Volume 2, 2026, Pages 253-265 *Journal of Smart and Sustainable Farming*
| Regular Article | Open Access

Digital Decision Support for Smallholder Farmers using Explainable Multi Criteria Agricultural Intelligence

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Article Info
Journal of Smart and Sustainable Farming
https://www.ansispublications.com/jssf/jssf.html

© The Author(s), 2026.
https://doi.org/10.64026/JSSF/2026021

Received 10 June 2026
Revised from 30 August 2026
Accepted 06 October 2026
Available online 03 November 2026
Published by Ansis Publications.

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Abstract - Under uncertain weather, fluctuating prices, constrained liquidity and limited access to advice, smallholder farmers have to make decisions on what to grow, but many digital advisory services provide a single, black-box answer that can't be questioned by farmers and extension agents. This article introduces an explainable multi-criteria decision support system which ranks candidate crops for each plot, explains in simple language the reasons for choosing a particular crop and provides confidence in the rank. A fuzzy agro-ecological suitability is combined with a water-stress yield model which incorporates Monte Carlo rainfall and price shocks, together with seven benefit and cost criteria, Analytic Hierarchy Process (AHP) weights and TOPSIS ranking. The closeness margin between the recommended crop and the runner-up crop is distributed in a pie chart across individual criteria and Dirichlet perturbation of the weight's measures recommendation stability. All data are simulated: 20 synthetic landscapes of 40×40 plots (2.5 km cells), six crops with indicative parameters, and a hypothetical expert panel (AHP consistency ratio 0.013). The recommended crop for each landscape was groundnut on 37.5%, sorghum on 31.0% and pearl millet on 17.4%. It produced a mean net return of 210 USD/ha and has a loss probability of 18.7% under out-of-sample seasons with 25% fatter rainfall and price shocks than assumed during the design process, while a traditional rule of thumb has a mean net return of 67 USD/ha and a loss probability of 38.9%. The Shapley attributions summed exactly to the closeness margin (maximum error 5.6e-16), and the mean stability was 0.84, with 53.3% of plots above 0.9. These results demonstrate the mechanics and behaviour of the framework in a controlled setting; they are not field evidence.

Keywords – Smallholder Farming, Decision Support, Explainable AI, Multi-Criteria Decision Analysis, AHP, TOPSIS, Shapley Values, Crop Selection, Simulation.

I. INTRODUCTION

The majority of farms in the world is small farms. Global compilations reveal that most farms are below 2 ha and make up a small proportion of agricultural land [1] and that the question of whether and how small farms (<2 ha) can support livelihoods has been a central one in rural development policies [2]. One of the most critical decisions each season is when these households are deciding which crop to plant on a particular plot. It must be negotiated against the possible margin, the risk of loss, the availability of water, availability of cash for seed and fertiliser prior to harvest, distance to a buyer, and need to feed the household. Errors cost because if a season fails, then all the savings that were accumulated over years is lost.

Digital agriculture has the potential to better inform those decisions. There has been significant research in the field of yield prediction, disease detection and advisory services using sensor networks and remote sensing, as well as using farm-management platforms and machine learning [3]. However, in reality, advisory tools that are delivered to smallholders tend to be black boxes; in other words, the score or crop name returned, but without its justification. There are three reasons why this is important. First, there is local knowledge that the model doesn't have, and farmers and extension agents can

only integrate that with the model if they saw what it weighed [4]. Second, farmers must receive a recommendation that is trusted, not assumed, because they are at risk of making a bad decision if it is based on a suggestion that they do not understand. Third, researchers on responsible innovation in smart farming have alerted that technologies that are designed without the input of their actors can further consolidate inequalities [5].

This is why explainability becomes a necessity and is not simply an added bonus for smallholder decision support. The models used in high-stakes decisions should be designed to be interpretable, as opposed to being explained after the fact [6] and the literature in the field of explainable AI (XAI) emphasizes that the type of explanation that is useful will depend on the audience and the decision [7]. Crop selection is naturally a multi-criteria problem with a modest number of alternatives and criteria, which makes transparent multi-criteria decision analysis (MCDA) an attractive foundation. What is often missing is the combination of (i) agronomic and economic models that represent risk explicitly, (ii) stakeholder-adjustable priorities, (iii) a principled attribution of each recommendation to its criteria, and (iv) an honest indication of when the recommendation is fragile.

This article proposes and tests such a combination. We make four contributions:

- A plot-level decision framework that links fuzzy suitability, a water-stress yield response, and Monte Carlo rainfall and price shocks to a seven-criterion decision matrix covering agronomic, economic, risk, water, liquidity, market and food-security dimensions.
- AHP-derived weights with scenario tilts that let a farmer group express different priorities (profit, risk aversion, food security, water scarcity) without rebuilding the model.
- An exact Shapley decomposition of the TOPSIS closeness margin between the recommended crop and the runner-up, from which plain-language reasons are generated, together with a weight-perturbation stability score that flags fragile recommendations.
- A fully reproducible simulation study, with out-of-sample stress-tested seasons, that compares the framework with yield-maximising, profit-maximising, weighted-sum, traditional-rule and random strategies.

The study will not attempt to demonstrate agronomic accuracy for any actual region but rather will be used to demonstrate the behavior of the study framework and the appearance of the study explanations. The rest of the article presents related work (Section 2), describes methods (Section 3), reports and discusses results including limitations (Section 4) and concludes (Section 5).

II. RELATED WORKS

Digital Decision Support for Smallholder Agriculture

Reviews of big data and smart farming describe a rapid growth of data sources and analytics in agriculture, while also noting that adoption by small farms is constrained by cost, connectivity and the fit between tools and farm decisions [3]. Surveys of deep learning in agriculture document strong performance on perception tasks such as plant disease and weed identification and on yield estimation, but the models typically output predictions rather than decisions with stated trade-offs [4]. A complementary line of work argues that agricultural data and models should be redesigned around decision-relevant knowledge products, in particular trade-off analysis that shows what a farm household gains and gives up under alternative actions [8]. Our framework follows that orientation: the unit of output is a ranked set of crops with their trade-offs, not a yield forecast.

Land Suitability Analysis and Multi-Criteria Evaluation

Land suitability analysis is the oldest and best-developed use of MCDA in agriculture. Critical overviews of GIS-based suitability analysis catalogue the combination of spatial criteria through weighted overlay and other multi-criteria rules and highlight recurring weaknesses, including opaque weighting and little treatment of uncertainty [9]. More recent reviews of agricultural land suitability analysis stress the need to integrate climate variability and change into suitability assessment [10]. Fuzzy set theory [11] is widely used to turn biophysical measurements into graded suitability memberships, which avoids the abrupt class boundaries of crisp rules. Agronomic response functions are also well established: the FAO yield-response-to-water framework relates relative yield loss to relative evapotranspiration deficit through a crop-specific factor [12], and crop water requirements are commonly derived from reference evapotranspiration and crop coefficients [13]. Suitability studies, however, usually stop at a biophysical map and do not integrate income risk, liquidity or food security, which are decisive for smallholders.

AHP and TOPSIS

The Analytic Hierarchy Process derives criterion weights from pairwise comparisons on a bounded ratio scale and provides a consistency check on the judgments [14]. TOPSIS ranks alternatives by their relative closeness to an ideal solution and distance from an anti-ideal one [15]. The pairing is popular because it is simple to explain to non-specialists and because pairwise comparison is a natural way to elicit priorities in participatory settings. Its limitation as an explanation device is that the final closeness score is not additive in the criteria, so the contribution of each criterion to a particular ranking is not directly visible.

Explainable AI and Shapley Attribution

Explainable AI aims to make model behaviour intelligible to people affected by it, and recent syntheses organise methods by whether transparency is built in or obtained post hoc, and by the audience [7]. A widely used post hoc approach is additive feature attribution based on Shapley values, which were introduced in cooperative game theory as the unique fair allocation satisfying efficiency, symmetry, dummy and additivity axioms [16], and were adopted for model explanation by unifying several attribution methods. When the number of features is small, as in a crop-choice problem with a handful of criteria, Shapley values can be computed exactly, avoiding the sampling approximations needed for high-dimensional models.

Gap Addressed in this Work

Existing work therefore offers suitability mapping without income risk, MCDA without per-recommendation attribution, and explainable machine learning that is rarely tied to the economics of smallholder crop choice. We close part of this gap by applying exact Shapley attribution to a TOPSIS ranking, whose coalition values are defined by re-normalising the weights over the criteria present, and by pairing that attribution with an explicit stability measure so that an explanation is accompanied by a statement of how much it can be relied upon.

III. METHODS

Framework Overview

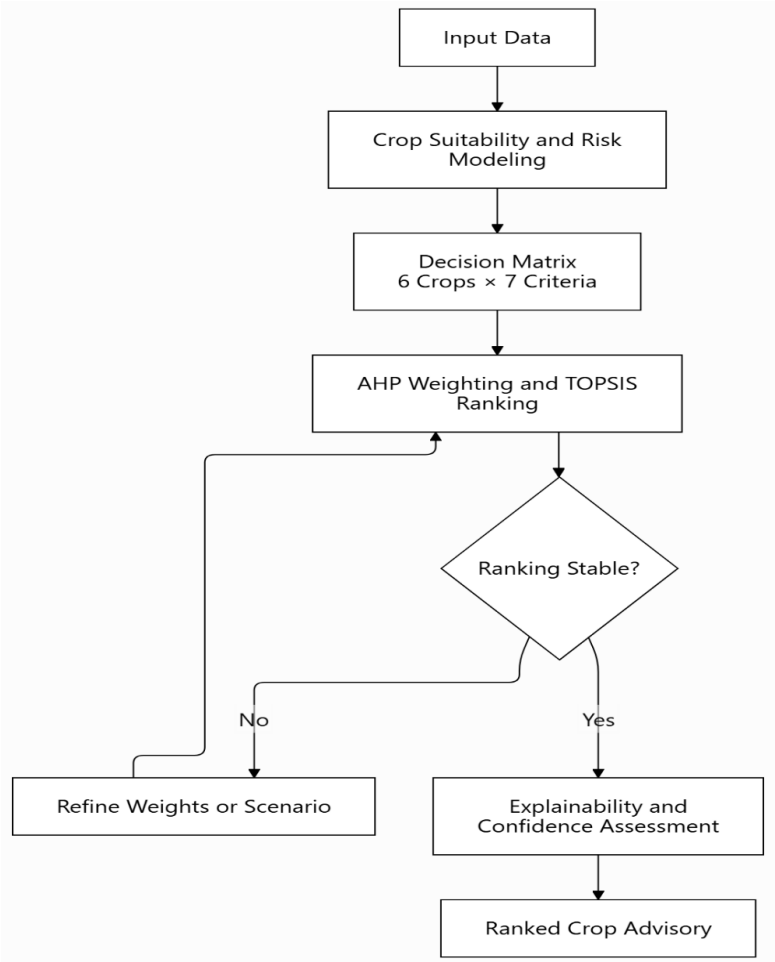


Fig 1. Overview of the Explainable Multi-Criteria Decision Support Framework. Numbers Indicate the Order of Computation.

The framework (**Fig. 1**) takes plot-level environmental and socio-economic layers as input and, for each plot and each candidate crop, computes suitability, expected return, loss probability and other indicators that populate a decision matrix. Criterion weights from AHP, optionally tilted to reflect a farmer group's priorities, are combined with the matrix in TOPSIS to rank the crops. The ranking is then explained by Shapley attribution of the margin over the runner-up, and its reliability is quantified by weight-perturbation stability. The advisory output shows the ranked crops, the reasons and a confidence flag.

Simulated Study Region

All environmental data in this study are simulated. For each of 20 replicate landscapes we generated a 40×40 grid of plots, each representing a 2.5 km × 2.5 km cluster of smallholder fields (100 km × 100 km in total). Spatially autocorrelated fields were produced by Gaussian filtering of white noise and combined with deterministic gradients: seasonal rainfall (with a west-to-east gradient and a coefficient of variation that falls as mean rainfall rises), mean temperature, slope, soil pH, soil organic carbon (OC) and available water capacity (AWC). A sinuous canal corridor, with additional scattered wells, defines the irrigated plots; two randomly placed towns define market distance; and household liquidity per hectare is drawn from a spatially correlated log-normal field. Summary statistics for the first landscape, which is used for all maps, are given in **Table 1**. Irrigated plots receive a fixed supplementary supply of 300 mm per season, and effective rainfall is taken as 75% of seasonal rainfall.

Table 1. Simulated Environmental and Socio-Economic Variables for the First Landscape (1,600 Plots)

Variable	Unit	Minimum	Mean	Maximum
Seasonal rainfall	mm	300	623	942
Rainfall coefficient of variation	–	0.24	0.35	0.47
Mean temperature	°C	22.0	29.0	34.0
Slope	%	0.2	5.4	16.2
Soil pH	–	4.9	6.8	8.8
Soil organic carbon	%	0.10	0.64	2.00
Available water capacity	mm per m	40	108	180
Distance to nearest market	km	2.0	33.4	76.2
Household liquidity	USD/ha	200	506	1500

Candidate Crops and Crop–Plot Models

Six candidate crops were considered: rice, maize, sorghum, pearl millet, groundnut and pigeon pea. Their parameters (**Table 2**) are indicative, chosen to reflect broad differences in water need, input cost, price and risk between crops rather than to reproduce any specific market or variety, and they are simulated inputs.

Table 2. Indicative (Simulated) Crop Parameters and Mean Suitability and Expected Net Return in the First Landscape

Crop	Y_{max} (t/ha)	Price (USD/t)	Cost (USD/ha)	ET_c (mm)	k_y	Price σ	kcal/kg	Mean S	Mean E[π] (USD/ha)
Rice	4.5	300	700	700	1.1	0.10	3600	0.60	-129
Maize	4	230	480	550	1.25	0.18	3650	0.64	-7
Sorghum	2	250	230	420	0.9	0.15	3390	0.86	166
Pearl millet	1.6	230	190	350	0.8	0.15	3610	0.88	120
Groundnut	1.6	580	420	500	0.7	0.25	3970	0.71	180
Pigeon pea	1.1	620	280	500	0.8	0.22	3430	0.81	217

Y_{max}: attainable yield; ET_c: seasonal crop water need; k_y: yield response factor; σ: log-standard deviation of the price shock; S: suitability; π: net return. Groundnut kcal/kg refers to pods. Simulated parameters.

Fuzzy suitability. For each crop, five biophysical attributes (temperature, pH, OC, AWC and slope) are mapped to trapezoidal membership functions [11]. For attribute value x and breakpoints, $a \le b \le c \le d$,

$$\mu(x) = \max\left(0, \min\left(1, \frac{x-a}{b-a}, \frac{d-x}{d-c}\right)\right) \quad (1)$$

and the agro-ecological suitability of crop j on plot i is the geometric mean of the M = 5 memberships, each floored at 0.02 so that a single poor attribute depresses but does not annihilate suitability:

$$S_{ij} = \left(\prod_{m=1}^{5} \mu_{ijm}\right)^{\frac{1}{5}} \quad (2)$$

Rainfall is deliberately excluded from S and handled through the water balance, so that water is not counted twice. In each of B simulated seasons s, rainfall R_{is} is drawn from a gamma distribution with the plot's mean and coefficient of variation. The ratio of actual to potential evapotranspiration is approximated by the water supply relative to the crop water need,

$$\rho_{ijs} = \min\left(1, \frac{\eta R_{is} + I_i}{ET_{c,j}}\right) \tag{3}$$

where $\eta = 0.75$ is the effective-rainfall fraction and I_i is the irrigation supply. Following the yield-response-to-water formulation [12], with crop water needs of the kind derived by evapotranspiration methods [13], the yield is

$$Y_{ijs} = Y_{max,j} S_{ij} \max\left[0, 1 - k_{y,j}(1 - \rho_{ijs})\right] \tag{4}$$

where $k_{y,j}$ is the yield response factor. With a lognormal price shock ε_{js} of unit mean and crop-specific volatility, the net return per hectare is

$$\pi_{ijs} = p_j \varepsilon_{js} Y_{ijs} - c_j \tag{5}$$

with price p_j and cost c_j. The loss probability and the water-deficit indicator are

$$L_{ij} = \frac{1}{B} \sum_{s=1}^{B} 1_{\pi_{ijs} < 0} \tag{6}$$

$$D_{ij} = \max\left(0, 1 - \frac{\eta R_{m,i} + I_i}{ET_{c,j}}\right) \tag{7}$$

where $R_{m,i}$ is mean seasonal rainfall and the indicator in Eq. (6) equals one when the net return is negative. Three further criteria complete the decision matrix: the input affordability burden (crop cost divided by household liquidity per hectare), market access $\exp(-d_i/\delta_j)$ where d_i is the distance to the nearest market and δ_j is a crop-specific decay distance reflecting storability and local demand (15–40 km), and calorie yield (mean yield multiplied by the crop's energy content, in Mkcal/ha) as a food-security proxy. The design-time quantities use 300 Monte Carlo seasons per plot.

Criteria, AHP Weights and Scenario Tilts

The decision matrix for each plot has six rows (crops) and seven columns (criteria). Four criteria are benefits (suitability, expected net return, market access, calorie yield) and three are costs (loss probability, water deficit, affordability burden). Criterion weights were derived with AHP from a pairwise comparison matrix on the 1–9 scale [14]. The judgments in this study are those of a hypothetical expert panel, chosen so that expected return, suitability and downside risk carry the most weight; in a real deployment they would be elicited from farmers and extension staff. The weights are the normalised principal eigenvector, and consistency is checked through the consistency ratio,

$$Aw = \lambda_{max} w, \quad CR = \frac{\lambda_{max} - n}{(n-1)RI} \tag{8}$$

Table 3. Criteria, Optimisation Direction and Weights: Baseline AHP Weights and Scenario-Tilted Weights (Hypothetical Panel)

Criterion	Type	Baseline	Profit-oriented	Risk-averse	Food-secure	Water-scarce
Agro-ecological suitability	Benefit	0.192	0.135	0.150	0.148	0.203
Expected net return	Benefit	0.281	0.494	0.219	0.217	0.228
Downside (loss) risk	Cost	0.160	0.112	0.312	0.124	0.130
Water deficit	Cost	0.087	0.061	0.068	0.067	0.212
Input affordability burden	Cost	0.082	0.058	0.096	0.064	0.067
Market access	Benefit	0.053	0.037	0.041	0.041	0.043
Calorie yield	Benefit	0.146	0.103	0.114	0.339	0.119

where A is the pairwise matrix, $n = 7$ and $RI = 1.32$ is the random index for seven criteria. Our matrix gave $\lambda_{max} = 7.102$ and $CR = 0.013$, below the customary threshold of 0.10. To represent different farmer priorities we tilt the baseline weights with multipliers τ_k and renormalise,

$$w'_k = \frac{\tau_k w_k}{\sum_{l=1}^{K} \tau_l w_l} \tag{9}$$

Four scenarios were defined: profit-oriented (net-return multiplier 2.5), risk-averse (loss-probability multiplier 2.5 and affordability burden multiplier 1.5), food-secure (calorie-yield multiplier 3) and water-scarce adaptive (water-deficit multiplier 3 and suitability multiplier 1.3). The resulting weights are in **Table 3**.

TOPSIS Ranking

For each plot separately, the criterion values of the six crops are vector-normalised, weighted, and compared with the ideal and anti-ideal solutions [15]. With x_{jk} the value of criterion k for crop j,

$$\mathrm{r_{jk}} = \frac{\mathrm{x_{jk}}}{\sqrt{\sum_{\mathrm{j=1}}^{\mathrm{J}} \mathrm{x_{jk}}^2}} \tag{10}$$

$$\mathrm{v_{jk}} = \mathrm{w_k r_{jk}} \tag{11}$$

$$\mathrm{D_j^{\pm}} = \sqrt{\sum_{\mathrm{k=1}}^{\mathrm{K}} \left(\mathrm{v_{jk}} - \mathrm{v_k^{\pm}}\right)^2} \tag{12}$$

$$\mathrm{C_j} = \frac{\mathrm{D_j^-}}{\mathrm{D_j^+ + D_j^-}} \tag{13}$$

where v_k^+ and v_k^- are the best and worst weighted values of criterion k among the crops on that plot (the sign convention follows the criterion type), D_j^+ is the distance to the ideal and D_j^- the distance to the anti-ideal. The recommended crop j^* has the highest closeness C_j and the runner-up j' the second highest. Because normalisation is carried out within each plot, closeness expresses how well a crop does relative to the alternatives available on that plot.

Shapley Explanation of the Recommendation

To explain why j^* outranks j', we treat the criteria as players in a cooperative game. For a coalition S of criteria, the weights are re-normalised over the members of S and the others are set to zero,

$$\mathrm{w_k^S} = \frac{\mathrm{w_k}}{\sum_{\mathrm{l \in S}} \mathrm{w_l}}, \quad \mathrm{k \in S} \tag{14}$$

and the coalition value $v_j(S)$ is the TOPSIS closeness computed with these weights. The empty coalition is assigned the neutral value 1/2. The Shapley contribution of criterion k to the closeness of crop j is [16]

$$\varphi_{\mathrm{jk}} = \sum_{\mathrm{S \subseteq K \setminus \{k\}}} \frac{|\mathrm{S}|!(\mathrm{K}-|\mathrm{S}|-1)!}{\mathrm{K}!} \left[\mathrm{v_j}(\mathrm{S} \cup \{\mathrm{k}\}) - \mathrm{v_j}(\mathrm{S})\right] \tag{15}$$

With $K = 7$ criteria there are 128 coalitions, so the values are computed exactly. The explanation shown to the user is the contribution of each criterion to the margin between the top two crops,

$$\Delta_{\mathrm{k}} = \varphi_{\mathrm{j*,k}} - \varphi_{\mathrm{j',k}} \tag{16}$$

which, by the efficiency property of Shapley values [17], satisfies

$$\sum_{\mathrm{k=1}}^{\mathrm{K}} \Delta_{\mathrm{k}} = \mathrm{C_{j*}} - \mathrm{C_{j'}} \tag{17}$$

A positive Δ_k means that criterion k favours the recommended crop over the runner-up; a negative value means it favours the runner-up. A template converts the two largest positive and the largest negative contributions into a sentence of the form "Crop A is preferred to crop B mainly because of X and Y, partly offset by Z." We verified Eq. (17) numerically on every plot.

Stability of the Recommendation

Weights obtained from judgments are uncertain, so we ask how often the recommendation would survive plausible changes to them. For $B_w = 200$ draws $w^{(b)}$ from a Dirichlet distribution centred on the baseline weights with concentration $\kappa = 60$, the stability of plot p is

$$\sigma_p = \frac{1}{B_w} \sum_{b=1}^{B_w} 1_{[\, j*(w(b)) = j* \,]} \tag{18}$$

With $\kappa = 60$ the standard deviation of a weight of 0.28 is about 0.06, which corresponds to a relative change of roughly 20%. Plots are flagged as high ($\sigma \geq 0.9$), moderate ($0.7 \leq \sigma < 0.9$) or low ($\sigma < 0.7$) stability; for low-stability plots the advisory shows the top two crops side by side.

Evaluation Protocol and Reproducibility

Because no real outcomes are available, we evaluate recommendations in simulated seasons that are independent of those used to build the decision matrix. For each of 20 landscapes, 500 *evaluation* seasons were drawn with a different random seed and with rainfall variability and price volatility inflated by a factor of 1.25, so that the evaluation environment is harsher than the one assumed at design time (a limited test of robustness to model misspecification). Six strategies choose one crop per plot: (i) the proposed AHP-TOPSIS ranking; (ii) a weighted-sum model using the same weights and global min–max normalisation; (iii) profit-maximising, the highest design-time expected net return; (iv) yield-maximising, the highest design-time expected yield; (v) a traditional rule of thumb (rice on irrigated plots, otherwise pearl millet below 500 mm, sorghum for 500–700 mm and maize above 700 mm); and (vi) random choice. The outcome metrics are the mean net return, the 10th percentile of net return, the loss probability, the water deficit and the calorie yield, averaged over plots, with the mean and standard deviation reported across landscapes. All results derive from a single script (*simulation.py*, supplied with this article), which writes the results file and figures.

IV. RESULTS AND DISCUSSION

Simulated Landscape and Decision Matrix

The first landscape has mean seasonal rainfall of 623 mm, ranging from 300 to 942 mm, rising towards the north-east **(Fig. 2**), with 24.6% of plots irrigated along the canal corridor. Rainfall variability is highest where rainfall is lowest (coefficient of variation up to 0.47), so the driest plots are also the riskiest.

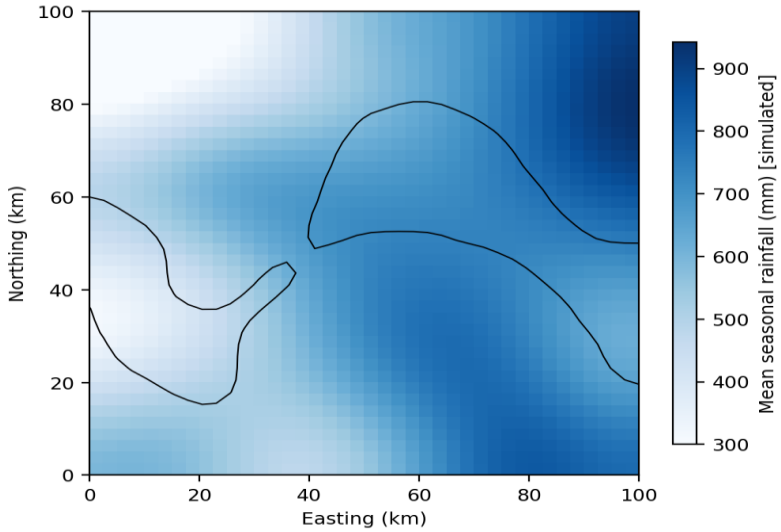


Fig 2. Simulated Mean Seasonal Rainfall (Mm) for the First Landscape. The Black Contour Outlines the Main Irrigated Corridor.

Across all plots and crops in this landscape the criteria varied widely (**Table 3** gives their definitions and weights). Suitability ranged from 0.08 to 1.00 (mean 0.75); expected net return from -642 to 593 USD/ha (mean 91); loss probability from 0.00 to 1.00; and the affordability burden from 0.13 to 3.50. At crop level (**Table 2**), sorghum and pearl millet were the most suitable on average (0.86 and 0.88), whereas rice had the lowest mean suitability (0.60) and a negative mean expected return (-129 USD/ha) because much of the landscape cannot meet its water demand. Pigeon pea (217 USD/ha) and groundnut (180 USD/ha) had the highest mean expected returns. This is an important reminder that expected return alone does not determine the multi-criteria ranking.

Recommended Crops and Their Spatial Pattern

Pooled over the 20 landscapes, the baseline ranking recommended groundnut on 37.5% of plots, sorghum on 31.0%, pearl millet on 17.4%, pigeon pea on 6.6%, maize on 4.7% and rice on 2.9% (**Table 5**). The map for the first landscape (**Fig. 3**) shows coherent regional zones rather than salt-and-pepper noise: rice is concentrated inside the irrigated corridor in the centre of the region; pearl millet occupies the drier north-west and several southern and central pockets; groundnut covers a broad central band and the northern interior; sorghum dominates the south-east and parts of the south; and pigeon pea appears in the wetter north-east and south-east corners. Such zones are plausible because the inputs are spatially autocorrelated, but they also illustrate how a plot-level tool can be aggregated into village-level guidance.

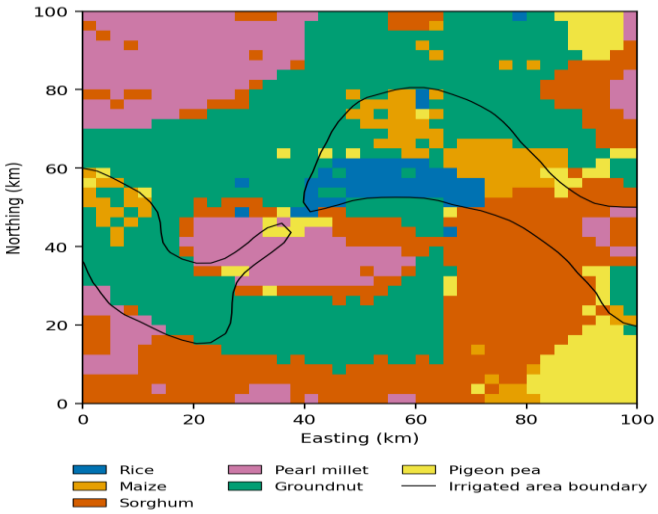


Fig 3. Crop With the Highest TOPSIS Closeness Under the Baseline Weights for the First Landscape.

Why a Crop is Recommended: Shapley Explanations

The efficiency identity held to numerical precision on all plots in all landscapes (maximum absolute error 5.6e-16), so the displayed contributions fully account for the margin. **Fig. 4** shows, for each recommended crop, the mean contribution of each criterion to the margin over the runner-up, and **Table 4** summarises the margins and stability.

The attributions differ systematically by crop. Groundnut is mainly recommended because of net return (10.5 points) and calorie yield (7.7), against an input-burden penalty (-7.3). Pigeon pea owes its recommendations to net return (11.2) and market access (10.7), and loses 20.1 points on calories. Pearl millet is favoured by suitability (8.7) and loss risk (5.1), and penalised on market access (-10.8), reflecting the short market decay distance assumed for it. Maize and rice, when recommended, do so on calories (31.8 and 28.8), with maize paying a net-return penalty of 13.2 points and rice an input-burden penalty of 28.2 points. Sorghum, the second most frequent recommendation, rests on thin margins (mean 3.7 closeness points) that come mainly from calories (8.4).

The dominant driver, defined as the criterion with the largest positive contribution on a plot, was calorie yield on 40.3% of plots, net return on 23.5%, suitability on 10.1%, market access on 9.3%, loss risk on 7.9%, water deficit on 6.2% and input burden on 2.6% (**Fig. 5**). Calorie yield is only the fourth-largest weight (0.146), yet it is the most frequent driver. In TOPSIS the influence of a criterion depends on its weight and on how much the normalised values differ between the competing crops on the plot, and calorie yield differs strongly between cereals and legumes. This is a useful illustration of why weights alone are a poor explanation of a recommendation and why attribution at the level of the individual decision is needed. Water deficit and loss risk dominate mainly in the drier west and north-west, where they separate drought-tolerant millets from water-demanding crops.

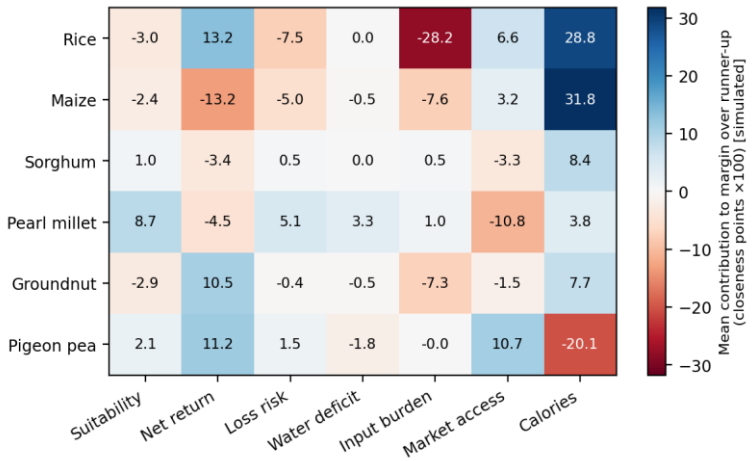


Fig 4. Mean Shapley Contribution of Each Criterion to the Closeness Margin of the Recommended Crop Over the Runner-Up, By Recommended Crop (Closeness Points ×100; Positive Values Favour the Recommended Crop). Pooled Over 20 Simulated Landscapes.

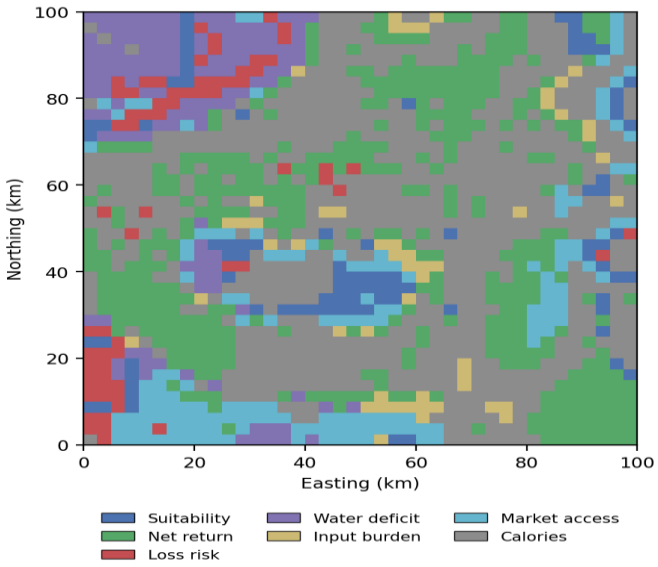


Fig 5. Criterion With the Largest Positive Shapley Contribution to the Recommendation on Each Plot, First Landscape (Simulated Data).

Table 4. Explanation and Stability Summaries by Recommended Crop

Recommended crop	Share of plots (%)	Mean margin (×100)	Mean stability	Largest mean positive contributor
Rice	2.9	10.0	0.84	Calories
Maize	4.7	6.2	0.79	Calories
Sorghum	31.0	3.7	0.83	Calories
Pearl millet	17.4	6.6	0.89	Suitability
Groundnut	37.5	5.5	0.84	Net return
Pigeon pea	6.6	3.6	0.73	Net return

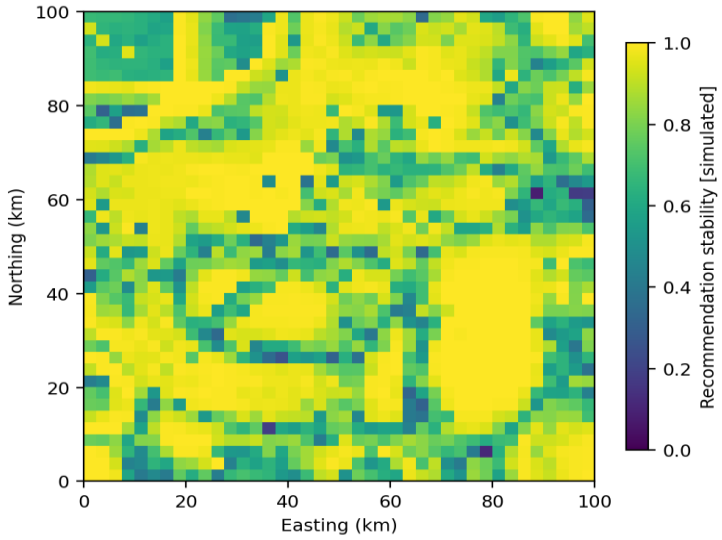


Fig 6. Stability of the Recommended Crop Under Dirichlet Perturbation of the Weights, First Landscape (Simulated Data). Values Near 1 Indicate That the Recommendation is Unchanged in Nearly All Perturbations.

Stability and Confidence

The mean stability was 0.84. of all plots, 53.3% were flagged high, 24.1% moderate and 22.6% low. Stability is positively related to the closeness margin (Pearson correlation 0.63); the mean margin was 5.2 closeness points. Stability was highest for pearl millet (0.89) and lowest for pigeon pea (0.73), whose margin was also among the smallest (**Table 4**). Spatially,

low-stability plots tend to cluster along the boundaries between crop zones (**Fig. 6**), where two crops are close competitors and a modest change in priorities flips the ranking. In an advisory setting this is precisely where farmers need to see both options and the reasons for each, and a stability flag makes that possible without exposing the farmer to the full complexity of the method.

Effect of Farmer Priorities

Changing the priorities changed the recommendations in a predictable way (**Table 5**). The profit-oriented scenario shifted area towards groundnut (43.2%) and pigeon pea (17.1%) and away from sorghum (19.1%). The food-secure scenario moved in the opposite direction, increasing sorghum to 40.7% and maize to 20.3% while reducing groundnut to 14.6% and pigeon pea to 0.4%. The water-scarce scenario increased pearl millet to 23.5% and cut the mean water deficit from 4.3% to 2.3%. The risk-averse scenario raised the 10th percentile return from 17.7 to 23.4 USD/ha and reduced the loss probability from 18.7% to 17.8%, at a cost of 4.6 USD/ha in mean net return. Each scenario improved the metric it emphasised, but none was free: the food-secure scenario raised the calorie yield from 5.17 to 6.41 Mkcal/ha while lowering the mean net return to 172 USD/ha and the 10th percentile return to -8.4 USD/ha.

Table 5. Area Share of the Top-Ranked Crop (%) and Mean Simulated Outcomes Under Baseline and Scenario Weights, Evaluated in Stress-Tested Seasons (Mean Over 20 Landscapes). Simulated Data

Scenario	Rice	Maize	Sorghum	Pearl millet	Groundnut	Pigeon pea	Net return (USD/ha)	Loss prob. (%)	Calories (Mkcal/ha)
Baseline (AHP panel)	2.9	4.7	31.0	17.4	37.5	6.6	210	18.7	5.17
Profit-oriented	3.2	1.0	19.1	16.5	43.2	17.1	221	19.0	4.64
Risk-averse	1.8	4.2	35.0	18.9	30.5	9.5	206	17.8	5.07
Food-secure	6.5	20.3	40.7	17.5	14.6	0.4	172	20.7	6.41
Water-scarce adaptive	2.9	4.7	36.7	23.5	27.4	4.8	199	18.0	5.28

The top-ranked crop was identical across scenarios on 51–87% of plots (**Fig. 7**). The baseline agreed most with the risk-averse scenario (86.9%) and the water-scarce scenario (83.6%), and least with the food-secure scenario (66.0%). The lowest agreement of all was between the profit-oriented and food-secure scenarios (50.5%). Thus, most plots have a robust best crop, while a substantial minority are sensitive to the farmer group's priorities. This supports exposing the priority settings to users rather than fixing them, and it quantifies how much that choice matters.

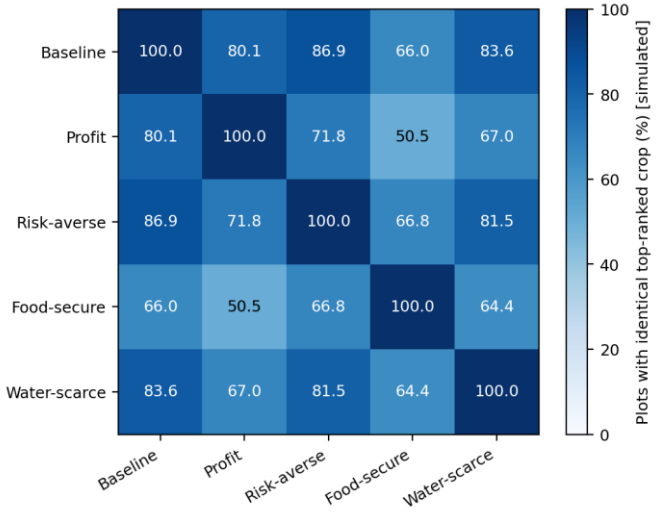


Fig 7. Percentage of Plots with the Same Top-Ranked Crop for Each Pair of Weight Scenarios (Mean Over 20 Simulated Landscapes).

Comparison with Alternative Strategies

Table 6 compares the strategies in the stress-tested evaluation seasons. The proposed method obtained a mean net return of 210 USD/ha, a 10th-percentile return of 17.7 USD/ha and a loss probability of 18.7%. The traditional rule of thumb

obtained 67 USD/ha, -92 USD/ha and 38.9%, and random choice 60 USD/ha, -116 USD/ha and 38.6%. Yield-maximising performed worst on returns (32 USD/ha mean and -208 USD/ha at the 10th percentile, loss probability 45.8%), although it produced the highest calorie yield (7.54 Mkcal/ha), because yield-maximisation favours water-demanding and costly crops that fail in dry seasons.

Table 6. Outcomes of Six Crop-Selection Strategies in Stress-Tested Simulated Seasons

Strategy	Net return (USD/ha)	10th pct. return (USD/ha)	Loss prob. (%)	Water deficit (%)	Calories (Mkcal/ha)	Same crop as proposed (%)
Proposed AHP-TOPSIS	210 (16)	17.7 (7.0)	18.7 (2.7)	4.3 (1.2)	5.17 (0.24)	100
Weighted-sum model	182 (13)	25.1 (7.7)	17.0 (2.8)	1.9 (1.1)	5.73 (0.28)	55.7
Profit-maximising	223 (16)	14.8 (7.1)	18.9 (2.5)	5.7 (1.1)	4.35 (0.23)	65.6
Yield-maximising	32 (19)	-208.1 (21.4)	45.8 (2.9)	13.6 (1.5)	7.54 (0.30)	20.9
Traditional rule of thumb	67 (20)	-92.1 (17.3)	38.9 (4.7)	2.2 (0.9)	6.28 (0.24)	25.8
Random choice	60 (16)	-116.4 (10.6)	38.6 (2.8)	9.9 (1.1)	4.87 (0.18)	16.7

The two strategies that are closest to the proposed method are the profit-maximiser and the weighted-sum model, and the comparison with them is more nuanced. Relative to the profit-maximiser, the proposed method gave up 12.7 USD/ha of mean net return (5.7%) but had a higher 10th-percentile return (17.7 versus 14.8 USD/ha), a lower water deficit (4.3% versus 5.7%) and a higher calorie yield (5.17 versus 4.35 Mkcal/ha); the loss probabilities were close (18.7% versus 18.9%). The weighted-sum model with the same weights chose the same crop as the proposed method on only 55.7% of plots. It gave a lower mean net return (182 USD/ha) but, in these simulations, a higher 10th-percentile return (25.1 USD/ha), a lower loss probability (17.0%), and a lower water deficit (1.9%). We therefore do not claim that TOPSIS dominates simpler aggregation. The two methods occupy different points on the return–risk trade-off, which stem partly from local (per-plot) versus global normalisation, and which of them is preferable depends on the priorities of the farmers using it. What the TOPSIS–Shapley combination adds is an exact, additive account of each recommendation, which a weighted sum offers trivially but TOPSIS does not without the Shapley step.

Compared with the traditional rule, the proposed method changed the crop on most plots (**Fig. 8**). Among plots where the rule suggests rice, only 11% retained rice, 30% moved to groundnut and 24% to sorghum. Among plots where the rule suggests maize, 4% retained maize and 43% moved to groundnut. Pearl millet was retained most often (56%), which matches its high suitability and stability. These shifts are not an evaluation of real farmer practice, since the rule of thumb is a simple simulated benchmark, but they show that the improvement in simulated returns arises from systematic reallocation rather than marginal changes.

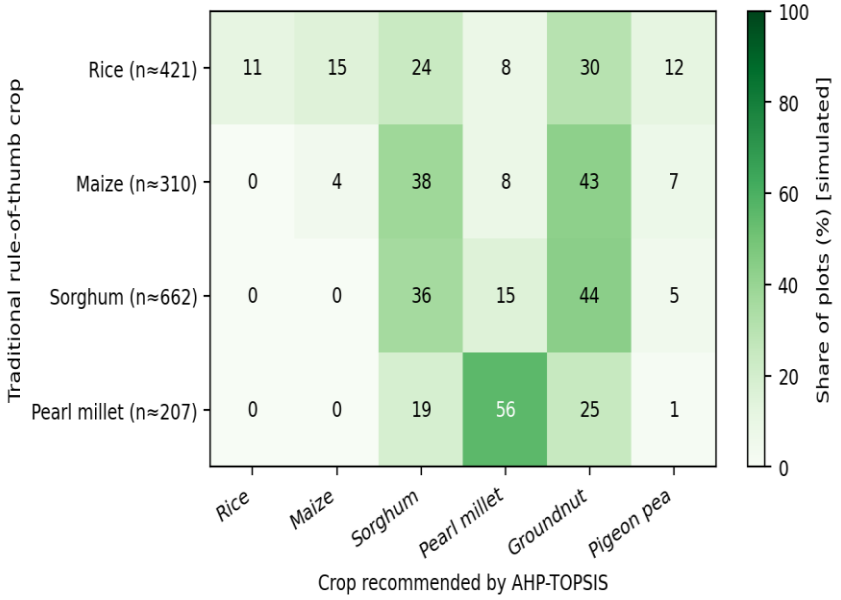


Fig 8. Share of Plots (Rows, By Crop Suggested by the Traditional Rule of Thumb) Assigned to Each Crop by the AHP-TOPSIS Ranking. Pooled Over 20 Simulated Landscapes. Row Labels Give the Mean Number of Plots Per Landscape.

Worked Example of a Farmer-Facing Explanation

To show what a user would see, we selected the plot in the first landscape (row 4, column 13) whose stability was closest to 0.75, i.e. a contested case. The plot is not irrigated, with 508 mm of mean seasonal rainfall, a mean temperature of 30.7 °C, soil pH 7.5, 42 km from the nearest market and household liquidity of 422 USD/ha. Sorghum is ranked first (closeness 0.872) and Pigeon pea second (0.852), a margin of 2.0 points, with stability 0.75. **Table 7** gives the criterion values and Shapley contributions.

Table 7. Worked Example: Criterion Values and Shapley Contributions to the Margin of Sorghum Over Pigeon Pea

Criterion	Value: Sorghum	Value: Pigeon pea	Contribution Δ (×100)
Agro-ecological suitability	1.00	1.00	-0.5
Expected net return	187	243	-14.1
Downside (loss) risk	0.05	0.06	-2.3
Water deficit	0.09	0.24	+10.8
Input affordability burden	0.55	0.66	+1.8
Market access	0.12	0.30	-14.5
Calorie yield	5.65	2.95	+20.8

Net return in USD/ha; calorie yield in Mkcal/ha; other values as defined in Section 3.3. Contributions sum to the margin.

Practical Implications and Limitations

Three features appear to be most valuable for deployment. First, the criteria are formulated in the measurement language of the farmers (in terms of money, loss, water, cash and food), and can be weighted by the group of the user. Second, each recommendation is accompanied by reasons and a confidence flag, a usage that is appropriate in a human-in-the-loop system, when the stakes are high [6]. Third, the calculations are light (exact Shapley values for a 1600-plot landscape can be achieved in seconds on a laptop computer) the framework can be run from a district server and results fed out via extension workers, SMS or voice interfaces.

There are some important limitations of the study. (i) All landscapes, crop parameters and results are simulated, absolute values are not predictions for any specific landscape and the agronomic parameters are indicative. (iii) The evaluation seasons contain the same model structure as the design-time matrix. The stress factor 1.25 is meant to assess robustness to mis-specified variability, but not robustness to structural errors like pests, disease or labour constraints not included in the model. (iii) The AHP judgments are based on a hypothetical panel, and weights which are elicited by actual users will determine the results. (iv) Shapley attributions are not representations of the causal system, but rather of the decision model, and their interpretation relies on the definition of the missing criteria here in terms of weight re-normalisation. (v) Plots are modelled independently, without neighbour effects, shared irrigation allocation or market saturation that would arise if many farmers followed the same advice. (vi) Within TOPSIS, per-plot normalisation makes closeness relative to the six candidate crops, so adding or removing a crop can change the ranking of the others. Field validation with farmers, comparison of the explanations with agronomists' reasoning, and usability testing of the advisory messages are the necessary next steps.

V. CONCLUSIONS

An explainable multi-criteria decision support framework is presented for smallholder crop selection and tested it in a fully simulated setting. Combining fuzzy suitability, a water-stress yield model with Monte Carlo shocks, AHP weights and TOPSIS, the framework produced spatially coherent recommendations, with groundnut, sorghum and pearl millet recommended on 37.5%, 31.0% and 17.4% of plots. In stress-tested seasons it earned 210 USD/ha on average with a loss probability of 18.7%, far better than a traditional rule of thumb (67 USD/ha; 38.9%) or random choice, and close to a profit-maximiser on mean return (223 USD/ha) while improving the 10th-percentile return, water use and calorie yield. A simple weighted-sum model with the same weights was better on some risk metrics, so the framework's main advantage is not superior returns but its transparency. Exact Shapley attribution of the TOPSIS margin showed that the factors driving a recommendation differ by crop and are not simply the highest-weighted criteria; calorie yield, for example, was the most frequent driver despite ranking fourth by weight. The stability score identified the 22.6% of plots where the recommendation is fragile, and farmer-priority scenarios changed the top crop on up to 49% of plots (profit-oriented versus food-secure), showing the value of letting users state their priorities. Future work will calibrate the crop and market parameters with agronomic and household survey data, elicit AHP weights participatively, validate the explanations with extension agents and farmers in a pilot district, and extend the model to labour constraints, pest risk and interactions between neighbouring plots. The simulation script and results file accompany this article so that every figure and table can be reproduced.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
No data was used to support this study.

Conflicts of Interests
The authors declare no conflict of interest.

Funding
No funding agency is associated with this research.

Competing Interests
There are no competing interests.

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ISSN: 3104-4654