responses (Marlinda et al., 2023). Therefore, determining the appropriate leading commodities is a strategic element in agricultural development planning.

Similar problems are occurring in Langkat Regency, one of the food crop production centers in North Sumatra. The determination of leading commodities in this region still relies on a single indicator such as harvest area, without considering economic value, technological efficiency, or sustainability. In fact, according to BPS (2024), although rice has the highest harvest area (24,760.51 hectares), it is not necessarily the most superior in terms of efficiency or market prospects. The food crop subsector in Langkat faces challenges such as stagnant productivity, low technology adoption, weak market integration, and minimal post-harvest infrastructure (Dinas Perindustrian dan Perdagangan, 2024). The commodities being cultivated often don't match market demand and climate challenges, leading to low added value and vulnerability to crop failure. The absence of strategic analysis makes agricultural programs directionless and wasteful of resources, necessitating the identification of superior commodities for more adaptive and sustainable agricultural policies.

This condition demands a more objective approach in determining leading commodities, as indicators like harvest area are not sufficient to represent economic contribution or sustainability. This research combines the Location Quotient (LQ) method to identify basic commodities based on regional advantages (Heldayani, 2022), (Monsaputra, 2024) and Fuzzy ARAS to rank them based on strategic criteria under uncertain conditions (Dhandy et al., 2022), (Fatih ATLI, 2024). Although LQ has been widely integrated with methods such as Shift Share, Klassen Typology (Azra' & Yaseen, 2024), (Kia & Ichsan, 2023) or Fuzzy AHP, these approaches are still limited by their hierarchical structure and less flexible global weights (Resi et al., 2024). Although used by Resi et al. (2024), Fuzzy AHP still relies on a rigid decision structure. In contrast, Fuzzy ARAS allows for direct evaluation based on experts' fuzzy values, making it more adaptable to the contextual and spatial dynamics of the agricultural sector. This research aims to fill this gap by offering a more contextual and flexible evaluation framework for the food crop subsector in Langkat Regency.

One relevant method for building a flexible evaluation framework is ARAS, which has been widely used in multi-criteria decision-making across various sectors, ranging from agriculture such as selecting red onion fertilizer (Nuriman et al., 2024), and quality-of-service-based suppliers (Aldo et al., 2023) to non-agricultural sectors such as hotel evaluation (Singgalen, 2023), textile industry suppliers (Ristono et al., 2024), and teacher performance (Akmaludin et al., 2023). However, ARAS is deterministic, making it less ideal for systems with high uncertainty, such as the food crop subsector. To address this, ARAS was developed into Fuzzy ARAS, which incorporates fuzzy logic, allowing for better handling of linguistic variables and input uncertainty. This method has been applied in flood risk-based investment location selection (Idris et al., 2024), water management with uncertain rainfall (Dehkordi et al., 2025), robotics technology evaluation (Singh, 2022), logistics distribution systems (Jovčić et al., 2020), and manufacturing robots (Tran et al., 2025). Nevertheless, the application of Fuzzy ARAS is still dominant in the industrial sector and has not been widely used to evaluate superior agricultural commodities, especially food crops (Fatih ATLI, 2024). These limitations create a significant methodological gap, considering the food crop subsector is highly influenced by spatial dynamics, market volatility, and environmental pressures that require evaluation systems that are flexible, adaptive, and capable of explicitly handling uncertainty.

Most previous studies still limit the selection of superior commodities to deterministic approaches such as LQ and ARAS separately, without considering the spatial complexity and data uncertainty typical of the agricultural sector. In fact, actual challenges such as climate change, market fluctuations, and resource limitations demand a more adaptive and flexible evaluation system. This research offers a new framework by integrating LQ as an initial identification tool based on regional excellence, with Fuzzy ARAS as a multi-criteria ranking method that is tolerant of uncertainty. The novelty of this approach lies in its ability to combine spatial dimensions and assessment flexibility into a single system that has not yet been systematically applied to the food crop subsector. The purpose of this study is to objectively and contextually identify superior food crop commodities in Langkat Regency as a basis for sustainable agricultural development planning.

2. Methods

This research employs a quantitative methodology by combining the Location Quotient and Fuzzy ARAS method in the selection process for superior commodities within the food crop subsector. The LQ analysis utilizes secondary data consisting of production outcomes for seven food crop commodities over 23 subdistricts in 2024, as illustrated in Table 1. The Fuzzy ARAS approach allocates all commodities according to ten strategic criteria: availability, capital, technology, raw materials, market demand, renewability, climatic and soil conditions, pest and disease resistance, labor absorption, and facilities and infrastructure. The evaluation was performed by ten experts via a questionnaire, and the weighting criteria were established using a fuzzy number methodology.

Table 1.
Data on Food Crop Yields for Langkat Regency in 2024

Subdistrict	Rice	Corn	Soya Bean	Peanuts	Green Beans	Cassava	Sweet Potatoes	Total
Bahorok	4.178,32	227,4	65,79	25,81	4,09	786,6	81,82	**5.369,83**
Sirapit	8.384,46	7.597,18	37,74	65,73	47,65	1.163,74	529,48	**17.825,98**
Salapian	902	5.934,68	0	29,3	0	129,36	19,6	**7014,94**
Kutambaru	0	296,06	0	0	0	0	0	**296,06**
Sei Bingai	22.872,85	45.853,86	0	79,5	0	1.929,34	635,82	**71371,37**
Kuala	6.144,65	8.932,06	23,01	95,43	11,5	1.261,45	493,9	**16.962,00**
Selesai	8.319,07	6.918,21	1,03	22,51	30,31	64	153,39	**15.508,52**

Binjai	13.891,57	2.006,00	0	0,72	0	85,1	17,04	**16.000,43**
Stabat	11.152,77	5.678,48	266,29	28,7	20,23	251,41	48,19	**17.446,07**
Wampu	5.133,20	850	0	6,2	5,88	99,29	32,56	**6.127,13**
Batang Serangan	0	72,94	0	1,84	0	40,5	5,72	**121**
Sawit Seberang	0	0	10,66	0	0	0	0	**10,66**
Padang Tualang	415	0	0	1,85	0	97,58	39,77	**554,2**
Hinai	17.187,47	640,2	466,58	27,8	91,39	386,53	51,88	**18.851,85**
Secanggang	39.987,91	1.861,20	108,57	61,49	20,01	643,76	184,88	**42.867,82**
Tanjung Pura	13.615,90	40,09	0	1,27	0	57,5	0	**13.714,76**
Gebang	16.976,57	83,23	252,96	2,73	4,02	259,27	0	**17.578,78**
Babalan	26.279,16	0	714,88	0,62	0	56,88	123,47	**27.175,01**
Sei Lepan	4.990,36	1.051,00	73,41	35,83	18,45	1.646,40	163,24	**7.978,69**
Brandan Barat	11.493,80	0	0	0	0	0	0	**11.493,80**
Besitang	8.017,01	131,58	0	1,33	0	102,25	5,75	**8.257,92**
Pangkalan Susu	20.227,52	299,09	0	32,03	18,72	700,34	120	**21.397,70**
Pematang Jaya	4.204,16	640,2	0	3,56	2,92	145,1	29,33	**5.025,27**
Total	244.373,75	89.113,46	2.020,92	524,25	275,17	9.647,13	2.735,84	**348.690,52**

Source: BPS Langkat Regency

2.1. Location quotient (LQ) method

Location Quotient (LQ) is a quantitative method used to determine the comparative advantage of a commodity in a specific location relative to a broader region. In the context of agriculture, LQ serves to assess whether a commodity in one sub-district has a relatively larger contribution to the total production of the district compared to the contribution of the same commodity to the total production at the provincial level (Sausan et al., 2022). Commodities with an value LQ > 1 are categorized as base commodities, as they indicate locational advantage within the region's production structure. The LQ formula is expressed mathematically as follows:

$$LQ = \frac{x_i / X_t}{y_i / Y_t} \tag{1}$$

Caption:

x_i : Total production i in the subdistrict area

X_t : Total production of subsector commodities t in the subdistrict

y_i : Total production i in the district area

Y_t : Total production of subsector commodities t in the district area

The LQ calculation produces three criteria, namely:

a. $\text{LQ} > 1$: Basic commodities have a comparative advantage and can be exported.
b. $\text{LQ} = 1$: Non-basic commodities, just enough to meet the needs of the region itself.
c. $\text{LQ} < 1$: Non-basic commodities, even, are not yet able to meet the needs of their own region, so they require supplies from outside.

2.2. Fuzzy additive ratio assessment (fuzzy ARAS) method

The Fuzzy ARAS method integrates the ARAS framework's capacity to analyze weighted alternatives with fuzzy logic to mitigate ambiguity and subjectivity in evaluations (Zagorskas & Turskis, 2020). The final utility value indicates how close an alternative is to the best solution, and in the context of this study, the commodity with the highest utility value is categorized as a superior commodity. The procedure for implementing the Fuzzy ARAS approach is delineated as follows:

a. Determine relevant criteria and alternative to establish a fuzzy decision matrix.
b. Fuzzify respondents' assessments of alternatives and criteria into triangular fuzzy numbers (TFN), consisting of lower (l), middle (m), and upper (u) values.
c. Aggregate the fuzzy values from all respondents for each choice across each criterion employing the Fuzzy Aggregation approach using Min–Geometric Mean–Max (Hezam et al., 2023). The aggregation process is represented by the following equation:

$$x_{ij} = \left(\min\left(l_{ijk}\right),\ \left(\prod_{k=1}^{K} m_{ijk}\right),\ \max\left(u_{ijk}\right) \right) \tag{2}$$

d. The normalization of the decision matrix seeks to standardize the TFN value scale by a formula specific to the criterion type (benefit or cost). The formula for normalizing the choice matrix is as follows:

   ✓ Benefit Criteria:

$$\tilde{x}_{ij} = \left(\frac{l_{ij}}{u_j^{\max}}, \frac{m_{ij}}{u_j^{\max}}, \frac{u_{ij}}{u_j^{\max}} \right) \tag{3}$$

   ✓ Cost Criteria (two stages):

   Inversion:

$$\tilde{r}_{ij} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}} \right) \tag{4}$$

   Normalization:

$$\tilde{x}_{ij} = \left(\frac{l'_{ij}}{u'^{\max}_{j}}, \frac{m'_{ij}}{u'^{\max}_{j}}, \frac{u'_{ij}}{u'^{\max}_{j}} \right) \tag{5}$$

e. Perform fuzzy weighting by multiplying the fuzzy normalization value by the fuzzy weight of each criterion, as shown in the following equation:

$$\tilde{v}_{ij} = \tilde{x}_{ij} \otimes \tilde{w}_j \tag{6}$$

Where $\tilde{w}_j$: criteria weight in TFN form.

f. Determine the ideal commodity for comparison by selecting the maximum value for the benefit criterion and the minimum value for the cost criterion.

g. Summing all the imprecise numbers (*l, m, u*) from equation (6) for each choice, using equation (7):

$$\tilde{S}_i = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij} \right) \tag{7}$$

h. Defuzzification of the fuzzy aggregate value for each choice involves converting the fuzzy value (l, m, u) derived from the aggregate result in Step 7 into a singular crisp value, using the subsequent equation:

$$D_i = \frac{l_i + m_i + u_i}{3} \tag{8}$$

i. Determine the ranking of each alternative by contrasting the de-fuzzification value of each option with that of the ideal alternative, using the subsequent equation:

$$K_i = \frac{D_i}{D_0} \tag{9}$$

3. Result and Discussion

This research uses two methods, namely: Location Quotient (LQ) to determine the main commodities in each sub-district and the Fuzzy ARAS method to assess all food crop commodities according to ten strategic criteria.

3.1 Analysis of basic food crop commodities using the Location Quotient (LQ) method

The Location Quotient (LQ) method identifies essential food crop commodities by comparing the contribution of each commodity across sub-districts to the total production of the regency and province. The value $LQ > 1$ indicates that the commodity is a basis. The calculation is based on data from Table 1, which includes the harvest area per commodity at the sub-district and provincial levels. Table 2 presents the outcomes of the LQ value calculation, indicating the sub-districts that possess a competitive advantage in specific commodities.

Table 2.
Results of LQ analysis

Subdistrict	Rice	Corn	Soya Bean	Peanuts	Green Bean	Cassava	Sweet Potatoes
Bahorok	1,11	0,17	2,11	3,20	0,97	5,29	1,94
Sirapit	0,67	1,67	0,37	2,45	3,39	2,36	3,79
Salapian	0,18	3,31	0	2,78	0	0,67	0,36
Kutambaru	0	3,91	0	0	0	0	0
Sei Bingai	0,46	2,51	0	0,74	0	0,98	1,14
Kuala	0,52	2,06	0,23	3,74	0,86	2,69	3,71
Selesai	0,77	1,75	0,01	0,97	2,48	0,15	1,26
Binjai	1,24	0,49	0	0,03	0	0,19	0,14
Stabat	0,91	1,27	2,63	1,09	1,47	0,52	0,35
Wampu	1,20	0,54	0	0,67	1,22	0,59	0,68
Batang Serangan	0	2,36	0	10,11	0	12,10	6,03
Sawit Seberang	0	0	172,54	0	0	0	0
Padang Tualang	1,07	0	0	2,22	0	6,36	9,15
Hinai	1,30	0,13	4,27	0,98	6,14	0,74	0,35
Secanggang	1,33	0,17	0,44	0,95	0,59	0,54	0,55
Tanjung Pura	1,42	0,01	0	0,06	0	0,15	0
Babalan	1,38	0	4,54	0,02	0	0,06	0,58
Sei Lepan	0,89	0,52	1,59	2,99	2,93	7,46	2,61
Brandan Barat	1,43	0	0	0	0	0	0
Besitang	1,39	0,62	0	0,11	0	0,45	0,09
Pangkalan Susu	1,35	0,05	0	1,00	1,11	1,18	0,71
Pematang Jaya	1,19	0,50	0	0,47	0,74	1,04	0,74

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The results of the Location Quotient (LQ) research presented in Table 2 indicate that rice has the most extensive coverage in Langkat Regency, categorized as a superior commodity across 13 subdistricts. Corn, peanuts, cassava, and sweet potatoes are superior commodities in eight subdistricts, which underscores their substantial presence and economic significance. Then, soya bean and green bean are classified as superior commodities in seven sub-districts, which reflects a rather limited distribution compared to other commodity categories. The following maps illustrate the distribution of basic commodities in Langkat Regency, with each map depicting the distribution of the seven superior commodities analyzed.

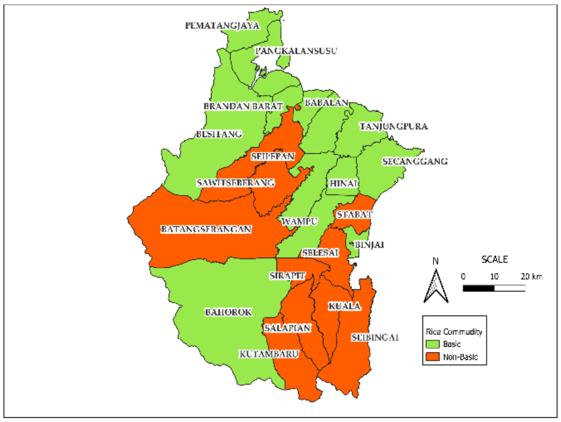
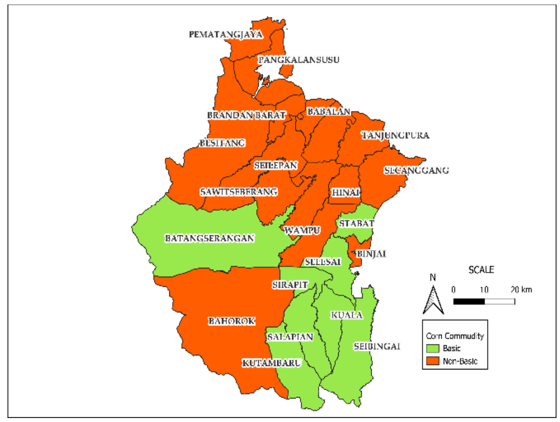


Figure 1 Map of Langkat Regency LQ Results for Rice Commodities



Figusre 2 Map of Langkat Regency LQ Results for Corn Commodities

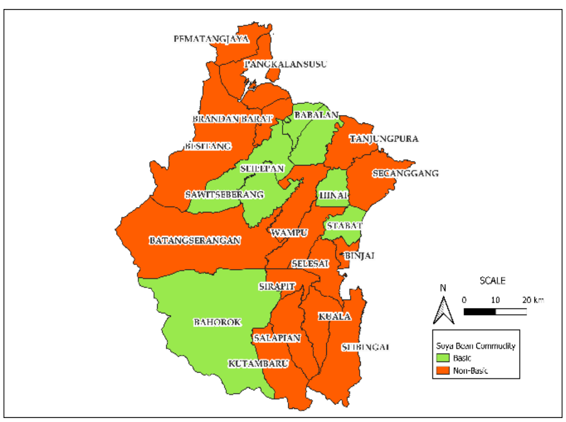


Figure 3 Map of Langkat Regency LQ Results of Soya Bean Commodities

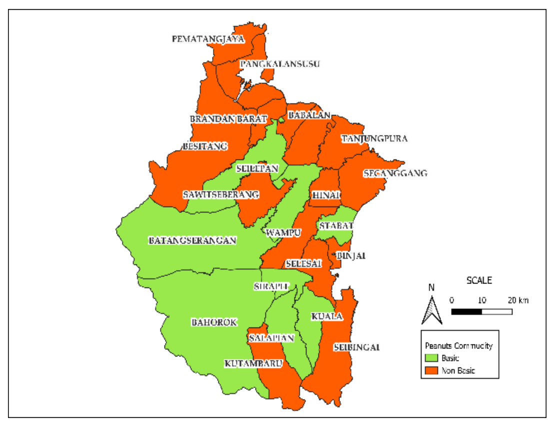


Figure 4 Map of Langkat Regency LQ Results of Peanuts Commodities

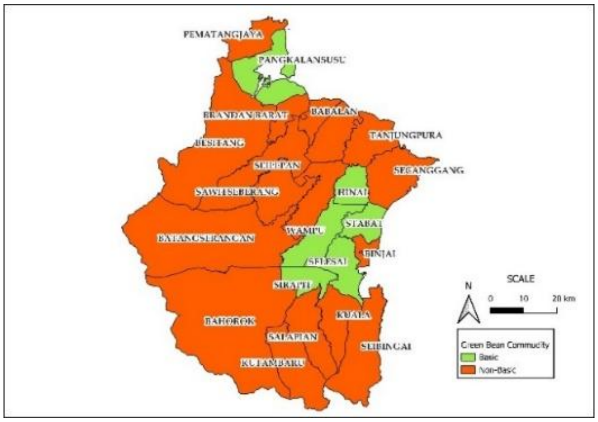


Figure 5 Map of Langkat Regency LQ Results of Green Bean Commodities

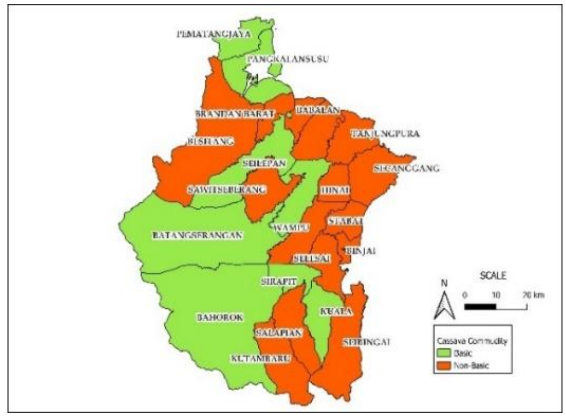


Figure 6 Map of Langkat Regency LQ Results of Cassava Commodities

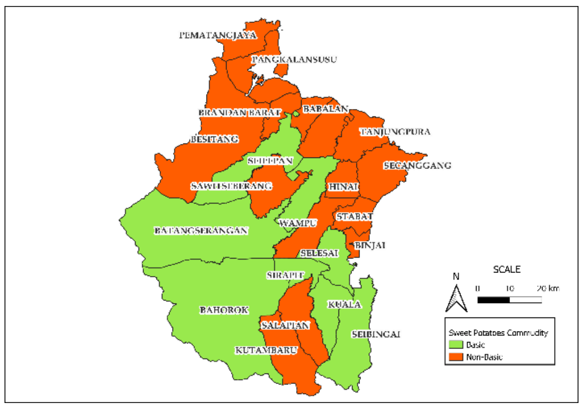


Figure 7 Map of Langkat Regency LQ Results of Sweet Potatoes Commodities

The results of the LQ analysis show that the distribution of base commodities in Langkat Regency is uneven across sub-districts. Rice is a commodity with the widest regional base, while other commodities such as corn, peanuts, cassava, and sweet potatoes are only a base in certain districts. Soybeans and mung beans even show a more limited base distribution. This distribution pattern reflects differences in agroclimatic conditions, production facilities, and preferred flagship commodities in each subdistrict. Therefore, this spatial interpretation is important as a basis for formulating agricultural development policies based on regional potential.

3.2 Determination of Superior Commodities Using the Fuzzy Additive Ratio Assessment (Fuzzy ARAS) Method

The Fuzzy ARAS method is applied in this study as an approach to determine superior commodities in the food crop subsector in Langkat Regency by considering 10 assessment criteria. Data analysis is conducted using the Fuzzy ARAS approach, which includes the following stages.

a. The initial stage in the Fuzzy ARAS method is the identification of criteria and alternatives with 10 strategic criteria: price (C1), capital (C2), technology (C3), availability of raw materials (C4), market demand (C5), renewability (C6), climate and soil conditions (C7), resistance to pests and diseases (C8), labor absorption (C9), and availability of facilities and infrastructure (C10), and 7 alternative food crop commodities: rice (A1), corn (A2), soybeans (A3), peanuts (A4), mung beans (A5), cassava (A6), and sweet potatoes (A7).
b. Table 3 shows the conversion of respondent ratings into triangular fuzzy numbers (TFN), with each linguistic value converted into a TFN consisting of three parameters (*l, m, u*), which describe the uncertainty in the evaluation of alternatives and criteria.

Tabel 3.
Linguistic variables and fuzzy number conversion

Linguistic Variables	TFN (*l*, *m*, *u*)
Very Low	(0,0; 0,1; 0,2)
Low	(0,1; 0,3; 0,5)
Enough	(0,3; 0,5; 0,7)
High	(0,5; 0,7; 0,9)
Very High	(0,8; 0,9; 1,0)

c. After the respondents' data is converted into TFN numbers, the aggregation process is carried out to obtain the TFN value for each alternative against each criterion. Aggregation is performed using Fuzzy Aggregation with the Min–Geometric Mean–Max Method in equation 2:

$$x_{11} = \left(l_{ij}, m_{ij}, u_{ij}\right)$$

$$l_{ij} = min\left(0.5,\ 0.5,\ 0.3,\ 0.5,\ 0.8,\ 0.3, 0.8,\ 0.5,\ 0.5,\ 0.3\right)$$

$$= 0.300$$

$$m_{ij} = \left(0.7 \times 0.7 \times 0.5 \times 0.7 \times 0.9 \times 0.5 \times 0.9 \times 0.7 \times 0.7 \times 0.5\right)^{1/10}$$

$$= 0.665$$

$$u_{ij} = max\left(0.9,\ 0.9,\ 0.7,\ 0.9,\ 1.0,\ 0.7,\ 1.0,\ 0.9,\ 0.9,\ 0.7\right)$$

$$= 1.000$$

For the calculation of other commodities, the aggregated fuzzy triangular values from all alternative combinations against the criteria are presented concisely in Table 4.

Table 4.
Fuzzy decision matrix based on TFN aggregation value

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0,300; 0,665; 1,000)	(0,100; 0,693; 1,000)	(0,100; 0,520; 1,000)	(0,300; 0,607; 1,000)	(0,300; 0,682; 1,000)	(0,100; 0,499; 0,900)	(0,300; 0,682; 1,000)	(0,100; 0,596; 0,900)	(0,100; 0,562; 1,000)	(0,100; 0,483; 1,000)
A2	(0,300; 0,622; 1,000)	(0,100; 0,548; 1,000)	(0,000; 0,516; 1,000)	(0,300; 0,649; 1,000)	(0,100; 0,557; 1,000)	(0,100; 0,483; 1,000)	(0,300; 0,557; 1,000)	(0,100; 0,632; 1,000)	(0,100; 0,571; 1,000)	(0,000; 0,478; 1,000)
A3	(0,100; 0,447; 1,000)	(0,000; 0,425; 1,000)	(0,000; 0,404; 1,000)	(0,000; 0,466; 1,000)	(0,100; 0,490; 1,000)	(0,000; 0,516; 0,900)	(0,100; 0,557; 1,000)	(0,100; 0,520; 0,900)	(0,100; 0,436; 0,900)	(0,000; 0,330; 0,900)
A4	(0,100; 0,526; 0,900)	(0,100; 0,534; 1,000)	(0,000; 0,425; 1,000)	(0,000; 0,436; 1,000)	(0,000; 0,548; 1,000)	(0,000; 0,483; 1,000)	(0,300; 0,643; 0,900)	(0,100; 0,534; 0,900)	(0,000; 0,334; 0,900)	(0,000; 0,347; 0,700)
A5	(0,100; 0,591; 1,000)	(0,100; 0,490; 1,000)	(0,000; 0,391; 1,000)	(0,000; 0,495; 1,000)	(0,100; 0,495; 1,000)	(0,100; 0,562; 1,000)	(0,300; 0,627; 0,900)	(0,100; 0,534; 0,900)	(0,000; 0,669; 0,900)	(0,000; 0,404; 0,900)
A6	(0,100; 0,495; 1,000)	(0,000; 0,316; 0,900)	(0,000; 0,341; 1,000)	(0,000; 0,487; 1,000)	(0,100; 0,520; 1,000)	(0,000; 0,607; 1,000)	(0,100; 0,544; 0,900)	(0,100; 0,520; 1,000)	(0,000; 0,400; 1,000)	(0,000; 0,384; 1,000)
A7	(0,100; 0,516; 0,900)	(0,100; 0,503; 1,000)	(0,000; 0,306; 1,000)	(0,000; 0,525; 0,900)	(0,100; 0,576; 1,000)	(0,100; 0,557; 1,000)	(0,100; 0,581; 0,900)	(0,100; 0,516; 0,900)	(0,000; 0,397; 0,900)	(0,000; 0,384; 1,000)

Table 4 shows the results of TFN aggregation for each alternative against the criteria using the Min–Geometric Mean–Max method. The values presented include three components: the lower bound, the middle value, and the upper bound, which describe the fuzzy estimation range for each alternative against the criteria. This table is used to compare the extent to which each alternative meets the criteria, considering data uncertainty.

d. The normalization of the fuzzy decision matrix is executed to standardize the evaluation scale based on the criteria type, resulting in standard values (l; m; u) as seen in Table 5.

Table 5.
Decision making matrix normalization results

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0,100; 0,150; 0,333)	(0,001; 0,001; 0,010)	(0,100; 0,483; 1,000)	(0,300; 0,607; 1,000)	(0,300; 0,682; 1,000)	(0,100; 0,499; 0,900)	(0,300; 0,682; 1,000)	(0,000; 0,596; 0,900)	(0,111; 0,646; 1,000)	(0,100; 0,648; 1,000)
A2	(0,300; 0,622; 1,000)	(0,100; 0,548; 1,000)	(0,000; 0,517; 1,000)	(0,300; 0,633; 0,900)	(0,300; 0,557; 0,900)	(0,100; 0,483; 1,000)	(0,300; 0,557; 1,000)	(0,100; 0,632; 1,000)	(0,111; 0,614; 1,000)	(0,000; 0,478; 1,000)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A3	(0,100; 0,224; 1,000)	(0,001; 0,001; 0,010)	(0,000; 0,404; 1,000)	(0,100; 0,495; 1,000)	(0,000; 0,490; 1,000)	(0,000; 0,516; 0,900)	(0,100; 0,557; 1,000)	(0,100; 0,520; 0,900)	(0,100; 0,460; 0,900)	(0,000; 0,330; 1,000)
A4	(0,100; 0,190; 0,900)	(0,002; 0,002; 0,900)	(0,000; 0,425; 1,000)	(0,100; 0,534; 0,900)	(0,000; 0,548; 1,000)	(0,000; 0,483; 1,000)	(0,300; 0,643; 0,900)	(0,100; 0,534; 0,900)	(0,100; 0,382; 0,900)	(0,000; 0,347; 0,900)
A5	(0,100; 0,169; 1,000)	(0,002; 0,002; 1,000)	(0,000; 0,391; 1,000)	(0,000; 0,371; 1,000)	(0,100; 0,495; 1,000)	(0,100; 0,562; 1,000)	(0,300; 0,627; 0,900)	(0,100; 0,538; 0,900)	(0,200; 0,699; 0,900)	(0,000; 0,404; 0,900)
A6	(0,100; 0,222; 1,000)	(0,003; 0,003; 1,000)	(0,000; 0,341; 1,000)	(0,000; 0,487; 1,000)	(0,100; 0,516; 1,000)	(0,300; 0,607; 1,000)	(0,100; 0,544; 0,900)	(0,100; 0,552; 0,900)	(0,100; 0,449; 0,900)	(0,000; 0,384; 1,000)
A7	(0,111; 0,194; 1,000)	(0,001; 0,002; 1,000)	(0,000; 0,306; 1,000)	(0,100; 0,525; 0,900)	(0,100; 0,576; 1,000)	(0,100; 0,557; 1,000)	(0,100; 0,581; 0,900)	(0,100; 0,516; 0,900)	(0,000; 0,397; 0,900)	(0,000; 0,384; 1,000)

Table 5 presents the results of normalizing the fuzzy decision matrix for each alternative against the criteria. The normalization process is performed to convert fuzzy values into a standard scale based on the type of criteria, resulting in standard values (*l, m, u*). This table is used to facilitate comparison between alternatives by considering the normalized standard scale.

e. The weighted normalization matrix is displayed in Table 7 as the product of the fuzzy values and the criterion weights.

Table 6.
Criteria Weight

Criteria	*l*	*m*	*u*
C1	0,051	0,098	0,183
C2	0,030	0,072	0,146
C3	0,053	0,101	0,188
C4	0,051	0,098	0,183
C5	0,033	0,075	0,151
C6	0,020	0,055	0,119
C7	0,097	0,143	0,227
C8	0,051	0,098	0,183
C9	0,082	0,130	0,217
C10	0,085	0,130	0,213

Table 7.
Weighted normalized matrix results

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0,005; 0,015; 0,061)	(0,000; 0,000; 0,000)	(0,005; 0,049; 0,188)	(0,015; 0,060; 0,183)	(0,010; 0,051; 0,107)	(0,002; 0,019; 0,119)	(0,029; 0,100; 0,227)	(0,000; 0,058; 0,183)	(0,009; 0,084; 0,217)	(0,009; 0,084; 0,213)
A2	(0,005; 0,016; 0,061)	(0,000; 0,000; 0,001)	(0,005; 0,052; 0,165)	(0,015; 0,062; 0,183)	(0,003; 0,042; 0,151)	(0,002; 0,015; 0,119)	(0,010; 0,060; 0,227)	(0,005; 0,062; 0,183)	(0,009; 0,080; 0,217)	(0,008; 0,062; 0,213)
A3	(0,005; 0,022; 0,183)	(0,000; 0,000; 0,146)	(0,000; 0,041; 0,188)	(0,009; 0,049; 0,169)	(0,003; 0,028; 0,151)	(0,002; 0,016; 0,107)	(0,085; 0,090; 0,227)	(0,009; 0,049; 0,183)	(0,009; 0,060; 0,217)	(0,004; 0,043; 0,213)
A4	(0,006; 0,019; 0,183)	(0,002; 0,002; 0,001)	(0,005; 0,043; 0,169)	(0,009; 0,052; 0,165)	(0,003; 0,041; 0,151)	(0,002; 0,019; 0,119)	(0,029; 0,095; 0,227)	(0,009; 0,052; 0,165)	(0,005; 0,045; 0,217)	(0,007; 0,027; 0,149)
A5	(0,005; 0,017; 0,183)	(0,002; 0,002; 0,001)	(0,039; 0,036; 0,188)	(0,006; 0,037; 0,165)	(0,003; 0,039; 0,151)	(0,009; 0,031; 0,119)	(0,029; 0,100; 0,227)	(0,009; 0,053; 0,183)	(0,009; 0,052; 0,217)	(0,007; 0,029; 0,191)
A6	(0,005; 0,020; 0,183)	(0,000; 0,000; 0,001)	(0,034; 0,051; 0,188)	(0,005; 0,037; 0,165)	(0,000; 0,037; 0,151)	(0,006; 0,019; 0,119)	(0,010; 0,095; 0,204)	(0,005; 0,054; 0,183)	(0,004; 0,058; 0,205)	(0,000; 0,050; 0,213)
A7	(0,006; 0,019; 0,183)	(0,000; 0,000; 0,001)	(0,000; 0,030; 0,188)	(0,005; 0,043; 0,165)	(0,003; 0,043; 0,151)	(0,002; 0,031; 0,119)	(0,010; 0,083; 0,204)	(0,005; 0,051; 0,183)	(0,007; 0,057; 0,207)	(0,005; 0,050; 0,213)

Table 6 shows the weights of the criteria (*l, m, u*) for each criterion used in the analysis. Table 7 presents the results of the weighted normalization matrix, which is the product of the normalized fuzzy values and the criterion weights. This matrix is used to account for the importance of each criterion in evaluating alternatives, thus enabling a more objective comparison between alternatives based on the criterion weights.

f. The ideal alternative is obtained from the highest value of each criterion in the weight matrix in Table 8.

Table 8.
Ideal alternative result

Criteria	Criteria Type	*l*	*m*	*u*
C1	Cost	0,005	0,015	0,061
C2	Cost	0,000	0,000	0,001
C3	Benefit	0,005	0,052	0,188
C4	Benefit	0,015	0,062	0,183
C5	Benefit	0,010	0,051	0,151

C6	Benefit	0,006	0,033	0,119
C7	Benefit	0,029	0,098	0,227
C8	Benefit	0,005	0,062	0,183
C9	Benefit	0,009	0,084	0,217
C10	Benefit	0,009	0,084	0,213

g. The fuzzy aggregate value for each alternative is calculated from the weighted normalization matrix in Table 9.

Table 9.

The result of the fuzzy aggregate value for each alternative

Alternative	*l*	*m*	*u*
A1	0,084	0,526	1,531
A2	0,047	0,483	1,525
A3	0,034	0,409	1,798
A4	0,048	0,421	1,546
A5	0,041	0,394	1,643
A6	0,026	0,415	1,769
A7	0,031	0,417	1,624

h. Defuzzification converts fuzzy values into a single definitive value by combining the lower, middle, and upper values, making it easier to compare alternatives. This is shown in Table 10, which illustrates how defuzzified values are used to rank alternatives based on predefined criteria.

Table 10.

Alternative defuzzification results

Alternative Defuzzification	Crisp Value
D1	0,714
D2	0,685
D3	0,747
D4	0,672
D5	0,693
D6	0,737
D7	0,691

Table 10 shows the defuzzification results for each alternative, which yields crisp or definite values. These crisp values are obtained after defuzzifying the fuzzy values, allowing for clearer decision-making.

i. From the crisp values obtained through defuzzification, the relative utility of each alternative is calculated to determine the priority ranking, as shown in Table 11.

Table 11.
Ranking of superior commodity weights in the food crop subsector

Alternative	Value (K_i)	Ranking
Rice	0,983	3
Corn	0,944	6
Soya Bean	1,029	1
Peanuts	0,926	7
Green Beans	0,955	4
Cassava	1,015	2
Sweet Potatoes	0,952	5

Based on the ranking results in Table 11, soybeans emerged as the superior commodity in the food crop subsector with the highest relative utility value of 1.029. Other commodities that also showed high performance were cassava (1.015), rice (0.983), green beans (0.955), sweet potatoes (0.952), and corn (0.944). Meanwhile, peanuts received the lowest utility value, which was 0.926. This finding indicates that soybeans have the highest priority level based on all the strategic parameters evaluated. These results are important as a foundation for formulating regional food policies, especially in determining the direction of developing highly competitive and sustainable superior commodity. Meanwhile, commodities with lower utility value can be directed towards strategies to improve production efficiency and expand their contribution to regional food security.

4. Conclusion

This research integrates the Location Quotient and Fuzzy ARAS methods to form an objective, multi-criteria, and adaptive evaluation framework for determining superior commodities in the food crop subsector. The analysis results show that rice is the base commodity in 13 sub-districts, reflecting its widespread spatial contribution based on its locational advantages. Meanwhile, soybeans were designated as the superior commodity because they received the highest score in the Fuzzy ARAS assessment, with a relative utility value of 1.029, followed by cassava (1.015) and rice (0.983), based on ten strategic criteria covering economic, technical, environmental, and social dimensions. The difference in results between the two methods indicates that LQ emphasizes regional advantages, while Fuzzy ARAS considers a more comprehensive strategic feasibility. Therefore, the integration of the two results in a complementary quantitative approach to supporting regional agricultural development decision-making.

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