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A Fuzzy Multi-Criteria Decision-Making Framework for Soil-Based Cultivation Block Selection in Citrus Orchards

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ABSTRACT

Selecting the optimal cultivation block in a multi-plot citrus orchard is a hard multi-criteria problem when the soil criteria mix categorical and numerical measurements. Descriptors like Munsell color, soil structure, and consistency sit alongside numerical pH, and conventional agronomic assessment offers no systematic way to weigh them against each other. This study builds a decision support system (DSS) that pairs the fuzzy analytic hierarchy process (FAHP) with two ranking methods, TOPSIS and Simple Additive Weighting (SAW). A rule-based triangular fuzzy number (TFN) protocol first converts the categorical descriptors into numerical inputs through documented rules. Field data came from seven plots across five citrus variety blocks at IP2SIP Tlekung, BRMP Jestro, Batu, East Java, covering texture, structure, color, consistency, and pH. FAHP weights gave a consistency ratio (CR) of 0.0446. Both TOPSIS and SAW ranked plot A1 (Keprok Batu 55 II, 4-year stand) first and A2 (Keprok Batu 55 I, 15-year stand) last, with Spearman $\rho = 0.8929$ ($p = 0.0068$). The top and bottom ranks were held across all 10 sensitivity scenarios. The framework gives orchard managers a reproducible way to prioritize block-level soil intervention, marking A1 as the benchmark block and A2 as the priority for pH correction.

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1. INTRODUCTION

Citrus cultivation is among the most economically significant horticultural activities in Indonesia. East Java has emerged as the primary citrus production hub, surpassing other major citrus-producing provinces including North Sumatra, Bali, West Kalimantan, and West Sumatra, due to intensive development of citrus farming in Banyuwangi, Jember, and Malang Regency [1]. Behind those production figures lies a network of research stations, cultivation blocks, and orchard management decisions that rarely receive systematic analytical attention. Soil on which citrus grows is not a static substrate; it changes with every irrigation cycle, fertilizer application, and pruning season [2]. Deficiencies in soil management have direct consequences for root penetration, nutrient uptake, and fruit yield [3].

Soil physical properties are among the most informative indicators of land suitability for citrus production, yet evaluating them simultaneously is genuinely difficult. A plot may have granular structure but acidic pH. Another may show favorable sandy loam texture alongside compacted, very firm consistency. The interaction between texture, structure, color, consistency, and pH does not reduce neatly to a single score [4]. Field observations at a regional citrus research station confirmed this difficulty across five cultivation blocks, each showing a distinct soil physical profile that defies simple ranking. Agronomists on site rely on subjective judgment to decide which blocks need priority management intervention. No systematic weighting mechanism exists to guide those decisions.

That subjectivity carries real costs. The Purut block exhibited angular blocky structure with very firm consistency and was irrigated only once per week, mechanically restricting root penetration [4]. The Lemon block recorded the lowest mean pH of all blocks at 5.6, a level at which Al^{3+} and Mn^{2+} ions suppress phosphorus availability and inhibit microbial activity [5]. Neither problem had been formally ranked against the others, and no priority order for management intervention had been established.

Multi-Criteria Decision Making (MCDM) methods address exactly this type of problem: several conflicting criteria, no single correct answer, and a need for a defensible ranking. Among the most widely applied frameworks in agricultural and environmental decision support is the Analytic Hierarchy Process (AHP), which structures expert judgment into pairwise comparisons to derive relative criterion weights [6]. Classical AHP treats each comparison as a crisp number, a simplification that ignores genuine uncertainty. Fuzzy AHP (FAHP) resolves this by representing each judgment as a Triangular Fuzzy Number (TFN) encoding a plausible range around a modal estimate [7][8]. Buckley's geometric mean method derives criteria weights from these fuzzy comparisons while preserving the structural logic of the original AHP [9].

Two MCDM ranking methods appear frequently in agricultural decision support literature: TOPSIS and SAW. TOPSIS ranks alternatives by geometric distance from the positive and negative ideal solutions simultaneously. SAW computes a weighted sum of normalized scores, a simpler approach widely used in practical settings [10]. When both methods applied to the same dataset produce consistent rankings, that agreement provides stronger evidence for a decision than either method alone. Yet the majority of DSS studies in the agricultural domain deploy only one MCDM method, leaving ranking robustness unverified [11]. Recent advances in soil-based MCDM demonstrate growing adoption of FAHP for criterion weighting in land suitability contexts: FAHP combined with SAW, TOPSIS, and Fuzzy TOPSIS has been applied across multiple land units for cultivation priority planning in arid regions [12], TOPSIS with parametric methods has been used for sugarcane suitability evaluation in southwestern Iran [11], and AHP integrated with GIS has been deployed for multi-crop agricultural planning in Egyptian arid regions [13]. However, all three studies relied exclusively on numerical laboratory-derived soil indicators, operated at the regional scale rather than at the cultivation block level within a single research station, and deployed a single ranking method without cross-method consensus validation, leaving the robustness of their rankings to alternative methodological assumptions unexamined.

A second problem receives insufficient attention: the translation of qualitative field measurements into quantifiable decision inputs. Munsell soil color notation, structure class, and consistency class are categorical descriptors. Most MCDM-based land suitability studies either discard categorical criteria in favor of numerical indicators only, or convert categories to arbitrary ordinal scores without a documented mapping rule [14]. Neither approach is satisfactory. Therefore, the aim of this study is to develop and validate a transparent fuzzy MCDM decision-support framework that ranks citrus cultivation blocks from mixed categorical and numerical soil data. It departs from existing soil MCDM work in three ways. It keeps the field-observable categorical descriptors and quantifies them through documented rules, instead of dropping them or scoring them by undocumented ordinal scales. It works at the cultivation-block scale inside one station, not at the regional scale. And it checks its rankings with two different aggregation methods instead of one. This study addresses both gaps through a full DSS pipeline with rule-based TFN fuzzification for all five soil criteria, FAHP weight derivation with CR validation, parallel TOPSIS and SAW ranking with Spearman rank correlation, and bidirectional sensitivity analysis. The contributions are: (1) a fully transparent, reproducible TFN fuzzification protocol for categorical and numerical soil field data; (2) dual-method MCDM validation via Spearman rank correlation; and (3) a practical DSS template for multi-block citrus orchard land management.

2. METHODOLOGY

2.1. Field Data Collection and DSS Pipeline

Field observations were conducted at IP2SIP Tlekung or BRMP Jestro, Batu, East Java, Indonesia (7°45'–7°54' S, 112°35' E), at elevations ranging from 895 to 936 m above sea level, with a mean annual temperature of 23°C and relative humidity of 80–90%. Five citrus variety blocks were observed: Keprok Batu 55 II (4-year stand), Keprok Batu 55 I (15-year stand), Siam Pontianak Sitara (11-year stand), Lemon (6-year stand), and Purut (2-year stand). Within each block, five sampling points were placed diagonally and composite disturbed soil samples were collected from depths greater than 15 cm following standard field procedures [15]. Soil texture was identified by feel method; structure was classified; moist consistency was rated; color was matched to the Munsell Soil Color Chart; and pH was measured in situ with a calibrated portable meter stabilized for at least one minute per point. Seven observation plots were designated as decision alternatives (A1–A7) since two blocks produced sub-plots with distinct soil conditions. Table 1 presents the complete raw field measurements.

The DSS framework proceeds through four sequential stages: (1) rule-based TFN construction converting all field measurements into Triangular Fuzzy Numbers; (2) FAHP weight derivation via Buckley's geometric mean with CR validation; (3) parallel TOPSIS and SAW ranking with Spearman rank correlation for consensus measurement; and (4) bidirectional sensitivity analysis perturbing each criterion weight by ±20%. The methods were chosen for specific reasons. FAHP is used instead of crisp AHP because the expert comparisons of soil criteria carry real uncertainty, which triangular fuzzy numbers capture better than single crisp values. TOPSIS and SAW were selected because they aggregate scores in different ways: TOPSIS uses geometric distance from the positive and negative ideal solutions, while SAW uses a linear weighted sum. When two methods that work differently still agree, the ranking is more credible than when two similar methods agree. PROMETHEE and VIKOR were not used because they need extra parameters, such as preference functions, thresholds, or the strategy weight v, and setting these would add subjectivity that the rule-based design is meant to avoid.

Table 1. Raw field measurements per alternative

Alt.	Block	pH	Munsell Color	Structure	Texture	Consistency
A1	Keprok Batu 55 II (4yr)	6.3	YR 3/4	Granular	Sandy loam	Very firm
A2	Keprok Batu 55 I (15yr)	6.6	YR 3/3	Granular	Sandy loam	Very firm
A3	Siam Pontianak	6.0	YR 3/3	Granular	Clay loam	Firm
A4	Purut-1	6.4	YR 2/2	Angular blocky	Sandy loam	Firm
A5	Purut-2	6.4	YR 2/2	Subangular blocky	Clay loam	Firm
A6	Purut-3	6.2	YR 2/2	Angular blocky	Clay loam	Firm
A7	Purut-4	6.1	YR 2/2	Angular blocky	Sandy loam	Friable

2.2. Rule-Based TFN Construction

Four of the five criteria in this study are categorical field descriptors: Munsell color, soil structure, soil texture, and consistency. Standard MCDM frameworks require numerical inputs [16]. Rather than applying arbitrary ordinal scores without documented justification, this study constructs each categorical value as a Triangular Fuzzy Number through explicit rules grounded in soil science for citrus cultivation. This makes the fuzzification step fully transparent and reproducible from the raw field records alone. A TFN is denoted M = (l, m, u), where l is the lower bound, m is the modal value, and u is the upper bound, with $l \leq m \leq u$. Defuzzification uses the centroid method, as shown in (1):

$$\text{defuzz}(\widetilde{M}) = \frac{l+m+u}{3} \quad (1)$$

All TFN values are normalized to [0, 1]. Higher values indicate more favorable soil conditions for citrus, making all criteria benefit-type [17]. Tables 2–6 document the complete mapping rules.

The class boundaries in Tables 2–6 follow soil-science criteria for citrus rather than ad hoc scoring. The pH scale (Table 2) gives its highest TFN to the 6.1–6.5 band because phosphorus and micronutrients are most available to citrus roots in this range, whereas values below 5.5 raise Al^{3+} toxicity and values above 7.0 suppress iron and manganese uptake [3], [5]. For Munsell color (Table 3), darker values (10 YR 2/2) score highest because they signal more organic matter and better aggregate stability than the lighter, yellower hues. Soil structure (Table 4) ranks granular above subangular and angular blocky because granular aggregates give citrus roots the pore space and penetration paths they need, while angular blocky structure restricts them [4]. Texture (Table 5) favors sandy loam over clay loam for its better drainage and aeration. Consistency (Table 6) scores friable highest and very firm lowest, since stronger soil resists root elongation [27]. Each class thus maps to a TFN whose modal value matches its agronomic suitability, and the centroid defuzzification in (1) reduces it to one benefit score on [0, 1].

Table 2. pH TFN mapping

pH Class	pH Range	TFN (l, m, u)
Optimal	6.1–6.5	(3.5, 4.0, 4.5)
Slightly acid	5.6–6.0	(2.5, 3.0, 3.5)
Slightly alkaline	6.6–7.0	(1.5, 2.0, 2.5)
Acid	5.1–5.5	(1.5, 2.0, 2.5)
Very acid	< 5.1	(0.5, 1.0, 1.5)

Table 3. Munsell color TFN mapping

Munsell Notation	Color Class	TFN (l, m, u)
10 YR 2/2	Very dark brown	(0.80, 1.00, 1.00)
10 YR 3/3	Dark brown	(0.60, 0.80, 0.90)
10 YR 3/4	Dark yellowish brown	(0.50, 0.70, 0.80)

Table 4. Soil structure TFN mapping

Structure Class	TFN (l, m, u)
Granular	(0.80, 1.00, 1.00)
Subangular blocky	(0.60, 0.80, 0.90)
Angular blocky	(0.40, 0.60, 0.80)

Table 5. Soil texture TFN mapping

Texture Class	TFN (l, m, u)
Sandy loam	(0.80, 1.00, 1.00)
Clay loam	(0.40, 0.60, 0.70)

Table 6. Soil consistency TFN mapping

Consistency Class	TFN (l, m, u)
Friable	(0.80, 1.00, 1.00)
Firm	(0.40, 0.60, 0.70)
Very firm	(0.10, 0.30, 0.50)

2.3. Fuzzy Analytic Hierarchy Process (FAHP)

Expert judgment was provided by a panel of three soil and horticulture researchers from the BRMP Jestro citrus research station, each with formal training in soil science or agronomy and direct field experience in citrus cultivation at the station. FAHP commonly draws on a few domain experts rather than a large survey sample, with the consistency ratio used to check that their pairwise judgments cohere. This combined judgment from the Research Team of BRMP Jestro, Kementerian Pertanian Republik Indonesia, was elicited through pairwise comparison using the fuzzified Saaty scale [6], [7]. Each Saaty integer s was mapped to a TFN as $(s-1,\, s,\, s+1)$; reciprocal judgments were computed as $(1/u,\, 1/m,\, 1/l)$. Only the upper triangle of the 5×5 matrix was elicited; the lower triangle was derived automatically as the element-wise reciprocal, guaranteeing structural consistency. Weights were derived using Buckley's geometric mean method [9], preferred over Chang's extent analysis because the latter can produce zero weights under certain matrix configurations. For each row i:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij}\right)^{1/n} \tag{2}$$

$$w_i = \text{defuzz}\left(\frac{\tilde{r}_i}{\sum_{k=1}^{n} \tilde{r}_k}\right) \tag{3}$$

Consistency was assessed on the defuzzified pairwise matrix following Saaty [6], using the consistency index (4) and the consistency ratio (5):

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

where $RI = 1.12$ for $n = 5$. Expert judgment is accepted when $CR \leq 0.10$.

2.4. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS ranks alternatives by closeness to the positive ideal solution (PIS) relative to the negative ideal solution (NIS)[10], [11]. The procedure follows five steps.

Step 1. Vector normalization is performed using (6):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

Step 2. Weighted normalized matrix is computed using (7):

$$v_{ij} = w_j \cdot r_{ij} \tag{7}$$

Step 3. PIS and NIS for benefit criteria are identified using (8):

$$v_j^+ = \max_i(v_{ij}), \qquad v_j^- = \min_i(v_{ij}) \tag{8}$$

Step 4. Euclidean distances to the ideal solutions are obtained from (9):

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2}, \qquad d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{9}$$

Step 5. Relative closeness coefficient is calculated using (10):

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{10}$$

Alternatives are ranked in descending order of CC_i [14].

2.5. Simple Additive Weighting (SAW)

SAW computes a weighted sum of max-normalized criterion scores. Its transparency makes it suitable for practitioners who need to communicate ranking rationale to non-technical stakeholders [18], [19].

Step 1. Max normalization for benefit criteria is applied using (11):

$$r_{ij} = \frac{x_{ij}}{\max_i(x_{ij})} \tag{11}$$

Step 2. Weighted total score is obtained from (12):

$$S_i = \sum_{j=1}^{n} w_j \cdot r_{ij} \tag{12}$$

Alternatives are ranked in descending order of S_i.

2.6. Spearman Rank Correlation and Sensitivity Analysis

Consensus between TOPSIS and SAW rankings was measured using Spearman's rank correlation [20] coefficient ρ, given by (13):

$$\rho = 1 - \frac{6\sum_{i=1}^{m} d_i^2}{m\,(m^2 - 1)} \tag{13}$$

where d_i is the rank difference for alternative i between the two methods and m is the number of alternatives.

Ranking stability was assessed through individual weight perturbation following Więckowski and Sałabun [21]. For perturbation factor f applied to criterion k, the perturbed weight is rescaled by (14) and the remaining weights are renormalized by (15):

$$w_k' = w_k \cdot f \tag{14}$$

$$w_j' = w_j \cdot \frac{1 - w_k \cdot f}{1 - w_k}, \quad \forall\, j \neq k \tag{15}$$

This guarantees $\sum_j w_j' = 1$ after each perturbation. Factors $f = 1.20$ $(+20\%)$ and $f = 0.80$ (-20%) were applied to each of the five criteria in turn, producing 10 perturbed scenarios plus the original baseline (11 scenarios total).

3. RESULTS AND DISCUSSION

3.1. TFN Decision Matrix

Table 7 presents the defuzzified decision matrix. A3 (Siam Pontianak) records the lowest texture score (0.5667) as the only clay loam block, consistent with finer particle accumulation at its higher elevation (929 m). A2 records the lowest pH score (2.0000) because a mean field pH of 6.6 places it in the slightly alkaline class, outside the citrus optimum of 5.5–7.0. A7 achieves the highest consistency score (0.9333) as the sole friable-consistency plot within the Purut block, reflecting localized differences in organic matter management.

Table 7. Defuzzified decision matrix

Alt.	C1 pH	C2 Color	C3 Structure	C4 Texture	C5 Consistency
A1	4.0000	0.6667	0.9333	0.9333	0.3000
A2	2.0000	0.7667	0.9333	0.9333	0.3000
A3	3.0000	0.7667	0.9333	0.5667	0.5667
A4	4.0000	0.9333	0.6000	0.9333	0.5667
A5	4.0000	0.9333	0.7667	0.5667	0.5667
A6	4.0000	0.9333	0.6000	0.5667	0.5667
A7	4.0000	0.9333	0.6000	0.9333	0.9333

3.2. FAHP Criterion Weights and Consistency Validation

Table 8 presents the derived criterion weights. pH received the highest weight (w = 0.4214) and structure the second highest (w = 0.2471), together accounting for 66.9% of total weight. This reflects the agronomic primacy of nutrient availability and physical root penetration as direct determinants of citrus productivity[22], [23]. Consistency validation yielded λ_max = 5.2000, CI = 0.0500, and CR = 0.0446. Since CR < 0.10, the expert judgment is accepted without revision.

Table 8. FAHP criterion weights

Criterion	Fuzzy Weight (l, m, u)	Crisp Weight	Rank
C1 pH	(0.4241, 0.4327, 0.4073)	0.4214	1
C2 Munsell Color	(0.1482, 0.1362, 0.1390)	0.1411	3 (tie)
C3 Soil Structure	(0.2246, 0.2479, 0.2688)	0.2471	2
C4 Soil Texture	(0.1482, 0.1362, 0.1390)	0.1411	3 (tie)
C5 Consistency	(0.0548, 0.0471, 0.0459)	0.0493	5

3.3. TOPSIS and SAW Ranking Results

Table 9 presents the full ranking results. A1 (Keprok Batu 55 II, 4-year stand) ranked first under both TOPSIS (CC = 0.7900) and SAW (S = 0.9263), owing to its combination of optimal-range pH (6.3) and uniformly granular structure. Its management regime three to four inorganic fertilizer applications per year, one organic application, and twice-weekly irrigation produces the best soil physical conditions at the station [4]. A2 (Keprok Batu 55 I, 15-year stand) ranked last under both methods (CC = 0.3430, S = 0.7307). Despite sharing the same structure and texture class as A1, a mean pH of 6.6 pushes it outside the citrus optimum. This pH elevation in the older stand results from prolonged base cation accumulation through organic matter decomposition [24], [25].

A7 (Purut-4) ranked third under TOPSIS (CC = 0.7037) but second under SAW (S = 0.9118), while A5 ranked second under TOPSIS but fourth under SAW. This divergence reflects the structural difference between TOPSIS's dual-distance geometry and SAW's additive compensation [24]. A7's uniquely favorable consistency (friable) increases its distance from the NIS under TOPSIS's Euclidean metric more strongly than SAW's weighted-sum formulation captures. Figure 1, demonstrated analytically that TOPSIS and SAW diverge most for alternatives with heterogeneous criterion profiles in the middle of the distribution, precisely the condition observed here.

Table 9. TOPSIS and SAW ranking results

Alt.	Block	d^+	d^-	CC	TOPSIS	SAW Score	SAW Rank
A1	Keprok Batu 55 II (4yr)	0.0263	0.0991	0.7900	1	0.9263	1
A5	Purut-2	0.0337	0.0916	0.7308	2	0.8811	4
A7	Purut-4	0.0398	0.0945	0.7037	3	0.9118	2
A4	Purut-1	0.0415	0.0927	0.6906	4	0.8924	3
A6	Purut-3	0.0482	0.0894	0.6495	5	0.8370	5
A3	Siam Pontianak	0.0525	0.0601	0.5334	6	0.7947	6
A2	Keprok Batu 55 I (15yr)	0.0903	0.0472	0.3430	7	0.7307	7

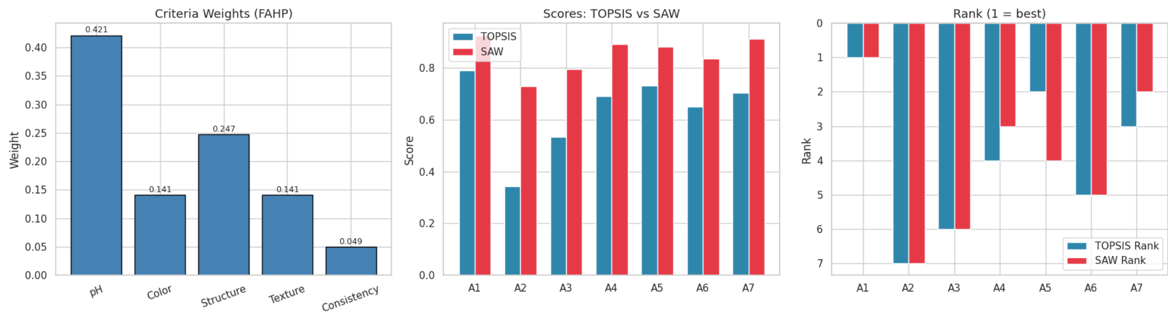

Figure 1. Comparison of FAHP Criteria Weights, TOPSIS and SAW Scores, and Ranking of Alternatives

3.4. Spearman Rank Correlation

The Spearman rank correlation between TOPSIS and SAW rankings was ρ = 0.8929 (p = 0.0068), indicating strong and statistically significant consensus at the full rank-vector level. Both methods agreed completely on rank 1 (A1) and rank 7 (A2). Disagreement was confined to the middle tier, consistent with [24]. The statistically significant p-value confirms that this agreement is not a chance result. This level of consensus is comparable to findings, where Fuzzy TOPSIS and SAW applied to three-crop cultivation priority showed ρ > 0.85 across all tested weight specifications.

3.5. Two-Directional Sensitivity Analysis

Table 10 presents rank stability across all 10 perturbation scenarios. A2, A3, A4, and A6 were fully stable under all perturbations in both methods. A1, A5, and A7 showed minor shifts of one position at most under specific structure weight perturbation scenarios. No alternative changed its management priority tier: no middle-ranked alternative moved to rank 1 or 7, and A1 and A2 remained the top and bottom recommendations in every scenario. This result confirms that the management conclusions are robust to plausible variation in expert weight specification within the ±20% band tested [21], [23].

Table 10. Rank stability summary

Alt.	Block	Baseline TOPSIS	Baseline SAW	Max Shift T	Max Shift S	Status
A1	Keprok Batu 55 II (4yr)	1	1	1	1	Minor shift
A2	Keprok Batu 55 I (15yr)	7	7	0	0	Stable
A3	Siam Pontianak	6	6	0	0	Stable
A4	Purut-1	4	3	0	0	Stable
A5	Purut-2	2	4	1	0	Minor shift
A6	Purut-3	5	5	0	0	Stable
A7	Purut-4	4	3	2	1	Minor shift

3.6. Practical Implications

Three management recommendations follow from the DSS output. First, the Keprok Batu 55 II block (A1) represents the current soil physical benchmark. Its management regime should serve as the reference standard for other blocks. Second, the Keprok Batu 55 I block (A2) requires pH monitoring and corrective fertilization; adjusting toward ammonium-based nitrogen sources would address the observed alkalinity drift

[26]. A2 should be the priority block for intervention: soil pH should be monitored at least once per growing season and brought back toward the 6.1–6.5 optimum through acidifying, ammonium-based nitrogen fertilization and, where needed, elemental sulfur application, with phosphorus availability re-checked after correction. Third, within the Purut block, A7's friable consistency after just two years of establishment distinguishes it from the angular blocky plots (A4, A6), suggesting that localized differences in organic matter input are already producing measurably different soil physical outcomes within the same block.

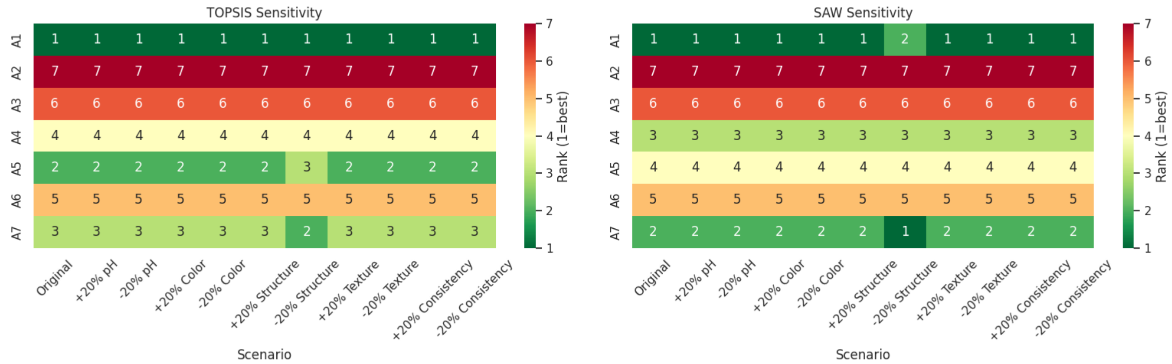

Figure 2. Sensitivity heatmaps

3.7. Discussion

Regarding criterion weights, the dominance of pH (w = 0.4214) and structure (w = 0.2471) is consistent with established soil science for citrus cultivation. Soil pH governs the solubility of all major and minor nutrients in the root zone; values outside the 6.1–6.5 optimum suppress phosphorus availability and trigger aluminum toxicity at low pH, or restrict iron and manganese uptake at high pH. The relatively low weight assigned to consistency (w = 0.0493) reflects the expert's position that consistency effects on root development are largely mediated through structure, which already carries a higher weight. This interpretation is supported by [27], who showed in a citrus pomelo orchard study that management-induced reductions in bulk density which correlates with consistency produced root penetration improvements only when aggregate structure simultaneously became more porous. Structure and consistency co-vary in tropical plantation soils under intensive management, so separating their contributions through independent weights introduces some redundancy. Future studies should consider testing the sensitivity of the weight structure to correlation-adjusted criteria through methods such as the criteria importance through inter-criteria correlation (CRITIC) approach.

The ranking outcome for A1 (Keprok Batu 55 II, 4-year stand) as the best-conditioned plot is consistent with findings from comparable MCDM-based orchard evaluations. Assessed cultivation priority for three crops across 66 land units using FAHP, SAW, TOPSIS, and Fuzzy TOPSIS, and found that plots scoring highest on pH and structure criteria under FAHP-derived weights consistently ranked first regardless of which ranking method was applied [12]. The pattern observed here pH-optimal, granular-structure plots dominating the top rank across both methods mirrors that finding at the plot scale rather than the regional scale. The last-place ranking of A2 (Keprok Batu 55 I, 15-year stand) also has a parallel in the literature. A 2024 study on long-term pomelo orchards in the Vietnamese Mekong Delta found that soil pH progressively drifted above 6.5 in blocks older than 12 years, driven by base cation release from accelerating organic matter decomposition under established canopies, and that this drift was associated with reduced phosphorus uptake efficiency regardless of fertilizer input [28]. That mechanism is precisely what appears to be operating in the Keprok Batu 55 I block, where 15 years of canopy development have pushed mean pH to 6.6.

The Spearman rank correlation of $\rho = 0.8929$ between TOPSIS and SAW requires careful interpretation. Values at this level sit in a zone where neither "strong agreement" nor "substantial divergence" is entirely accurate. The two methods agree on the extremes: ranks 1 and 7, but disagree on the relative ordering of A5 and A7 within the Purut block. This pattern has a clear methodological explanation. TOPSIS applies Euclidean distance to both the positive and negative ideal, meaning that an alternative with a very high score on one criterion (A7's friable consistency) gains disproportionate distance from the negative ideal on that criterion dimension relative to what SAW's linear aggregation would reflect. Ref [24] demonstrated this asymmetry formally: TOPSIS tends to promote alternatives with extreme scores on individual criteria relative to SAW when those criteria have high dimensional separability from others in the weight-normalized space. The practical consequence for BRMP Jestro is that A7 and A5 cannot be unambiguously ranked relative to each other on current data. The reversal is confined to the middle tier: both methods place A1 at rank 1 and A2 at rank 7 without exception, so the management-priority conclusions, which depend only on the best and worst plots, are unaffected by the choice between TOPSIS and SAW. Collecting one additional soil indicator for example, organic carbon content, which drives both consistency and color ratings would likely resolve the ambiguity by giving A7's friable consistency an independent chemical basis.

The most distinctive methodological contribution of this study relative to the existing literature is the rule-based TFN construction for categorical soil descriptors. Most land suitability assessments combining MCDM with soil data use exclusively numerical inputs derived from laboratory analysis, such as electrical conductivity, organic carbon percentage, and available phosphorus, excluding field-observable categorical descriptors because no standard fuzzification protocol exists for them. The protocol developed here for Munsell color, structure class, texture class, and consistency class is grounded in the soil science classification standards used by Indonesian agricultural research institutions [15], making it directly applicable to other BRMP and BSIP stations operating within the same national field observation framework. The full mapping table is documented at the individual-class level, so any researcher with access to the same munsell chart and consistency rating guide can reproduce every cell of the decision matrix from the raw field notes in Table 1. That level of reproducibility is absent from categorical MCDM studies that convert field descriptors to ordinal scores without documenting the conversion rule.

Several limitations visible from the results deserve explicit acknowledgment beyond those listed in the Conclusion. First, the Purut block sub-plots (A4–A7) were treated as independent alternatives, but they are spatially contiguous within a single two-year-old stand. Their soil differences reflect within-block variability that is real but may partly reflect measurement point selection rather than management-driven divergence. A systematic grid-based sampling design within the Purut block would allow within-block spatial autocorrelation to be estimated and reported, strengthening the claim that A7's friable consistency is management-attributable rather than a random sampling artifact. Second, the expert judgment was elicited from a single institution's research team at a single point in time. Expert-derived FAHP weights are sensitive to the professional background and cropping system experience of the respondents; weights derived from a broader panel of citrus soil scientists across East Java's producing regions might shift the relative importance of pH versus structure, which would alter middle-tier rankings even if it left the top and bottom unchanged. Third, the rankings are validated internally, through cross-method consensus and weight perturbation, but have not yet been checked against measured agronomic outcomes. The DSS predicts that A1 offers the most favourable soil physical conditions and A2 the least, yet field yield and fruit-quality records for the two blocks were not available for this study, so the rankings should be read as a soil-based priority order rather than a confirmed productivity ranking. Fourth, the evaluation is limited to soil physical and chemical-reaction criteria; climatic factors, water availability, and economic costs of intervention were outside its scope.

4. CONCLUSION

This study set out to develop and validate a transparent fuzzy MCDM decision-support framework for ranking citrus cultivation blocks from mixed categorical and numerical soil data. The pipeline converted field-observed soil descriptors into numerical inputs through a documented rule-based fuzzification protocol, derived criterion weights from validated expert judgment, and ranked seven plots using two complementary aggregation methods. Soil reaction and structure carried the most weight, which matches their known role in citrus root function and nutrient uptake. Both ranking methods placed the youngest Keprok Batu 55 block first and the oldest stand last, and these two rankings held under systematic weight perturbation. This gives orchard managers a reproducible way to set priorities for block-level soil intervention. Its main contributions are a transparent fuzzification protocol for categorical soil descriptors, dual-method validation that exposes mid-tier ranking uncertainty hidden in single-method studies, and a bidirectional sensitivity analysis. Future work should broaden the expert panel with formal inter-rater reliability testing, add soil chemical and economic criteria, validate rankings against measured yield, and explore hybrid MCDM machine-learning approaches for land-suitability assessment.

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from NAWN. Requests should be directed to the corresponding author.

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