Integrating ELECTRE–TOPSIS Decision Support System for Sustainable Inorganic Fertilizer Management in Lowland Rice

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ABSTRACT

Excessive and unmanaged use of inorganic fertilizers in rice cultivation has become a critical global concern, contributing to soil degradation, water pollution, and greenhouse gas emissions. Addressing this challenge requires a shift from conventional expert-based fertilizer recommendations toward data-driven, digitally intelligent approaches aligned with the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action). This study proposes an integrated Decision Support System (DSS) that combines the ELECTRE (Elimination Et Choix Traduisant la Réalité) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) Multi-Criteria Decision Making (MCDM) methods for sustainable inorganic fertilizer recommendation in lowland rice cultivation. Soil nutrient parameters specifically Nitrogen (N), Phosphorus (P), Potassium (K), and soil texture were used as decision criteria, with 17 fertilizer dosage alternatives derived from BPTP (Balai Pengkajian Teknologi Pertanian) South Sulawesi data. System performance was evaluated against 10 real soil test cases. Results demonstrate that TOPSIS achieved 80% accuracy compared to 50% for ELECTRE, with TOPSIS producing differentiated preference scores that enable clearer prioritization of environmentally appropriate fertilizer dosages. These findings suggest that the TOPSIS-based DSS can effectively support sustainable nutrient management by preventing over-fertilization, optimizing fertilizer use efficiency, and promoting soil health. The proposed system contributes a replicable digital decision model for precision and sustainable agriculture, with direct relevance to SDG implementation in rice-producing regions of Southeast Asia.

Introduction

Global food security and environmental sustainability are increasingly at odds due to the overuse of inorganic fertilizers in rice cultivation. Excessive application of nitrogen (N), phosphorus (P), and potassium (K) fertilizers degrades soil organic matter, promotes eutrophication of water bodies, and accelerates nitrous oxide (N_2O) emissions a greenhouse gas approximately more potent than CO_2. Rice systems receiving irregular or excessive NPK show higher reactive nitrogen losses, stronger greenhouse gas forcing from N_2O, and increased risks to water and soil quality. These outcomes arise because surplus fertilizer shifts nitrogen cycling toward loss pathways and destabilizes soil chemistry and biology. Excess N application is linked to greater N2O, NH3 and NO3– losses and downstream eutrophication risks [1]. These consequences directly undermine the United Nations Sustainable Development Goals, particularly SDG 2 (Zero Hunger), which demands sustainable food production systems; SDG 12 (Responsible Consumption and Production), which calls for the efficient use of natural resources; and SDG 13 (Climate Action), which requires urgent measures to combat climate change and its impacts [2]

The Food and Agriculture Organization of the United Nations (FAO) has long advocated for Site-Specific Nutrient Management (SSNM) as a framework for aligning fertilizer application with actual soil nutrient statu and crop requirements [3]. SSNM principles recognize that different soil types, even within the same agricultural region, present distinct chemical compositions that necessitate tailored fertilization strategies. A balanced fertilization program one that matches the right type and dosage of fertilizer to site-

specific soil conditions can significantly improve nutrient use efficiency, reduce agricultural input costs, and minimize environmental footprints [4], [5]. Lowland rice (Oryza sativa L.), as the primary staple crop in Southeast Asia, represents a critical context in which SSNM principles must be operationalized at scale.

Despite the scientific foundation for SSNM, fertilizer recommendations in many developing agricultural regions, including South Sulawesi, Indonesia, remain largely reliant on generalized guidelines and manual expert consultation. This approach is limited by its dependence on individual expert availability, subjective judgment, and poor adaptability to real-time soil variability [6], [7]. The gap between scientifically grounded nutrient management and its practical implementation represents a significant challenge. There is a pressing need for digital decision intelligence tools capable of translating soil test data into precise, locally calibrated fertilizer recommendations tools that are transparent, reproducible, and capable of operating without continuous expert intervention [8], [9].

This study addresses this gap by proposing an integrated Multi-Criteria Decision Making (MCDM) Decision Support System (DSS) that combines the ELECTRE and TOPSIS algorithms for sustainable inorganic fertilizer recommendation in lowland rice. Using soil nutrient data (N, P, K, and texture) from the Balai Pengkajian Teknologi Pertanian (BPTP) South Sulawesi as the decision criteria, the system evaluates 17 fertilizer dosage alternatives and validates results against 10 real soil test cases. The proposed DSS represents a scalable, data-driven contribution to precision and sustainable agriculture directly supporting SDG implementation in rice-producing regions.

Methods

Research Framework

The research followed a structured DSS development framework integrating soil science principles with MCDM computational methods. The workflow proceeded through five sequential stages: (1) soil nutrient data acquisition via laboratory soil testing; (2) definition of decision criteria aligned with sustainability indicators;

(3) parallel application of ELECTRE and TOPSIS algorithms; (4) comparative ranking of fertilizer alternatives; and (5) derivation of the optimal sustainable fertilizer dosage recommendation. This pipeline ensures that every recommendation is grounded in empirical soil data and evaluated through transparent algorithmic logic, reducing subjectivity inherent in expert-only advisory systems.

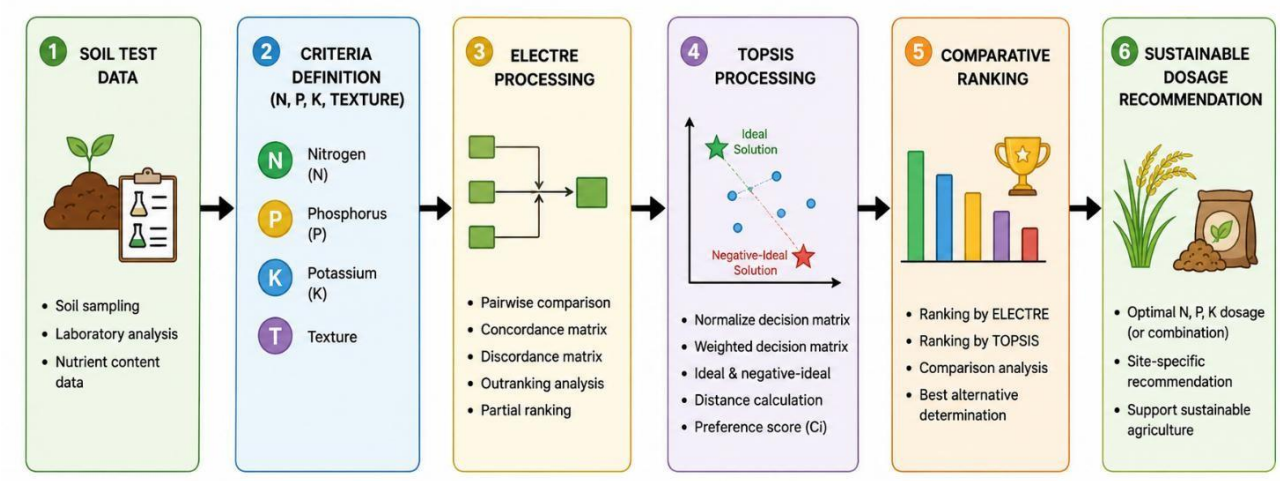


Figure 1. Research Framework Flow

Sustainability Perspective in Criteria Selection

The four decision criteria Nitrogen (N), Phosphorus (P), Potassium (K), and soil texture were selected for their direct correspondence to sustainable nutrient management indicators. Nitrogen status guides the prevention of ammonia volatilization and nitrous oxide emission; excess N application is a leading driver of agricultural greenhouse gas output [10]. Phosphorus status informs strategies to prevent phosphate runoff into waterways, a primary contributor to aquatic eutrophication [11]. Potassium levels indicate soil buffering capacity and plant

stress resilience, enabling dosage optimization that avoids unnecessary chemical inputs [12]. Soil texture (clay, loam, or sandy) determines nutrient retention capacity, directly influencing how fertilizer

should be split and timed to maximize uptake efficiency and minimize leaching [13]. Together, these four criteria form a sustainability-aligned decision matrix that operationalizes SSNM principles within a digital framework.

ELECTRE Method

ELECTRE (Elimination Et Choix Traduisant la Réalité) is an outranking-based MCDM method that evaluates alternatives through pairwise comparisons [14]. The computation proceeds as follows: (1) the decision matrix is normalized using vector normalization; (2) a weighted normalized matrix is computed by multiplying each criterion column by decision-maker-assigned weights; (3) concordance and discordance index sets are constructed for each pair of alternatives; (4) concordance and discordance matrices are computed from the respective index sets; (5) dominant concordance and discordance matrices are derived using threshold values calculated from the average of all matrix elements; (6) an aggregate dominance matrix (E) is produced as the element-wise product of the two dominant matrices; and (7) alternatives with the fewest dominating relationships are eliminated, leaving the most favourable alternatives. In this study, ELECTRE evaluated 17 fertilizer dosage alternatives across 4 criteria, with dominant alternatives selected as recommended dosages.

TOPSIS Method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) selects the alternative with the shortest geometric distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) [15]. The computational steps are: (1) normalize the decision matrix using vector normalization; (2) construct the weighted normalized matrix; (3) determine the PIS and NIS; (4) calculate Euclidean distances of each alternative from PIS (D^+) and NIS (D^-); and (5) compute the preference score Vi

$= D^- / (D^+ + D^-)$, where a higher Vi indicates closer proximity to the ideal sustainable solution [16]. A key advantage of TOPSIS in this context is that each alternative receives a unique, continuous preference score, enabling unambiguous prioritization of fertilizer dosages and avoiding the tied-rank problem that affects ELECTRE's output.

Data Source

Primary data were obtained through field observation and structured interviews with agronomists and soil scientists at Balai Pengkajian Teknologi Pertanian (BPTP) South Sulawesi, Makassar, Indonesia. The dataset comprises 17 inorganic fertilizer dosage alternatives (combinations of Urea, SP-36, and KCl single fertilizers) evaluated across four decision criteria (N, P, K, and soil texture), reflecting site-specific soil conditions in Maros Regency lowland rice fields. System validation was conducted using 10 real soil test cases drawn from laboratory analyses, with BPTP expert recommendations serving as the reference standard for accuracy evaluation. The dataset is structured around a nutrient status classification system where N, P, K levels are categorized as Low (R), Medium (S), or High (T), and soil texture is classified as Sandy, Loam, or Clay consistent with the PTT (Integrated Crop Management) framework of the Indonesian Ministry of Agriculture [17]

Tables 1 and 2 present the complete dataset of fertilizer dosage alternatives and their corresponding nutrient suitability assessments used as the MCDM decision matrix in this study. Suitability codes (S = Suitable, C = Adequate, TS = Not Suitable) were converted to numerical scores (5, 3, 1 respectively) to enable ELECTRE and TOPSIS computation. The fertilizer dosage recommendations were validated against BPTP South Sulawesi benchmark data, ensuring that all 17 alternatives reflect empirically verified, site-tested agronomic practice.

Table 1. Fertilizer Dosage Recommendations for Lowland Rice by Nutrient Status Formula

Code	Formula (Nutrient Status)	Fertilizer Dosage (kg/ha)		
		Urea	SP-36	KCl (– Straw)
A01	RRR	290	100	100
A02	RRS-RRT	290	100	50
A03	RSR	290	75	100

A04	RSS-RST	290	75	50

Code	Formula (Nutrient Status)	Fertilizer Dosage (kg/ha)		
		Urea	SP-36	KCl (–Straw)
A05	RTR	290	50	100
A06	RTS-RTT	290	50	50
A07	SRR	250	100	100
A08	SRS-SRT	250	100	50
A09	SSR	250	75	100
A10	SSS-SST	250	75	50
A11	STR	250	50	100
A12	STS-STT	250	50	50
A13	TRS-TRT	200	100	50
A14	TSR	200	75	100
A15	TSS-TST	200	75	50
A16	TTR	200	50	100
A17	TTS-TTT	200	50	50

Note:
R = Low,
S = Medium,
T = High nutrient status.
KCl dosage reflects "minus straw" condition; add 50 kg/ha for "plus straw" applications. Base yield target: 5 t/ha; add 25 kg Urea per additional ton.

Table 2. Fertilizer Dosage Recommendations for Lowland Rice by Nutrient Status Formula

Code	Formula (Nutrient Status)	Nutrient Suitability			
		N (C1)	P (C2)	K (C3)	Texture (C4)
A01	RRR	**TS**	**TS**	**TS**	**S**
A02	RRS-RRT	**TS**	**TS**	**C**	**S**
A03	RSR	**TS**	**C**	**TS**	**S**
A04	RSS-RST	**TS**	**TS**	**C**	**C**
A05	RTR	**TS**	**S**	**TS**	**C**
A06	RTS-RTT	**TS**	**C**	**C**	**C**
A07	SRR	**C**	**TS**	**TS**	**C**
A08	SRS-SRT	**C**	**TS**	**C**	**C**
A09	SSR	**C**	**C**	**TS**	**C**
A10	SSS-SST	**C**	**C**	**C**	**C**
A11	STR	**C**	**S**	**TS**	**C**
A12	STS-STT	**C**	**S**	**C**	**C**
A13	TRS-TRT	**S**	**TS**	**C**	**TS**
A14	TSR	**S**	**C**	**TS**	**TS**
A15	TSS-TST	**S**	**C**	**C**	**TS**

A16	TTR	**S**	**S**	**TS**	**TS**
A17	TTS-TTT	**S**	**S**	**C**	**TS**

Suitability Code Legend and Score Conversion:

S	Suitable	Score	**5**
C	Adequate	Score	**3**
TS	Not Suitable	Score	**1**

Results and Discussion System Modelling

The DSS was designed around a multi-actor workflow involving agricultural researchers and extension workers as primary administrators, and farmers or field agents as end users. The system architecture centers on a soil nutrient input module where N, P, K status and soil texture are entered following laboratory soil testing. These inputs are processed through both the ELECTRE and TOPSIS computational engines in parallel, which evaluate the inputs against the 17 fertilizer dosage alternatives (Tables 1 and 2). The system outputs a ranked recommendation list, with the highest-ranked alternative identified as the optimal sustainable dosage. The parallel implementation of both methods allows for comparative evaluation of their respective recommendations against verified expert benchmarks, providing transparency and methodological validation within the DSS [18].

Comparison of ELECTRE and TOPSIS Results

Table 3 presents the results of 10 soil test cases evaluated using both ELECTRE and TOPSIS, compared against BPTP South Sulawesi expert recommendations as the accuracy benchmark.

Table 3. Comparison of ELECTRE and TOPSIS Recommendations vs. BPTP Reference (10 Test Cases)

No.	Soil Condition (N, P, K, Texture)	ELECTRE Result	TOPSIS Result	BPTP Reference	ELECTRE	TOPSIS
1	N: High, P: Medium K: Medium, Texture: Clay	A17-TTS-TTT	A17-TTS-TTT	A17-TTS-TTT	✓	✓
2	N: Low, P: Low K: Low, Texture: Loam	A05-RTR	A03-RSR	A03-RSR	✗	✓
3	N: Low, P: Low K: Low, Texture: Sandy	A05-RTR	A03-RSR	A01-RRR	✗	✗
4	N: Low, P: Low K: Low, Texture: Clay	A15-TSS-TST	A12-STS-STT	A12-STS-STT	✗	✓
5	N: Medium, P: Low K: Low, Texture: Loam	A17-TTS-TTT	A12-STS-STT	A12-STS-STT	✗	✓
6	N: Medium, P: High K: Medium, Texture: Clay	A17-TTS-TTT	A17-TTS-TTT	A17-TTS-TTT	✓	✓
7	N: Medium, P: Medium K: High, Texture: Clay	A17-TTS-TTT	A17-TTS-TTT	A17-TTS-TTT	✓	✓
8	N: High, P: Medium K: Medium, Texture: Loam	A17-TTS-TTT	A17-TTS-TTT	A17-TTS-TTT	✓	✓
9	N: High, P: Medium K: Medium, Texture: Sandy	A12-STS-STT	A12-STS-STT	A12-STS-STT	✓	✓

10	N: Medium, P: High K: Low, Texture: Loam	A17-TTS-TTT	A12-STS-STT	A16-TTR	✗	✗

Accuracy Analysis

Accuracy was computed using the formula: Accuracy (%) = (Σ Correct Test Results / Total Test Cases) × 100%.

Table 4. Accuracy Summary of ELECTRE and TOPSIS Methods

Method	Correct Cases	Accuracy (%)
ELECTRE	5 / 10	**50%**
TOPSIS	8 / 10	**80%**

TOPSIS achieved 80% accuracy (8 correct out of 10 cases), compared to 50% for ELECTRE (5 correct out of 10 cases). The higher accuracy of TOPSIS is attributable to its continuous preference scoring mechanism. Unlike ELECTRE, which assigns binary dominance values that can result in multiple alternatives receiving tied scores, TOPSIS produces unique Vi values for each alternative [19]. This distinction proved decisive in Cases 2, 4, and 5, where ELECTRE's tied rankings led to selection of suboptimal dosages, while TOPSIS correctly identified the reference recommendation. Cases 3 and 10 represent genuinely ambiguous soil conditions where both methods diverged from the BPTP reference, suggesting that borderline soil nutrient status may require supplementary contextual information beyond the four criteria used in this study.

Discussion

The superior performance of TOPSIS in prioritizing environmentally appropriate fertilizer dosages carries significant implications for sustainable agriculture. TOPSIS's ability to rank alternatives by their proximity to both ideal and anti-ideal solutions means that the system identifies the dosage closest to optimal nutrient balance while being farthest from over-fertilization scenarios [16]. In practical terms, this translates to recommendations that minimize excess nitrogen and phosphorus application, thereby reducing the risk of soil acidification, nutrient runoff, and greenhouse gas emission from rice paddies [10], [20].

The DSS's grounding in site-specific soil data (N, P, K, and texture) directly operationalizes the SSNM principle that fertilizer decisions must reflect local soil conditions rather than generic agronomic guidelines [4], [8]. The numerical conversion of suitability codes (S=5, C=3, TS=1) provides a structured and reproducible scoring framework that allows MCDM algorithms to process agronomic expert knowledge systematically—bridging the gap between qualitative field assessments and quantitative decision computation [21]. By digitizing this decision process, the system reduces dependence on continuous expert availability, which remains a significant constraint in rural agricultural extension services across South Sulawesi [22].

The 80% accuracy achieved by TOPSIS demonstrates that digital decision intelligence can reliably approximate expert-level recommendations, with the remaining 20% discrepancy attributable to borderline soil conditions warranting additional diagnostic criteria such as organic matter content or micronutrient levels in future iterations [23]. From a sustainability governance perspective, the proposed DSS aligns with FAO and ASEAN digital transformation agendas for agriculture. Precision, data-driven fertilizer management directly

supports SDG 2 by enhancing crop productivity efficiency, SDG 12 by reducing fertilizer waste, and SDG 13 by mitigating soil and water-mediated greenhouse gas pathways. The replicability of the proposed DSS architecture, which integrates standardized MCDM algorithms with regionally sourced soil data, indicates strong potential for adaptation and implementation across other lowland rice-producing regions in Indonesia and ASEAN. Such data-driven and transferable decision-support frameworks have been widely recognized for enhancing the scalability, consistency, and sustainability of agricultural decision-making under diverse environmental conditions [24], [25].

Conclusions

This study demonstrates that an integrated ELECTRE–TOPSIS Decision Support System can effectively operationalize sustainable inorganic fertilizer management for lowland rice cultivation, providing a data-driven alternative to conventional expert-only recommendation systems. By evaluating 17 fertilizer dosage alternatives against four sustainability-relevant soil criteria—Nitrogen, Phosphorus, Potassium, and soil texture the DSS produced recommendations validated against BPTP South Sulawesi expert benchmarks, achieving 80% accuracy with TOPSIS and 50% with ELECTRE across 10 real soil test cases. The superiority of TOPSIS in this context is primarily attributable to its continuous preference scoring mechanism, which enables unambiguous prioritization of environmentally optimal fertilizer dosages and avoids the tied-ranking limitations of ELECTRE. These findings establish TOPSIS as the more suitable algorithm for sustainable fertilizer recommendation DSS applications in data-constrained agricultural settings. Beyond methodological performance, the proposed DSS constitutes a practical contribution to the digital transformation of agricultural decision-making in South Sulawesi and comparable rice-producing regions. By translating soil test data into precise, locally calibrated fertilizer recommendations without requiring continuous expert intervention, the system directly supports SDG 2 through enhanced production efficiency, SDG 12 through responsible nutrient resource management, and SDG 13 through the reduction of agriculture-driven greenhouse gas emissions. Future research should explore the incorporation of additional soil health indicators including organic carbon content, soil pH, and micronutrient availability to address the residual accuracy gap and extend the system's applicability to diverse agroecological conditions across ASEAN.

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