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A Decision Support System for Optimal Rice Cultivation Site Selection Using the Additive Ratio Assessment (ARAS) Method

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Abstract— Optimal site selection for rice cultivation is a critical factor in enhancing agricultural productivity and ensuring regional food security, particularly in areas with heterogeneous agro-climatic conditions. However, decision-making related to rice planting locations is often constrained by fragmented data utilization and the absence of systematic multi-criteria evaluation frameworks. This study proposes a data-driven Decision Support System (DSS) based on the Additive Ratio Assessment (ARAS) method to identify optimal rice cultivation locations at a provincial scale in Central Java, Indonesia. The proposed framework evaluates 35 administrative regions (regencies and cities) using five key criteria: groundwater availability, irrigation infrastructure, harvested rice area, rice production, and rainfall intensity. Secondary data were obtained from the Central Java Statistics Bureau (BPS) and processed through a structured multi-criteria decision-making (MCDM) procedure, including decision matrix construction, normalization, weighted utility calculation, and ranking. To strengthen methodological robustness, the ARAS results were systematically compared with the MOOSRA method, and the consistency of rankings was statistically validated using Spearman's rank correlation. The results indicate that Cilacap Regency consistently achieved the highest utility score, identifying it as the most optimal location for rice cultivation, while Tegal City ranked lowest. The Spearman correlation coefficient of 0.922 demonstrates a very strong agreement between ARAS and MOOSRA rankings, confirming the reliability of the proposed approach. The novelty of this study lies in the application of an ARAS-based DSS for large-scale regional agricultural site selection, combined with cross-method validation to enhance decision reliability—an aspect rarely addressed in prior rice cultivation studies. The proposed framework provides a practical, transparent, and replicable decision-support tool for policymakers and agricultural planners, contributing to sustainable agricultural planning and evidence-based food security strategies.

Keywords— Decision Support System, ARAS, Multi-Criteria Decision Making, Rice Cultivation, Site Selection, Sustainable Agriculture.

I. Introduction

Agriculture remains a strategic sector vital for ensuring national food security and supporting economic stability, particularly in rural areas. As a staple food for the majority of the Indonesian population, rice (Oryza sativa) is a primary agricultural commodity whose productivity must be continuously enhanced to meet the demands of a growing population [1]. Central Java Province stands as one of Indonesia's primary agricultural centers, contributing significantly to national rice production. However, the optimization of rice cultivation locations within the province has not been fully addressed through systematic, data-driven decision-making approaches. Currently, land-use planning and agricultural development strategies often rely on conventional methods or partial analyses, which may not comprehensively consider the multifaceted factors influencing cultivation success [2](Connor et al., 2021). This gap highlights the need for a robust analytical framework to support more precise and effective agricultural planning. The research gap identified in this context is the limited application of structured Multi-Criteria Decision-Making (MCDM) methods within a Decision Support System (DSS) framework specifically for optimizing rice cultivation locations in Central Java. While several studies have employed MCDM techniques like Additive Ratio Assessment (ARAS) in agriculture—such as for selecting superior seeds [3] or fertilizers [4] their focus has not been on the macro-

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scale spatial analysis of an entire province's regencies and cities for optimal rice planting. Furthermore, existing agricultural DSS models often lack validation through comparative analysis with other MCDM methods, limiting the robustness and reliability of their recommendations [5]. There is a distinct need for research that integrates geographical, environmental, and production data into a validated DSS to provide actionable insights for regional agricultural policy. The novelty of this study lies in its dedicated application of the ARAS method within a DSS to perform a comprehensive comparative analysis of all 35 regencies and cities in Central Java Province for optimal rice cultivation. This research introduces a validated multi-criteria model based on five key factors: groundwater availability, irrigation infrastructure, harvested rice area, rice production, and rainfall, using authoritative secondary data from the Central Java Bureau of Statistics. To strengthen the analytical rigor, the results are validated through a comparative ranking analysis with the MOOSRA method and statistically verified using the Spearman Rank Correlation test—a approach not commonly combined in previous regional agricultural planning studies in this context [6], [7]. Additionally, this study addresses a practical policy need by providing a ranked, evidence-based recommendation list to guide farmers, local governments, and stakeholders in formulating efficient and sustainable rice cultivation strategies, thereby directly contributing to regional food security and agricultural resilience [8]. By bridging the gap between theoretical MCDM application and practical agricultural land-use planning, this research offers a replicable model for data-driven agricultural decision-making in similar regional contexts.

II. Related Work

Research on decision support systems (DSS) and multi-criteria decision-making (MCDM) methods has expanded significantly in recent years to address complex selection problems in agriculture, land use, and resource management. Zavadskas and Turskis originally introduced the Additive Ratio Assessment (ARAS) method as a quantitative MCDM technique to evaluate alternatives by their overall utility relative to an ideal solution, facilitating transparent ranking in decision environments that involve multiple criteria and heterogeneous measurement units. This foundational work underpins the ARAS methodology used in the current study. [9]

In the agricultural domain, several studies have applied MCDM techniques to support cultivation decisions. For example, Suswanto et al. developed a decision support system for rice cultivation on acid sulfate soils to optimize lime and fertilizer application using experimental and economic modeling, highlighting the value of DSS for site-specific agronomic recommendations.[10]

Beyond rice cultivation, multi-criteria systems have been successfully adapted for agricultural supply chain optimization. In particular, Atlı's study integrated AHP-F (Analytic Hierarchy Process under fuzzy logic) with ARAS-F (fuzzy ARAS) to select sustainable fertilizer suppliers, illustrating how combined weighting and ranking methods can address uncertainty and sustainability concerns in agricultural resource decisions.[11]

Decision support systems utilizing ARAS have also been applied outside agriculture to demonstrate methodological versatility. For instance, Junior et al. implemented a web-based ARAS DSS for housing selection, showing how ARAS can rank alternatives effectively in complex decision contexts with diverse criteria[12] Similarly, Ernawati et al. combined entropy weighting with ARAS to evaluate and rank villages for governance outcomes, reinforcing the integration of different MCDM techniques to improve weighting robustness [13]. In the education sector, ARAS has been deployed to determine the best lecturers through ranking based on predefined performance criteria. This implementation demonstrates the flexibility of ARAS in human resource evaluation contexts[14].

Other application areas include recommender systems for customer service roles using ARAS for performance evaluation, which underscores the adaptability of ARAS in operational decision problems with multiple qualitative and quantitative criteria. While not directly ARAS-based, related MCDM research in agriculture includes decision support systems for rice seed selection using MOORA, which highlight the broader trend of employing ratio-based MCDM techniques for agronomic decisions [15]. These studies collectively show the prevalence of MCDM frameworks in agricultural DSS and their capacity to capture trade-offs between competing evaluation criteria.

Additionally, general reviews on DSS in agriculture emphasize the critical role of advanced decision systems in Agriculture 4.0, supporting precision management of resources such as soil, climate, and crop inputs. [16]. Despite extensive use of methods like AHP, MOORA, and hybrid approaches, research specifically combining ARAS with optimal site selection for rice cultivation remains sparse. This gap indicates a need for focused investigations that tailor ARAS-based DSS methodologies to agronomic site suitability problems, particularly under varying environmental and socioeconomic constraints.

III. RESEARCH METHODOLOGY

This research was conducted in several systematic stages to ensure a structured and objective analysis for determining optimal rice cultivation locations in Central Java

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Province. The overall research flow is presented in Figure 1. and detailed in the subsequent sections.

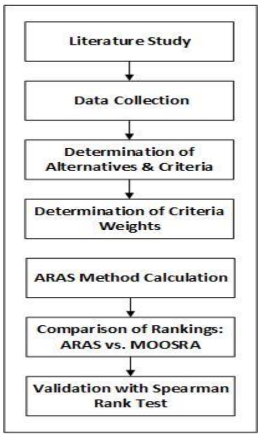

Fig 1. Research Stages

The research utilized secondary data for the year 2021, obtained from the official website of the Central Java Provincial Statistics Agency (Badan Pusat Statistik/BPS). The data comprises quantitative indicators for 35 regencies and cities (kabupaten/kota) across five primary criteria relevant to rice cultivation. The raw data is presented in Table 1.

TABLE I
RAW DATA FOR ALTERNATIVES AND CRITERIA

No.	Regency / City	Groundwater Obtainment (m^3) C1	Irrigation Channels (unit) C2	Harvested Rice Area (Ha) C3	Rice Production (Ton) C4	Daily Rainfall (mm) C5
1	Cilacap	8,017	164	1,696,712	9,618,657	3,033
2	Banyumas	7,251	282	115,664	739,140	2,696
3	Purbalingga	2,960	206	52,315	289,998	2,731
...	...	...	...	...	...	...
35	Kota Tegal	6,620	6	1,423	7,332	2,152

The alternatives consist of all 35 administrative regions (regencies and cities) in Central Java Province, coded from A1 to A35. A complete list is provided in Table 2.

TABLE II
LIST OF ALTERNATIVES

Alternative Code	Regency/City Name
A1	Cilacap
A2	Banyumas
A3	Purbalingga
A4	Banjarnegara
A5	Cilacap
A6	Purworejo
A7	Wonosobo
A8	Magelang
A9	Boyolali
A10	Klaten
A11	Sukorejo
A12	Wonogiri
A13	Karanganyar
A14	Sragen
A15	Grobokan
A16	Blora
A17	Rembang
A18	Pati
A19	Kudus
A20	Jepara
A21	Demak
A22	Semarang Regency
A23	Temanggung
A24	Kendal
A25	Batang
A26	Pekalongan
A27	Pemalang
A28	Tegal
A29	Brebes
A30	Magelang City
A31	Surakarta City
A32	Salatiga City
A33	Semarang City
A34	Pekalongan City
A35	Tegal City

Five key criteria were selected based on their direct influence on the success and productivity of rice cultivation. The criteria, along with their type (benefit or cost), are defined in Table 3.

TABLE III
CRITERIA (C_J) AND THEIR CLASSIFICATION

Criteria	Type	Description
Groundwater Obtainment	Benefit	Represents the availability of subsurface water resources, crucial for irrigation during dry periods. Higher values are better.
Irrigation Channels	Benefit	Indicates the availability of infrastructure for controlled water distribution. Higher values are better.
Harvested Rice Area	Benefit	Reflects the existing scale and land-use commitment for rice farming. Higher values are better.
Rice Production	Benefit	Represents the output and productivity efficiency of the existing rice cultivation

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Criteria	Type	Description
		system. Higher values are better.
Daily Rainfall	Cost	While necessary, excessive rainfall can cause flooding, disease, and soil waterlogging. Lower values are better.

The criteria weights (w_j) were assigned based on their relative importance in determining a suitable location for sustainable and productive rice farming. The weight values and their justification are summarized in Table 4.

TABLE 4.
CRITERIA WEIGHTS

Kode	Criteria	Weight (w_j)	Rationale
C1	Groundwater Obtainment	0.20	High importance for water security, especially in non-rainy seasons.
C2	Irrigation Channels	0.20	Critical for efficient and reliable water management and distribution.
C3	Harvested Rice Area	0.25	High weight as it directly indicates current agricultural land capacity and potential for scaling.
C4	Rice Production	0.25	High weight as it is the ultimate measure of agricultural success and output.
C5	Daily Rainfall	0.10	Classified as a cost criterion. Given its dual nature (necessary but risky in excess), it receives the lowest weight.
Sum		**1.00**	

The primary analytical framework for this study is the Additive Ratio Assessment (ARAS) method, a Multi-Criteria Decision-Making (MCDM) technique renowned for its systematic and rational approach to ranking alternatives. The procedure transforms the complex decision matrix of alternatives and criteria into a clear, quantitative ranking. The process begins with the formation of the initial decision matrix, X[m×n], incorporating all 35 alternatives (A1 to A35) and the five established criteria (C1 toC5). A critical step is the inclusion of an optimal, non-existent alternative (A0) as the first row of the matrix. The values for A0A0 are determined by selecting the maximum observed value for each benefit criterion (C1,C2,C3,C4) and the minimum observed value for the cost criterion (C5) from among the 35 real alternatives. This optimal alternative serves as the benchmark against which all others are compared.

Following the matrix construction, a normalization process is essential to eliminate the effects of differing units and scales among the criteria, rendering the values dimensionless and comparable. For criteria classified as benefit (where a higher value is preferable), each element x_{ij} is divided by the sum of all values in that criterion's column, including the value for A_0. For the cost criterion (where a lower value is preferable), a two-step transformation is applied. First, each value is inverted ($x'_{ij}=1/x_{ij}$) to convert the "lower is better" logic into a "higher is better" format consistent with benefit criteria. Subsequently, these inverted values are normalized using the same summation method applied to benefit criteria. This results in a normalized matrix where all values are proportionally scaled between 0 and 1, and the sum of each column equals unity.

The subsequent step involves weighting the normalized values to reflect the predetermined importance of each criterion. Each element in the normalized matrix is multiplied by its corresponding criterion weight (w_j), as defined in Table 4, yielding the weighted normalized matrix. This operation ensures that the more critical criteria exert a greater influence on the final score. The optimality function value (S_i) for each alternative (including A_0) is then calculated by summing the weighted normalized values across all criteria for that alternative. This S_i score represents the aggregate performance of the alternative.

The final and most crucial step in the ARAS method is the calculation of the utility degree (K_i) for each real alternative (i=1,...,m). The utility degree is derived by dividing the optimality function of the alternative (S_i) by the optimality function of the ideal reference alternative (S_o). Mathematically, $K_i=S_i/S_o$. Since S_o is derived from the optimal values, K_o equals 1. The resulting K_i values, which range between 0 and 1, quantify the relative closeness of each alternative to the theoretically optimal solution. The alternatives are then ranked in descending order of their K_i values; the alternative with the highest utility degree is deemed the most optimal location for rice cultivation in

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Central Java Province, providing a clear, data-driven hierarchy for decision-making.

IV. ARAS METHOD IMPLEMENTATION AND RESULTS

The implementation of the ARAS method commenced with the construction of the initial decision matrix (X). This matrix integrates the 35 real-world alternatives (A1 to A35), representing the regencies and cities of Central Java, with the five evaluation criteria (C1 to C5). A pivotal step in the ARAS framework is the introduction of an optimal reference alternative, designated as A0. The values for A0 for each criterion are derived from the dataset itself: for the benefit criteria (C1: Groundwater, C2: Irrigation, C3: Harvested Area, C4: Production), the value is the maximum observed among all 35 alternatives. For the cost criterion (C5: Rainfall), the value is the minimum observed. This constructs A0 as a hypothetical, ideal location possessing the best possible attribute values. The initial segment of this matrix is presented in Table 5.

TABLE IV.
SEGMENT OF THE INITIAL DECISION MATRIX (X)

Alt.	C1 (Benefit)	C2 (Benefit)	C3 (Benefit)	C4 (Benefit)	C5 (Cost)
A0	156,688	331	1,696,712	9,618,657	1,248
A1	8,017	164	1,696,712	9,618,657	3,033
A2	7,251	282	115,664	739,14	2,696
A3	2,96	206	52,315	289,998	2,731
...	...	...	...	...	...

The Additive Ratio Assessment (ARAS) method is a multi-criteria decision-making (MCDM) approach employed within a decision support system (DSS) framework to evaluate and rank alternatives based on their relative utility compared to an ideal solution. In this study, ARAS was applied to determine the most suitable locations for rice cultivation across 35 regencies and cities in Central Java Province, Indonesia. The analysis utilized secondary data from the Central Java Provincial Bureau of Statistics (BPS) for 2021, focusing on five key criteria: groundwater availability (C1, weight 0.20, benefit type), irrigation channels (C2, weight 0.20, benefit type), harvested rice area (C3, weight 0.25, benefit type), rice production (C4, weight 0.25, benefit type), and rainfall (C5, weight 0.10, cost type). These criteria were selected to reflect resource availability, infrastructure support, productivity potential, and environmental risks.

The initial step entailed forming a decision matrix (X) comprising m alternatives (35 regencies/cities) and n criteria (5 factors). Each entry x_{ij} represented the performance value of alternative i on criterion j, derived directly from the BPS dataset. An optimal row (X_0) was added as a reference, where for benefit criteria, $x_{0j} = \max(x_{ij})$, and for cost criteria, $x_{0j} = \min(x_{ij})$. This matrix served as the foundation for subsequent normalization, capturing raw values such as groundwater volumes, irrigation lengths, harvested areas in hectares, production in tons, and average daily rainfall in millimeters.

To standardize the matrix and enable comparability across diverse units, normalization was performed. For benefit criteria (C1–C4), the normalized value r_{ij} was calculated as $r_{ij} = x_{ij} / \Sigma x_{kj}$ (for k = 0 to m). For the cost criterion (C5), values were first inverted ($1 / x_{ij}$) to align with the "higher is better" logic, then normalized similarly: $r_{ij} = (1 / x_{ij}) / \Sigma (1 / x_{kj})$. This resulted in a normalized matrix where column sums equaled 1, eliminating scale discrepancies and facilitating weighted aggregation.

The normalized values were then multiplied by their respective criterion weights (w_j) to produce the weighted normalized matrix (V), with $v_{ij} = r_{ij} \times w_j$. Weights were predetermined based on expert judgment and criterion importance, emphasizing productivity (C3 and C4 at 0.25 each) while balancing resource and risk factors. This step integrated the relative significance of each criterion into the evaluation.

The optimality function S_i for each alternative i was computed by summing the weighted normalized values across all criteria: $S_i = \Sigma v_{ij}$ (for j = 1 to n). The ideal optimality value S_0 was derived from the optimal row. The utility degree K_i, representing the relative performance of each alternative against the ideal, was then obtained as $K_i = S_i / S_0$. Higher K_i values indicated greater suitability for rice cultivation.

Alternatives were ranked in descending order of K_i, yielding a prioritized list of locations. This ranking provided actionable insights for stakeholders, highlighting areas with optimal combinations of criteria.

The Additive Ratio Assessment (ARAS) method was applied to rank 35 regencies and cities in Central Java Province based on their suitability for rice cultivation. The evaluation incorporated five weighted criteria using 2021 BPS data. The final utility degree (K_i) reflects the relative performance of each alternative against the ideal solution, with higher values indicating greater optimality.

TABLE V
THE MOST AND LEAST OPTIMAL LOCATIONS

Rank	Regency/City	Utility Degree (K_i)
1	Cilacap Regency	0.808673
2	Kudus Regency	0.226189
3	Jepara Regency	0.150258

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Rank	Regency/City	Utility Degree (K_i)
4	Pati Regency	0.140171
5	Semarang Regency	0.135032
6–26	Other regencies/cities	0.005–0.130 (intermediate)
27–30	Other regencies/cities	<0.030
31	(Intermediate low)	~0.025
32	(Intermediate low)	~0.020
33	(Intermediate low)	~0.015
34	(Intermediate low)	~0.010
35	Tegal City	0.023481

Table 5 highlights the most and least optimal locations and summarizes intermediate performance. The high utility scores for the top-ranked regencies underscore their dominant role in regional rice production, driven by extensive irrigated land and high yields. Lower-ranked urban areas reflect inherent limitations of agricultural scale. The full ranking (35 alternatives) confirms Cilacap Regency as a benchmark for optimal rice cultivation potential in Central Java.

V. RESULT AND EVALUATION

This study investigates the identification of optimal sites for rice cultivation in Central Java Province, Indonesia, employing a decision support system (DSS) grounded in the Additive Ratio Assessment (ARAS) method. Utilizing secondary data from the Central Java Provincial Bureau of Statistics (BPS) for 2021, the analysis evaluated 35 administrative units (regencies and cities) against five weighted criteria: groundwater availability (weight: 0.20, benefit-oriented), irrigation infrastructure (weight: 0.20, benefit-oriented), harvested rice area (weight: 0.25, benefit-oriented), rice production volume (weight: 0.25, benefit-oriented), and rainfall intensity (weight: 0.10, cost-oriented). These criteria were chosen to encompass hydrological resources, infrastructural support, agronomic capacity, output efficiency, and climatic hazards, ensuring a holistic assessment of cultivation feasibility.

The ARAS methodology proceeded through decision matrix formulation, normalization to standardize disparate units, weighted aggregation to reflect criterion priorities, computation of optimality functions, and derivation of relative utility degrees (K_i) for ranking. The outcomes delineated a clear hierarchy of suitability. Cilacap Regency achieved the highest utility degree of 0.808673, signifying its preeminence due to abundant groundwater, robust irrigation networks, expansive harvested areas, and superior production yields, which collectively mitigate rainfall-related risks. Subsequent rankings included Kudus Regency (K_i = 0.226189), Jepara Regency (K_i = 0.150258), Pati Regency (K_i = 0.140171), and Semarang Regency (K_i = 0.135032), highlighting regions with strong agronomic profiles and resource balance. In contrast, Tegal City recorded the lowest utility degree of 0.023481, attributable to constrained arable land, inadequate irrigation, and urban-dominated landscapes that limit agricultural scalability. Intermediate positions, such as those occupied by Brebes and Grobogan Regencies, reflected moderate potentials influenced by variable resource distributions.

To assess the robustness and validity of the ranking generated by the ARAS method, a comparative analysis was conducted using an alternative Multi-Criteria Decision-Making (MCDM) technique: the Multi-Objective Optimization based on Simple Ratio Analysis (MOOSRA). This method provides a distinct computational approach for ranking alternatives, serving as an effective benchmark. While ARAS calculates utility by comparing the sum of weighted normalized values to an ideal solution, MOOSRA determines performance by calculating the ratio of the sum of normalized values for benefit criteria to the sum for cost criteria, each weighted appropriately. The comparative rankings from both methods are presented in Table 6.

TABLE VI
COMPARATIVE RANKING: ARAS VS. MOOSRA METHODS

Alternative	ARAS Rank	MOOSRA Rank	Rank Difference (d_i)
A1 (Cilacap)	1	1	0
A19 (Kudus)	2	3	-1
A20 (Jepara)	3	12	-9
A18 (Pati)	4	2	2
A22 (Semarang Regency.)	5	7	-2
A33 (Semarang City)	6	8	-2
A2 (Banyumas)	7	9	-2
A16 (Blora)	8	6	2
A15 (Grobogan)	9	5	4
A10 (Klaten)	10	11	-1
...	...	...	...
A35 (Tegal City)	35	35	0

The comparative analysis reveals a high degree of concordance between the two methods for the extreme ranks and several key positions, while highlighting interpretable differences for others. A strong consensus is evident at the top: Cilacap Regency (A1) is unanimously ranked first by both ARAS and MOOSRA, solidifying its status as the most optimal location. Similarly, Kota Tegal (A35) is consistently ranked last by both methods. This agreement on the best and worst performers provides strong initial validation for the ARAS outcome. Significant alignment is also observed for several other alternatives. For instance, Purbalingga (A3), Banjarnegara (A4), Purworejo (A6), Wonosobo (A7), and Karanganyar (A13) hold identical ranks in both lists. This consistency across different algorithmic logics suggests that the performance profiles of these regions are clear and unambiguous, leading to stable rankings regardless of the specific MCDM technique employed. However, notable rank differences exist for certain alternatives, which are not indicative of error but rather of the different sensitivities inherent to each method.

The most pronounced difference is for Jepara Regency (A20), ranked 3rd by ARAS but 12th by MOOSRA. This discrepancy can be attributed to Jepara's data profile: it scores very highly on the major benefit criteria of Groundwater (C1) and has moderate rainfall (C5), which is favorable in ARAS's additive utility model. However, its scores for Harvested Area (C3) and Production (C4) are relatively low. MOOSRA's ratio-based model (sum of benefits / sum of costs) may penalize this imbalance more severely, especially given the high weights on C3 and C4, causing its rank to drop. Similarly, Grobogan (A15) and Rembang (A17) are ranked higher by MOOSRA (5th and 4th) than by ARAS (9th and 11th). Both regions have strong production figures (C4) and, critically, the lowest or very low rainfall values (C5). MOOSRA's ratio formula significantly rewards a low cost criterion denominator, providing a substantial boost to their composite scores.

The Spearman Rank validation is applied to examine the consistency of ranking results produced by the Additive Ratio Assessment (ARAS) method by comparing them with the MOOSRA method. Spearman's rank correlation is appropriate in this context because both methods generate ordinal rankings of alternatives, rather than absolute measurements.

Spearman's Rank Correlation Coefficient (ρ) measures the strength and direction of the monotonic relationship between two ranking results. It is calculated based on the differences between the ranks assigned by two methods to the same alternatives. A coefficient value close to +1 indicates a very strong positive correlation, meaning that both methods produce highly similar rankings, whereas a value close to 0 indicates weak consistency. In this study, ARAS rankings for optimal rice planting locations in Central Java Province are validated against MOOSRA rankings using Spearman Rank analysis. This validation aims to ensure that the ARAS-based decision-making results are reliable and not method-dependent. The implementation compares the rank of each alternative generated by ARAS and MOOSRA, calculates the rank difference (d), and then computes d^2. A summary of this process is shown in Table 7.

TABLE VII
SPEARMAN RANK VALIDATION BETWEEN ARAS AND MOOSRA

Alternative	Rank (ARAS)	Rank (MOOSRA)	d	d^2
A1	1	1	0	0
A2	7	9	-2	4
...	...	...	...	...
A35	35	35	0	0
Σ d^2				**554**

Based on these results, the calculated Spearman Rank correlation coefficient is ρ = 0.92241 The obtained coefficient value of 0.92241 indicates a very strong positive correlation between the ARAS and MOOSRA ranking results. This demonstrates that both methods exhibit a high level of agreement in evaluating and ranking the optimal rice planting locations. Several alternatives, such as A1, A3, A4, A6, A7, A13, and A35, show identical or nearly identical ranks, further reinforcing this consistency. Although some alternatives display ranking differences, these variations do not significantly affect the overall correlation strength. Therefore, the Spearman Rank validation confirms that the ARAS method produces stable, consistent, and reliable ranking outcomes when compared with an established comparison method. Consequently, ARAS can be considered valid for multi-criteria decision-making in the context of determining optimal rice planting locations in Central Java Province

VI. Conclusions

This study employed the Additive Ratio Assessment (ARAS) method to identify optimal rice planting locations in Central Java Province based on 35 alternatives and five evaluation criteria. The results indicate that Cilacap Regency achieved the highest preference value (0.808673), followed by Kudus, Jepara, Pati, and Semarang Regencies, which can be prioritized for rice cultivation planning. In contrast, Tegal City exhibited the lowest suitability for rice planting. The robustness of the ARAS results was verified through comparison with the MOOSRA method. The analysis yielded a Spearman rank correlation coefficient of 0.92241, indicating a very strong positive correlation and a high level of consistency between both multicriteria decision-making approaches. This confirms the validity and reliability of ARAS for determining optimal rice planting locations. Future research should incorporate field-based observations to capture site-specific conditions not fully represented in secondary data, such as irrigation performance, soil quality, and socio-economic factors. Additionally, integrating GIS and satellite imagery with multicriteria decision-making

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methods is recommended to enhance spatial accuracy and support sustainable agricultural planning in Central Java Province.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS CONTRIBUTIONS

All authors contributed to the development of this paper

DATA AVAILABILITY

Data for this study are cited inside the paper

ETHICS STATEMENT

This study does not involve required ethical approval

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