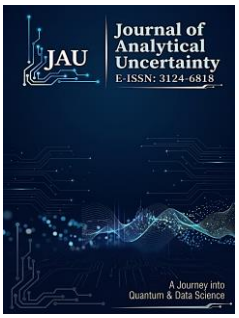
OPEN ACCESS PEER-REVIEWED

JAU Vol.2, No.1, 2026 - Page: 75-89
doi.org/10.63924/jau.v2i1.358
e-ISSN: 3124-6818



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Reliability-Calibrated q-Rung Orthopair Fuzzy Decision Support for Uncertainty-Aware Crop Prioritisation

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Abstract

Crop prioritisation requires simultaneous evaluation of productivity, production stability, input burden, soil condition, and irrigation dependence under uncertain evidence. This study proposes a Reliability-Calibrated q-Rung Orthopair Fuzzy Distance-to-Ideal method (RC-qROF-DI) for transparent, non-predictive agricultural decision support. Unlike conventional applications that elicit membership, non-membership, and hesitation independently, RC-qROF-DI transforms observed desirability and empirical reliability into an admissible orthopair representation in which unresolved evidence is determined by data quality. The method was evaluated using 10,000 complete observations covering six crops and 20 soil, climate, management, contextual, and yield variables. Six decision criteria were constructed: mean yield, yield variability, fertilizer use, pesticide use, organic carbon, and irrigation dependence. Entropy weights were combined with q-rung orthopair distance-to-ideal ranking. At the primary Fermatean setting, sugarcane ranked first with a closeness coefficient of 0.5747, followed by potato (0.5473), wheat (0.4341), maize (0.4241), cotton (0.4195), and rice (0.4096). The first three positions were preserved across the intuitionistic, Pythagorean, Fermatean, and higher-rung specifications; full-ranking Spearman agreement with the primary model ranged from 0.9429 to 1.0000. All ±10% weight perturbations preserved the ranking. Across 500 stratified bootstrap samples, sugarcane ranked first in 86.4% and potato in 13.4%. The framework provides an auditable link from numerical evidence to fuzzy support, opposition, indeterminacy, and ranking uncertainty. Its output is a within-dataset production-profile prioritisation, not a location-specific agronomic recommendation.

Keywords: Crop Prioritisation, q-Rung Orthopair Fuzzy Sets, Fuzzy Decision-Making, Distance-To-Ideal, Sustainable Agriculture, Uncertainty

Introduction

Agricultural decision making requires simultaneous consideration of productivity, production stability, environmental burden, resource availability, and local feasibility. A crop that produces a high mean yield may require greater fertilizer, pesticide, or controlled irrigation. Conversely, a crop with modest yield may be less demanding but more variable or less compatible with the observed production environment. These conditions make crop prioritisation a multi-criteria decision problem rather than a single-variable maximisation task [1], [2].

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Received: April 02, 2026 - Accepted: November 15, 2026 - Published online: November 17, 2026

Data-driven agricultural research has expanded rapidly. Predictive studies combine soil, climate, satellite, crop, and management variables to estimate yield [3]–[7]. Crop-recommendation systems commonly use classifiers and ensembles [8]–[10], while recent work has added predictive uncertainty [11]. These approaches answer which crop is likely to suit a new input profile. A different but complementary problem arises when decision makers must compare crop production profiles across several conflicting criteria and retain a traceable account of unresolved evidence. The present study addresses this second problem through an interpretable fuzzy multi-criteria decision-support model rather than a predictive learner.

Fuzzy-set theory provides a direct mathematical representation of gradual evidence [12]. Atanassov's intuitionistic fuzzy set represents membership, non-membership, and hesitation [13]. Pythagorean fuzzy sets enlarge the feasible assessment region [14], while q-rung orthopair fuzzy sets generalise these models through an adjustable rung parameter [15]. For a q-rung orthopair pair, strong support and strong opposition may coexist when the admissibility condition is satisfied. This is valuable in agriculture, where a crop may be supported by yield and stability but opposed by input requirements or water dependence. Aggregation operators [16], [17] and distance measures [18]–[20] have made q-ROFS useful for multi-attribute decisions. A recent systematic review also shows that fuzzy logic has been applied to agricultural diagnosis, prediction, selection, and management, while identifying persistent needs for transparent data grounding and stronger validation [20].

Despite these developments, three problems remain. First, membership and non-membership values are often assigned through linguistic scales even when a substantial observational dataset is available. Second, hesitation or indeterminacy is frequently treated as an independent judgment instead of being tied to the reliability of the evidence. Third, many studies report a single final ranking without testing rung sensitivity, weight perturbation, criterion removal, and sampling variation. These limitations weaken reproducibility and can create unjustified confidence in the selected alternative.

This study addresses these problems through a non-predictive q-rung orthopair fuzzy multi-criteria implementation. No regression, classification, neural network, SHAP model, AHP procedure, or expert-generated pairwise matrix is used. The aim is to develop and evaluate a reliability-calibrated q-ROF distance-to-ideal method for uncertainty-aware crop production-profile prioritisation. The objectives are to: (1) construct a crop-level decision matrix from observed data; (2) introduce a reliability-calibrated transformation from empirical desirability to q-ROF evidence; (3) rank the crop alternatives at the primary Fermatean setting, $q = 3$; and (4) evaluate robustness against nested fuzzy baselines, rung selection, criterion-weight perturbation, criterion removal, and stratified bootstrap variation.

The contribution to knowledge has four parts. First, the proposed encoding makes evidence commitment identifiable because q-powered support and opposition sum to an empirical reliability coefficient. Second, indeterminacy is derived from evidence reliability rather than assigned independently. Third, the model establishes a reproducible bridge from numerical agricultural observations to q-ROF decision evidence without expert-generated fuzzy ratings. Fourth, validation separates structural stability across the nested intuitionistic, Pythagorean, Fermatean, and higher-rung models from sensitivity to weights, criteria, and sampling variation. These contributions position RC-qROF-DI as an auditable intelligent decision-support method, while its conclusions remain conditional on the selected data and criteria.

Literature Review

Agricultural prediction and recommendation

Crop-yield research has used agronomic, climatic, environmental, and remote-sensing variables across different geographic scales. Aworka et al. [3] and Cedric et al. [4] demonstrated data-driven yield analysis in African settings. Cheng et al. [5], Li et al. [6], and Ju et al. [7] showed that multi-source indicators can improve yield estimation. These studies establish the importance of multi-domain agricultural data, but their primary outputs are predicted yield values rather than uncertainty-aware comparisons of crop alternatives.

Agricultural recommendation systems extend prediction toward action. Senapaty et al. [8] developed a machine-learning crop recommendation system, Musanase et al. [9] linked crop and fertilizer recommendations, Hasan et al. [10] used ensemble learning for crop suitability, and Alam et al. [11] incorporated predictive uncertainty. Their contribution is operational relevance, but the decision logic is inseparable from fitted classifiers or ensembles. The present study addresses a different question: whether an auditable fuzzy method can rank crops directly from observed multi-criteria evidence without training a predictive model.

The broader need to retain a traceable relationship between observed evidence and intelligent-system interpretation is also visible in human-centred application research. Ataguba et al. [21], for example, combined quantitative and qualitative evidence when examining pregnancy-app reviews. Although the application domain differs, that work reinforces the importance of interpretable evidence transformation rather than opaque output alone.

Development of orthopair fuzzy sets

Zadeh's classical fuzzy set represents a single membership degree [12]. Atanassov introduced a non-membership degree and a residual hesitation component, subject to a linear admissibility constraint [13]. Yager's Pythagorean fuzzy formulation replaced the linear constraint with a squared constraint and permitted a larger feasible region [14]. The general q-rung orthopair fuzzy set further extended the admissible space through $\mu^q + \nu^q \leq 1$ [15]. Intuitionistic and Pythagorean fuzzy sets are recovered at $q = 1$ and $q = 2$, respectively, while $q = 3$ corresponds to the Fermatean admissibility condition.

Research has subsequently developed q-ROF aggregation operators. Liu and Wang [16] proposed operators for multiple-attribute decision making, and Wei et al. [17] introduced Heronian mean operators that represent interactions among attributes. These methods improve aggregation flexibility, but they usually assume that the original q-ROF evaluations already exist. They do not solve the empirical problem of converting a numerical agricultural dataset into defensible orthopair evidence.

q-ROF distance and selection methods

Distance measures are central to alternative discrimination because they quantify proximity to desirable and undesirable reference states. Ejegwa et al. [18] developed a numerical q-ROF distance method for robotics selection. Ejegwa et al. [19] introduced a q-ROF distance metric for energy-source selection. Other q-ROF decision studies have used generalized orthopair reasoning and related compromise procedures to rank alternatives under uncertainty [22]. These works demonstrate the transfer relevance of q-ROF distance structures across domains, but their input assessments are commonly elicited from decision makers.

Fuzzy logic in agriculture

Agricultural fuzzy applications include irrigation control, crop diagnosis, soil assessment, yield evaluation, resource allocation, and recommendation. Nwokoro et al. [20] reviewed the state of the art and found substantial methodological diversity, ranging from classical rule-based systems to higher-order fuzzy decision models. The review also indicates that many studies do not connect fuzzy degrees to transparent empirical reliability or provide broad robustness tests.

The distinction among intuitionistic, Pythagorean, picture, Fermatean, and q-rung orthopair models is important. Picture fuzzy sets are appropriate when positive, neutral, negative, and refusal responses are explicitly collected. The present dataset contains numerical observations and no neutral or refusal judgments. Introducing picture fuzzy degrees would therefore require artificial information. q-ROFS is better aligned with the available evidence because crop performance can be expressed as support, opposition, and unresolved uncertainty.

Recent q-ROF research confirms growing interest in flexible decision models for sustainability and crop selection. Erdebilli and Sıcakyüz [23] integrated q-ROF information into sustainable supply-chain selection, while Rahim et al. [24] proposed a p,q-quasirung orthopair hybrid aggregation operator for multi-criteria crop selection. These studies demonstrate the value of flexible orthopair spaces, but they retain expert or group-decision assessments as their input basis. RC-qROF-DI addresses a different methodological gap by deriving the orthopair evidence

and its indeterminacy from observational crop data and then testing the resulting ranking under several sources of uncertainty.

Comparative position and research gap

Table 1 positions the proposed method against representative approaches. The gap is not the absence of another aggregation operator. It is the lack of a reproducible bridge from numerical agricultural observations to reliability-aware q-ROF evidence, followed by explicit stability testing.

Table 1: Comparative position of the proposed method

Approach	Input basis	Uncertainty representation	Limitation addressed here
ML crop recommendation [8]–[11]	Training records	Predictive probability/error	Requires fitted predictive model
Expert q-ROF aggregation [16], [17]	Linguistic ratings	Support and opposition	q-ROF inputs remain subjective
q-ROF distance selection [18]–[20]	Expert decision matrix	Orthopair distance	Reliability is not data-calibrated
Agricultural fuzzy applications [20]	Rules, sensors, experts, data	Method-dependent	Validation is often limited
Proposed RC-qROF-DI	Observed crop-level data	Support, opposition, derived indeterminacy	Pure fuzzy encoding with empirical reliability and robustness tests
p,q-quasirung crop selection [24]	Expert/group assessments	Flexible orthopair aggregation	Evidence reliability is not derived from observations

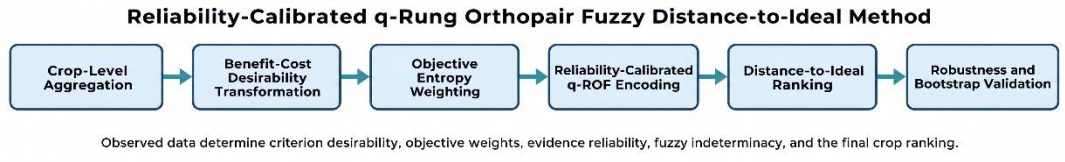
Unlike prediction methods, RC-qROF-DI does not estimate an unseen yield. Unlike conventional fuzzy elicitation, it does not manufacture expert ratings. Unlike a picture fuzzy model, it does not assume neutral and refusal observations. Its principal advance is the identity $\mu_{ij}^{q} + \nu_{ij}^{q} = r_{ij}$, which directly connects fuzzy commitment to the reliability of the observed evidence.

Methods

Study design

The study uses a quantitative computational decision-design approach. The units of analysis are crop alternatives, and the source records are used to estimate crop-level performance and evidence reliability. The complete sequence is data quality assessment, crop-level aggregation, benefit/cost transformation, objective weighting, reliability calibration, q-ROF encoding, distance-to-ideal ranking, and robustness evaluation. Figure 1 presents the workflow.

Figure 1. Workflow of the proposed reliability-calibrated q-ROF distance-to-ideal method.



Data source and structure

The analysis uses the author-supplied file *Dataset_NEW(1).csv*. It contains 10,000 observations and 20 variables. No missing values or exact duplicate records were detected. The dataset contains six crop alternatives: cotton, maize, potato, rice, sugarcane, and wheat. Crop frequencies range from 1,633 to 1,702, providing near-balanced alternative coverage.

The variables cover soil nutrients and characteristics, climate, geographic context, season, crop type, irrigation, chemical inputs, and crop yield. Table 2 summarises the data domains. The analysed file corresponds to the publicly available Crop Yield Prediction dataset created by Arif Miah and distributed through Kaggle under the Apache 2.0 licence. The repository information and access details are reported in the Data availability statement. Because the dataset is an integrated secondary source without row-level source identifiers, the analysis supports internal empirical validation but not a claim of external representativeness.

Table 2: Dataset domains and analytical roles

Domain	Variables	Role in this study
Soil	N, P, K, soil pH, moisture, soil type, organic carbon	Crop profiles and soil-carbon criterion
Climate	temperature, humidity, rainfall, sunlight, wind speed	Contextual description
Geography	region, altitude, season	Coverage and stratification context
Management	irrigation type, fertilizer used, pesticide used	Input-burden criteria
Crop and outcome	crop type, yield	Alternatives, productivity and stability

Decision alternatives and criteria

The alternatives are the six crop types. Six criteria were selected to balance productivity, stability, inputs, soil condition, and reliance on controlled irrigation. Mean crop yield and organic carbon are benefit criteria. Yield coefficient of variation, fertilizer use, pesticide use, and irrigation dependence are cost criteria. Irrigation dependence is the proportion of records whose irrigation type is canal, drip, or sprinkler rather than rainfed. This definition measures reliance on controlled irrigation categories; it does not measure water volume.

Decision scope and construct validity. The model compares observed crop production profiles within this dataset; it does not infer the best crop for a new farm, location, season, or soil sample. Mean yield is treated as absolute observed productivity, so naturally high-biomass crops can obtain an advantage when the crop-specific measurement scale is not benchmarked externally. Yield variability, chemical inputs, organic carbon, and irrigation dependence provide countervailing evidence, but they do not make the output a complete life-cycle sustainability assessment. The valid interpretation is therefore conditional multi-criteria prioritisation under the recorded production structure. Farm-level recommendation would require location-specific covariates, crop-specific agronomic benchmarks, and external validation.

For crop i and numerical variable j, the crop-level mean is:

$$\bar{x}_{ij} = \frac{1}{n_i}\sum_{k=1}^{n_i} x_{ijk}. \quad (1)$$

Yield variability is represented by the coefficient of variation:

$$CV_i = \frac{s_i}{\bar{y}_i}, \quad (2)$$

where s_i and $\bar{y}_i$ are the crop-specific standard deviation and mean yield. Irrigation dependence is:

$$I_i = \frac{1}{n_i}\sum_{k=1}^{n_i} \mathbb{1}\left(\text{irrigation}_{ik} \neq \text{rainfed}\right). \quad (3)$$

q-Rung orthopair fuzzy preliminaries

Let X be a universe of discourse. A q-rung orthopair fuzzy set is:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle : x \in X\}, \quad (4)$$

subject to:

$$0 \leq \mu_A(x)^q + \nu_A(x)^q \leq 1, \qquad q \geq 1. \quad (5)$$

The indeterminacy degree is:

$$\pi_A(x) = [1 - \mu_A(x)^q - \nu_A(x)^q]^{1/q}. \quad (6)$$

The score and accuracy functions are:

$$S(A) = \mu_A^q - \nu_A^q, \quad (7)$$

$$H(A) = \mu_A^q + \nu_A^q. \quad (8)$$

Larger $S(A)$ indicates stronger support, while $H(A)$ indicates the committed evidence available for discrimination.

Data-calibrated desirability

For a benefit criterion, the observed crop statistic is transformed to unit desirability as:

$$d_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}. \quad (9)$$

For a cost criterion:

$$d_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}. \quad (10)$$

Thus, $d_{ij} \in [0,1]$, and a larger value is desirable for every criterion. This transformation is transparent and invariant to positive linear changes of measurement units.

Objective criterion weights

To avoid unsupported subjective weights, information entropy is used. The proportion of alternative i under criterion j is:

$$p_{ij} = \frac{d_{ij} + \varepsilon}{\sum_{i=1}^{m}(d_{ij} + \varepsilon)}, \quad (11)$$

where ε is a small positive constant used only to avoid $\ln(0)$. Criterion entropy is:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij} \ln p_{ij}. \quad (12)$$

The objective weight is:

$$w_j = \frac{1 - e_j}{\sum_{l=1}^{n}(1 - e_l)}, \qquad \sum_{j=1}^{n} w_j = 1. \quad (13)$$

A criterion receives a larger weight when it discriminates more strongly among the alternatives.

Proposed reliability-calibrated q-ROF encoding

The main methodological contribution is a data-driven reliability coefficient and an admissible q-ROF transformation. For numerical criterion j, evidence reliability is:

$$r_{ij} = \frac{n_i}{n_{\max}}\left(\frac{1}{1 + CV_{ij}}\right), \quad (14)$$

where CV_{ij} is the within-crop coefficient of variation. For the binomial irrigation-dependence criterion, $r_{ij} = n_i / n_{\max}$. The first factor represents sample coverage and the second penalises dispersion. Values are bounded to $(0,1)$.

The observed desirability and reliability are encoded as:

$$\mu_{ij} = \left(r_{ij} d_{ij}\right)^{1/q}, \quad (15)$$

$$\nu_{ij} = \left[r_{ij}\left(1 - d_{ij}\right)\right]^{1/q}, \quad (16)$$

$$\pi_{ij} = \left(1 - r_{ij}\right)^{1/q}. \quad (17)$$

The encoding is automatically admissible because:

$$\mu_{ij}^q + \nu_{ij}^q = r_{ij} d_{ij} + r_{ij}\left(1 - d_{ij}\right) = r_{ij} \leq 1. \quad (18)$$

It follows that:

$$1 - \mu_{ij}^q - \nu_{ij}^q = 1 - r_{ij} = \pi_{ij}^q. \quad (19)$$

This identity is the conceptual strength of the method. High-quality, stable, well-covered evidence produces a larger committed orthopair mass. Variable or weakly covered evidence produces greater indeterminacy. No independent hesitation score needs to be invented.

Distance-to-ideal ranking

The positive and negative q-ROF ideal solutions are:

$$A^+ = \{(1,0,0)_j : j = 1, \ldots, n\}, \quad (20)$$

$$A^- = \{(0,1,0)_j : j = 1, \ldots, n\}. \quad (21)$$

The weighted q-order distances are:

$$D_i^+ = \left\{\frac{1}{2}\sum_{j=1}^{n} w_j \left[\left|\mu_{ij} - 1\right|^q + \left|\nu_{ij}\right|^q + \left|\pi_{ij}\right|^q\right]\right\}^{1/q}, \quad (22)$$

$$D_i^- = \left\{\frac{1}{2}\sum_{j=1}^{n} w_j \left[|\mu_{ij}|^q + |v_{ij} - 1|^q + |\pi_{ij}|^q\right]\right\}^{1/q}. \quad (23)$$

The closeness coefficient is:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \qquad 0 \le C_i \le 1. \quad (24)$$

Alternatives are ranked in descending order of C_i. A larger coefficient indicates greater proximity to the positive ideal and greater separation from the negative ideal.

Robustness evaluation

The primary analysis uses $q = 3$, providing a Fermatean admissible region within the general q-ROF model. Rung sensitivity evaluates $q = 1,2,3,4,$ and 5. Criterion weights are increased and decreased one at a time by 10%, 20%, and 30%, followed by renormalisation. Rank agreement is measured using Spearman's rho and Kendall's tau. Leave-one-criterion-out analysis tests dependence on individual criteria. Finally, 500 stratified bootstrap samples are drawn with replacement within crop type; the complete decision matrix, weights, reliability coefficients, and ranks are recalculated for every sample.

Computational implementation and reproducibility

The implementation follows a deterministic sequence: validate the records; aggregate observations by crop; construct benefit and cost criteria; transform each criterion to unit desirability; estimate entropy weights; calculate criterion-specific reliability; encode membership, non-membership, and indeterminacy; construct positive and negative ideals; compute weighted distances and closeness coefficients; and rank alternatives. The same pipeline is rerun for each rung, weight perturbation, leave-one-criterion-out condition, and stratified bootstrap sample. Random sampling in the bootstrap should use a fixed seed in the archived code so the reported rank probabilities can be reproduced. No train-test split is required because the method ranks observed alternatives and does not estimate out-of-sample predictions.

Findings

Dataset and crop criterion profiles

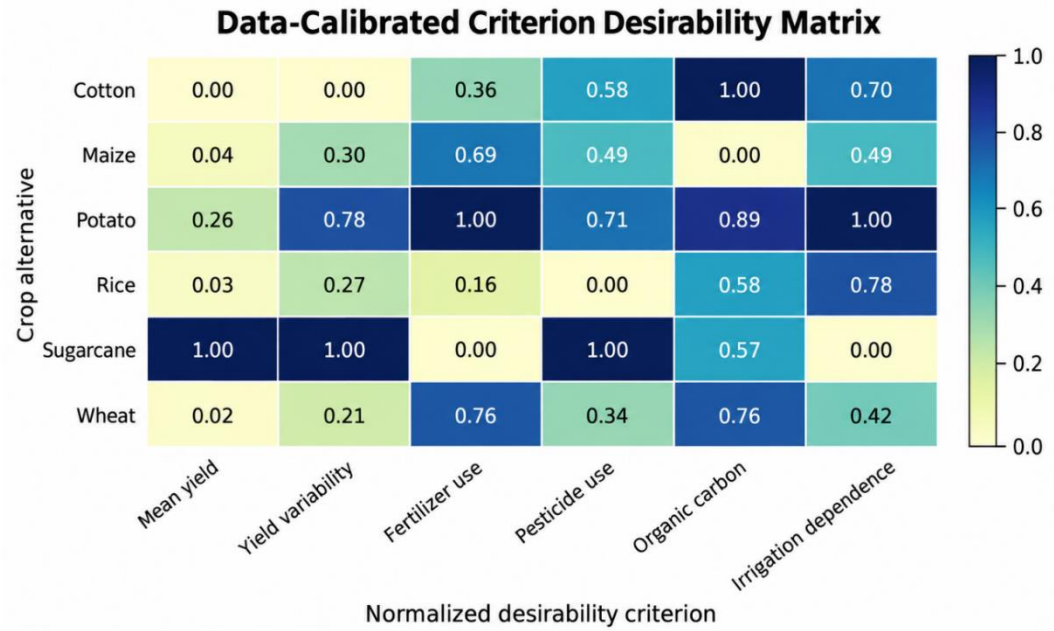
The dataset was complete and balanced across crops. Table 3 presents the empirical decision matrix. Sugarcane had the highest mean yield and lowest yield coefficient of variation, but also the highest fertilizer use and greatest irrigation dependence. Potato combined the second-highest yield with the lowest mean fertilizer use, relatively low pesticide use, and the lowest irrigation dependence. Cotton had the highest organic-carbon mean but the lowest yield and highest yield variability. These conflicts justify a multi-criteria rather than yield-only ranking.

Table 3: Empirical crop decision matrix

Crop	n	Yield	Yield CV	Fertilizer	Pesticide	Organic C	Irrigation dep.
Cotton	1666	7.428	0.233	207.016	12.501	0.966	0.747
Maize	1658	10.076	0.169	204.476	12.537	0.945	0.751
Potato	1670	24.891	0.068	202.073	12.454	0.964	0.741
Rice	1702	9.402	0.176	208.625	12.719	0.957	0.745
Sugarcane	1633	74.830	0.022	209.842	12.344	0.957	0.761

Figure 2 shows the normalized desirability matrix. The contrast is especially strong for yield and yield stability. Input and soil-profile criteria provide counter-evidence that prevents the ranking from being a direct reproduction of mean yield.

Figure 2: Normalized benefit and cost desirability values for the six crop alternatives.



The data-calibrated criterion desirability matrix in Figure 2 shows that higher values indicate greater desirability after criterion normalization, with 0 and 1 representing the least and most desirable performance, respectively

Objective weights

Mean yield received the largest entropy weight, 0.4221, because it provided the greatest observed discrimination among crops. Yield variability received 0.1555, fertilizer use 0.1364, pesticide use 0.1026, irrigation dependence 0.0965, and organic carbon 0.0870. The weights sum to one. Figure 3 shows that productivity dominates the empirical information structure, but 57.79% of the total weight remains distributed across stability and sustainability-related criteria.

Figure 3: Objective entropy weights derived from the crop decision matrix.

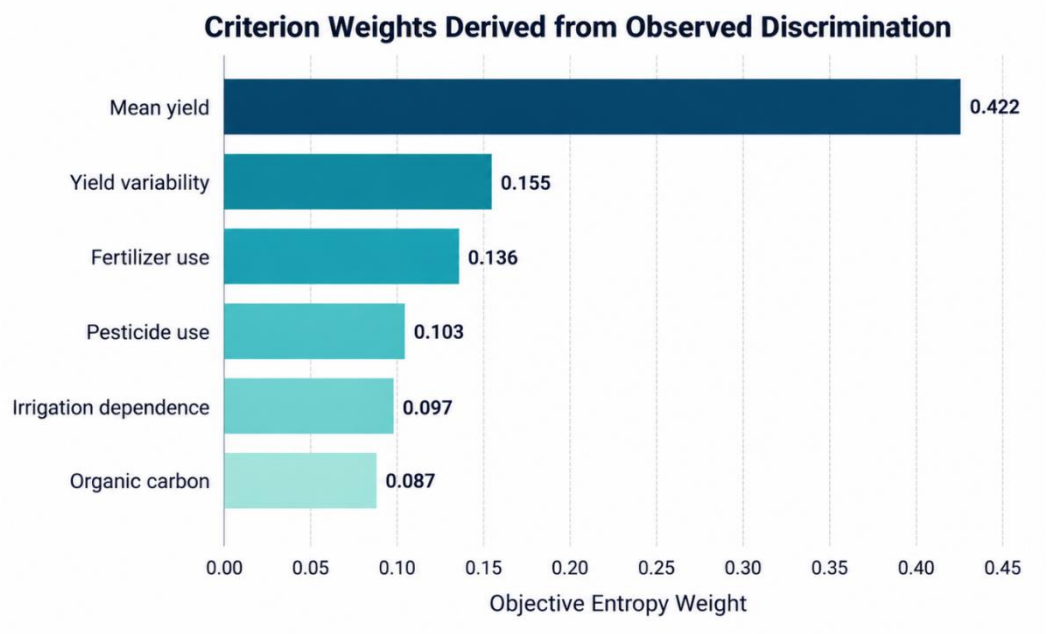


Figure 3 presents the objective entropy weights derived from the observed discriminatory power of the sustainability criteria. Mean yield received the largest weight (0.422), followed by yield variability (0.155) and fertilizer use (0.136), demonstrating the dominant influence of productivity while retaining stability and sustainability-related criteria.

Primary q-ROF ranking

Table 4 reports the q = 3 RC-qROF-DI results. Sugarcane ranked first with $C_i = 0.5747$. Potato was a close second at 0.5473. A larger separation occurred between potato and wheat, which ranked third at 0.4341. Maize, cotton, and rice occupied the remaining positions.

Table 4: Primary RC-qROF-DI results at q = 3

Rank	Crop	D_i^+	D_i^-	C_i
1	Sugarcane	0.6682	0.9027	0.5747
2	Potato	0.6398	0.7735	0.5473
3	Wheat	0.7901	0.6061	0.4341
4	Maize	0.8039	0.5920	0.4241
5	Cotton	0.8853	0.6397	0.4195
6	Rice	0.8216	0.5701	0.4096

Figure 4: Primary crop ranking based on the reliability-calibrated model

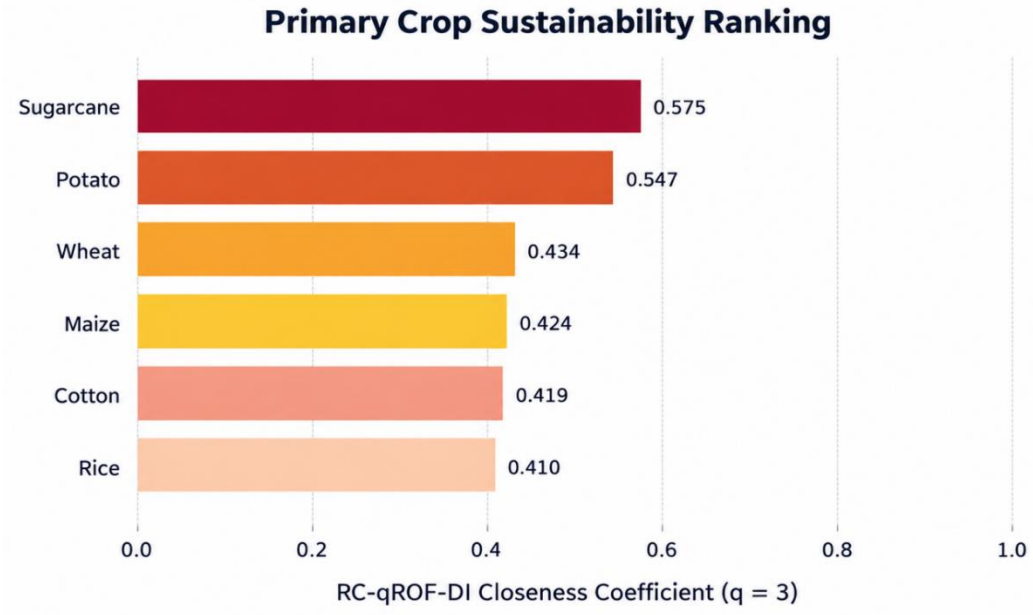


Figure 4 presents the primary sustainability ranking obtained with RC-qROF-DI at q = 3. Sugarcane achieved the highest closeness coefficient (0.575), followed by potato (0.547), while rice recorded the lowest coefficient (0.410).

Rung sensitivity

The top three alternatives were unchanged for every tested rung: sugarcane first, potato second, and wheat third. Maize and cotton exchanged fourth and fifth positions between the lower-rung and Fermatean models; at $q = 5$, rice moved to fifth and cotton to sixth. Table 5 and Figure 5 therefore show strong top-rank stability but some lower-rank sensitivity.

Table 5: Ranks across orthopair rung values

Crop	q=1	q=2	q=3	q=4	q=5
Cotton	4	4	5	5	6
Maize	5	5	4	4	4
Potato	2	2	2	2	2
Rice	6	6	6	6	5
Sugarcane	1	1	1	1	1
Wheat	3	3	3	3	3

Figure 5: Closeness coefficients for intuitionistic, Pythagorean, Fermatean, and higher-rung specifications.

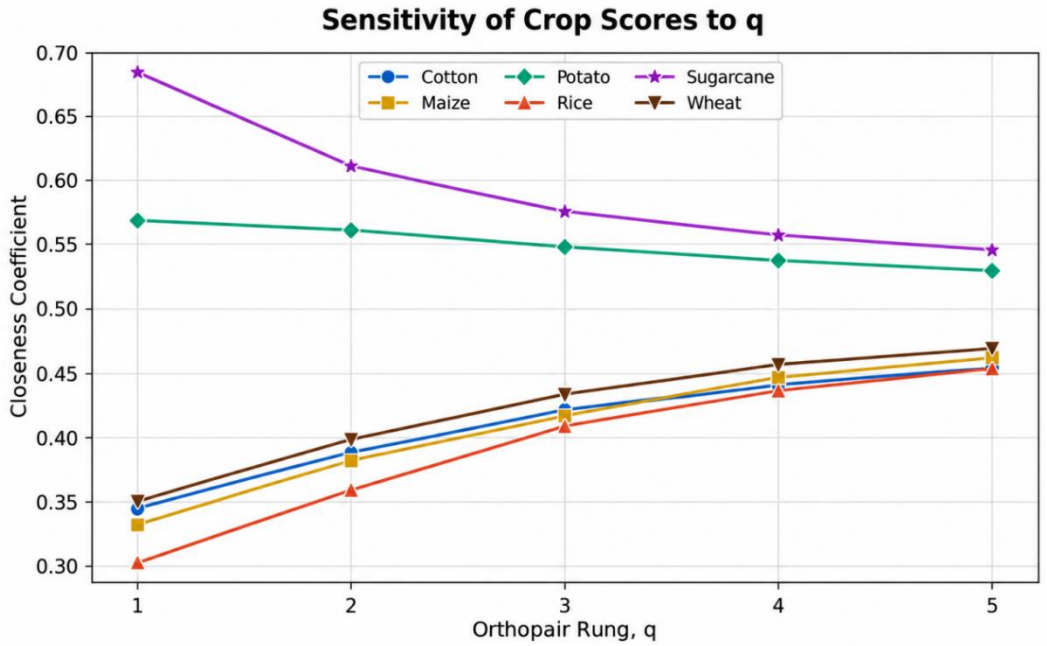


Figure 5 shows the sensitivity of crop sustainability scores to variations in the orthopair rung q. Sugarcane and potato consistently retained the two leading positions, while the remaining crops exhibited gradually increasing closeness coefficients as q increased, indicating reasonable ranking stability across the examined values.

Comparison with nested fuzzy baselines

The rung experiment also provides structurally nested fuzzy baselines: q = 1 corresponds to an intuitionistic fuzzy admissibility region, q = 2 to a Pythagorean region, and q = 3 to the primary Fermatean region. Relative to q = 3, the complete ranking was identical at q = 4 (Spearman ρ = 1.0000; Kendall τ = 1.0000). The q = 1 and q = 2 rankings differed only through the exchange of maize and cotton, while q = 5 differed through the exchange of cotton and rice; each produced Spearman ρ = 0.9429 and Kendall τ = 0.8667 relative to q = 3. Sugarcane, potato, and wheat retained the first three positions in every nested model. Thus, the substantive conclusion is not dependent on choosing the Fermatean rung, although lower-order alternatives remain sensitive to the admissible orthopair space.

Weight and criterion sensitivity

At ±10%, every one-at-a-time weight perturbation produced the same ranking as the primary model. At ±20%, mean Spearman agreement was 0.9952 and mean Kendall agreement was 0.9889; the worst values were 0.9429 and 0.8667. At ±30%, mean Spearman agreement was 0.9857 and mean Kendall agreement was 0.9667. Sugarcane remained first in all one-at-a-time weight perturbations (Table 6).

Table 6: Weight perturbation rank agreement

Perturbation	Mean Spearman	Minimum Spearman	Mean Kendall	Minimum Kendall
±10%	1.0000	1.0000	1.0000	1.0000
±20%	0.9952	0.9429	0.9889	0.8667
±30%	0.9857	0.9429	0.9667	0.8667

Leave-one-criterion-out agreement ranged from Spearman 0.7143 to 1.0000. Removing fertilizer use produced the greatest overall rank movement, although sugarcane remained first. Removing mean yield changed the leading crop to potato and produced Spearman 0.8857 and Kendall 0.7333. This result is substantively important: the preference for sugarcane depends on treating productivity as a core criterion, whereas potato provides the strongest profile when mean yield is deliberately excluded.

Bootstrap stability

The 500 stratified bootstrap resamples quantify uncertainty due to sampling variation. Sugarcane ranked first in 86.4% of samples, potato ranked first in 13.4%, and cotton ranked first in 0.2%. Potato occupied second place in 81.0% of samples, while sugarcane occupied second place in the remaining 13.6%. Lower positions were more variable. Figure 6 distinguishes a stable leading pair from uncertain lower-order alternatives.

Figure 6: Empirical probability of each rank across 500 stratified bootstrap samples.

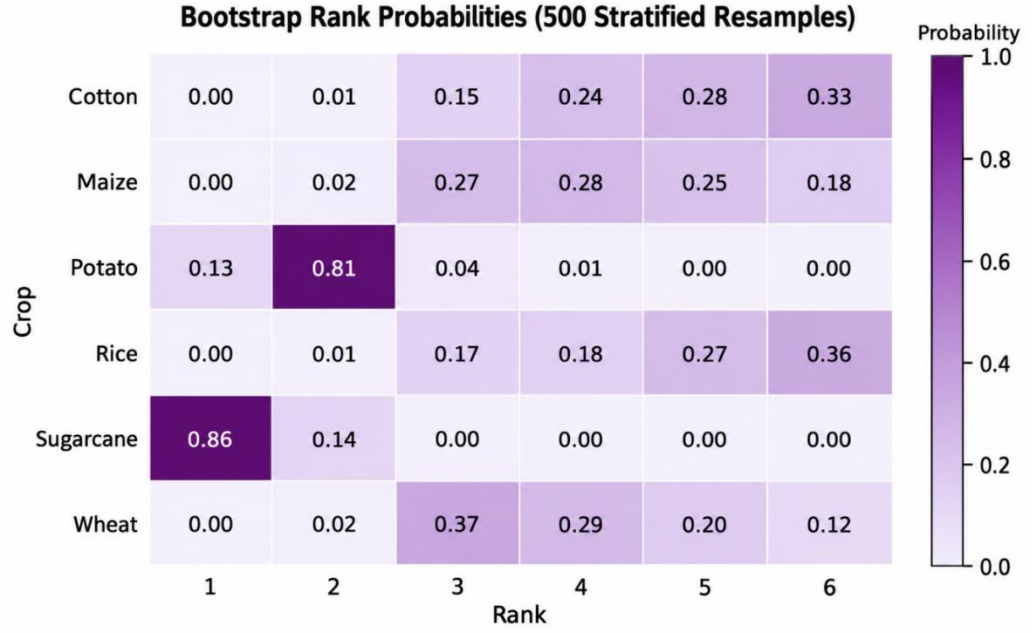


Figure 6 summarizes the bootstrap rank probabilities obtained from 500 stratified resamples. Sugarcane exhibited a high probability of retaining first position (0.86), while potato showed a strong probability of occupying second position (0.81). The remaining crops displayed wider rank distributions, indicating comparatively greater uncertainty in their final positions.

Discussion

Interpretation of the ranking

The primary result identifies sugarcane and potato as the leading alternatives under the observed decision structure. Sugarcane's first position is driven by its much higher mean yield and markedly lower relative yield variability. These benefits compensate for its higher fertilizer use and irrigation dependence. Potato's second position reflects a more balanced sustainability profile: it has the lowest fertilizer use, lowest irrigation dependence, low pesticide use, and substantially lower yield variability than cotton, maize, rice, and wheat.

The small difference between the first two closeness coefficients, 0.0274, should guide interpretation. Sugarcane is not overwhelmingly superior when all criteria are considered. The bootstrap results confirm this: sugarcane is most frequently first, but potato becomes first in a meaningful minority of samples. A responsible decision report should therefore identify a leading set rather than conceal uncertainty behind one rank.

Strength of the proposed method

The central strength of RC-qROF-DI is the relationship between data reliability and fuzzy indeterminacy. Conventional applications usually begin with linguistic q-ROF values supplied by experts [16]–[20]. This is appropriate when judgments are the only available evidence, but it is less defensible when a numerical dataset exists. The proposed method uses observed desirability to determine the direction of evidence and within-crop dispersion plus sample coverage to determine how strongly that evidence is committed.

The identity $\mu^q + \nu^q = r$ also improves auditability. A reviewer can trace every membership value to the original criterion, normalization direction, sample size, and variation. Indeterminacy increases automatically when the evidence is less reliable. This differs from methods in which

hesitation is assigned as a third subjective number or computed only as the residual of two arbitrary inputs.

Comparison with existing fuzzy studies

Compared with intuitionistic fuzzy methods [13], the proposed general q-ROF structure permits explicit analysis of the effect of the admissibility rung. Compared with Pythagorean fuzzy approaches [14], it retains the same method while extending sensitivity beyond $q = 2$. Compared with q-ROF aggregation operators [16], [17], it contributes an empirical input-construction rule rather than assuming that q-ROF numbers already exist. Compared with the robotics and energy selection distance methods [18], [19], it embeds sample coverage and criterion dispersion directly in the orthopair representation.

The method also differs from the agricultural systems reviewed by Nwokoro et al. [20]. It is neither a rule-based controller nor a fuzzy attachment to a machine-learning model. Its evidence comes from observed crop profiles, its criterion weights come from the decision matrix, and its uncertainty comes from measured reliability. This gives the fuzzy component an independent and testable role.

Why q-ROFS is preferable to picture fuzzy modelling here

Picture fuzzy sets can represent positive, neutral, negative, and refusal degrees. They are strong when an instrument explicitly asks respondents to express these four positions. The dataset used here contains no neutral or refusal responses. A picture fuzzy implementation would consequently require a new expert or stakeholder survey, or it would have to infer unobserved categories. q-ROFS avoids this mismatch by representing the two directions available in the evidence, support and opposition, while preserving uncommitted evidence as indeterminacy.

Robustness and decision implications

The validation results show different forms of stability. The first two positions are invariant to the rung parameter, and the full ranking is invariant to ±10% weight perturbations. Larger perturbations produce modest changes among lower-ranked crops but do not displace sugarcane from first place. Criterion removal provides a more demanding test. The change to potato when yield is removed shows that the model is sensitive to the decision objective, as it should be. A sustainability analysis that intentionally excludes productivity answers a different question from a balanced productivity-sustainability analysis.

The method should therefore be used as a transparent scenario tool. Decision makers can examine the principal ranking, a yield-excluded sustainability scenario, local criterion priorities, and bootstrap uncertainty. The ranking should not replace soil testing, crop-specific agronomic guidance, market assessment, or local water-resource evaluation.

Intelligent decision-support implications

RC-qROF-DI contributes decision intelligence through traceability rather than predictive automation. For any crop-criterion pair, a user can inspect the original aggregate, desirability direction, entropy weight, reliability coefficient, orthopair representation, distance contribution, and effect on rank stability. This audit trail supports human oversight: analysts can distinguish a high score supported by reliable observations from one accompanied by substantial indeterminacy. A deployable system could expose the principal ranking alongside a yield-excluded scenario, criterion-removal diagnostics, bootstrap rank probabilities, and locally specified stakeholder weights. Such a system should present alternatives and uncertainty for deliberation rather than issue an autonomous planting instruction.

Limitations

Several limitations constrain the findings. First, although the dataset is publicly available through Kaggle, it is an integrated secondary source without row-level identifiers linking observations to original agencies, locations, collection dates, or measurement protocols. Second, absolute yields are compared across biologically different crops. Sugarcane naturally produces greater mass per unit area than cereal crops, so its yield advantage must not be interpreted as universal agronomic or sustainability superiority. Third, fertilizer and pesticide units and recommended agronomic

ranges require independent verification, irrigation dependence records categories rather than water volume, and organic carbon is an observed field condition rather than a crop-caused outcome. Fourth, entropy weights measure between-crop discrimination and do not represent farmer, policy, environmental, economic, or nutritional preferences. Fifth, the analysis is cross-sectional and crop-aggregated; it does not provide causal inference or out-of-sample farm-level prediction. Finally, the reliability function is an operational measure based on coverage and dispersion, not a validated measure of data provenance or measurement error. Independent datasets, crop-specific benchmarks, stakeholder validation, and prospective testing are required before operational deployment.

Conclusion

This study developed and evaluated RC-qROF-DI, a reliability-calibrated q-rung orthopair fuzzy method for uncertainty-aware crop production-profile prioritisation. The four objectives were achieved by constructing a six-criterion crop decision matrix, deriving admissible orthopair evidence from desirability and empirical reliability, ranking six alternatives under the primary Fermatean specification, and evaluating sensitivity to nested fuzzy models, weights, criterion removal, and sampling variation.

Using 10,000 agricultural records, the primary $q = 3$ model ranked sugarcane first and potato second. The first three positions were preserved across $q = 1$ to $q = 5$, the complete ranking was stable under all ±10% weight perturbations, and 500 bootstrap samples selected sugarcane first in 86.4% and potato first in 13.4%. Removing mean yield changed the preferred alternative to potato, showing that the result is robust locally but conditional on whether absolute productivity is included as a principal criterion.

The contribution is methodological rather than a universal claim about crop superiority. RC-qROF-DI links numerical observations to fuzzy support, opposition, indeterminacy, and ranking uncertainty without expert-generated fuzzy ratings or a predictive black box. Its principal advantage over the nested baselines is not a claimed universally better ranking, but an explicit, auditable calibration of fuzzy commitment to empirical reliability. The framework is suitable for scenario-based decision support when its dataset, criteria, units, and value assumptions are clearly disclosed.

Recommendations for further research

Further research should validate RC-qROF-DI using independently sourced agricultural datasets with documented units, locations, dates, and provenance; replace absolute cross-crop yield with crop-specific benchmark attainment or economic and nutritional productivity where appropriate; compare entropy weights with farmer-, agronomist-, and policy-derived weights; test alternative reliability functions and distance metrics; report runtime and scalability; and evaluate a user-facing decision-support prototype prospectively with agricultural stakeholders.

Ethics approval

Not required. This study used a publicly available secondary agricultural dataset and did not involve human participants, animals, personal identifiers, or experimental intervention.

Acknowledgments

The authors acknowledge the dataset creator and the Kaggle platform for making the agricultural records available for scholarly analysis.

Competing interests

All the authors declare that there are no conflicts of interest.

Funding

This research received no external funding.

Underlying data

The dataset analysed in this study comprises 10,000 records and is publicly available as the Smart Crop Recommendation Dataset, created by Md Mia Dul Islam, version 1, on Kaggle. It was accessed on 10 September 2026 and is available athttps: //www.kaggle.com/datasets/miadul/smart-crop-recommendation-dataset.
Derived data supporting the findings are available from the corresponding author on reasonable request.

Code availability

The analytical code used for aggregation, weighting, q-rung orthopair fuzzy encoding, ranking, perturbation analysis, and bootstrap validation is available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Chukwudi Obinna Nwokoro contributed to conceptualization, methodology, data curation, formal analysis, visualization, writing the original draft, and reviewing and editing the manuscript. Paul Augustine Ejegwa contributed to conceptualization, mathematical validation, methodology verification, interpretation of findings, and reviewing and editing the manuscript. Both authors approved the final manuscript.

Declaration of artificial intelligence use

Artificial intelligence-based language tools were used for language refinement and assistance with the presentation of selected figures during manuscript preparation. We confirm that all AI-assisted processes were critically reviewed by the authors to ensure the integrity and reliability of the work. The final decisions, mathematical formulation, analyses, interpretations, and conclusions presented in this article were solely made and verified by the authors.

How to cite

Nwokoro, C. O., & Ejegwa, P. A. (2026). Reliability-Calibrated q-Rung Orthopair Fuzzy Decision Support for Uncertainty-Aware Crop Prioritisation. *Journal of Analytical Uncertainty*, *2*(1), 75–89. https://doi.org/10.63924/jau.v2i1.358

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