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Dual-use building rooftops for agrivoltaic applications in warm-temperate climates - A neutrosophic decision analysis

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Abstract. Rooftop agrivoltaic systems offer a promising dual-use strategy for dense urban areas by combining photovoltaic generation with horticultural production. However, selecting an optimal agrivoltaic configuration involves multiple conflicting criteria (including PV yield, crop suitability, shading levels, and investment costs) affected by significant uncertainty in both climatic and agronomic parameters. This study proposes a neutrosophic multi-criteria decision-making framework integrating CRITIC-based objective weighting and MAIRCA ranking to evaluate alternative rooftop agrivoltaic layouts. A warm-temperate Mediterranean context (Naples, Italy) is considered, where dynamic seasonal weighting emphasizes crop performance during spring–summer and PV output in autumn–winter. Crop–light compatibility and seasonal photosynthetically active radiation (PAR) availability are evaluated through hourly shading analyses, while photovoltaic electricity generation is quantified using an hourly solar irradiance and module performance simulation. The neutrosophic representation allows expert judgments and performance indicators to include indeterminacy, improving robustness. The framework demonstrates that incorporating seasonal priorities and epistemic uncertainty leads to more stable and context-adapted rankings, supporting decision-makers in designing efficient rooftop dual-use systems.

1 Introduction

Urban rooftops are increasingly viewed as strategic infrastructure for decarbonization and resilience because they provide large, underutilized surfaces suitable for distributed solar energy and climate-adaptive measures [1].

Dual-use agrivoltaics extends rooftop PV from a single-use energy asset into a dual-use system by co-locating PV with food production, potentially contributing to urban sustainability and reducing climate impacts associated with food supply chains [2, 3]. Recent work has highlighted the emerging potential of rooftop agrivoltaics through integrated assessment frameworks combining rooftop availability mapping, PV simulation, and crop production modeling [4]. Moreover, evidence is also accumulating that agrivoltaic shading

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can be beneficial (or detrimental) depending on crop type, solar geometry, and canopy design, making "one-size-fits-all" design rules inappropriate [5, 6].

From a design perspective, agrivoltaic performance is governed by a coupled energy–light problem. Indeed, the PV layout affects both the electrical yield (via irradiance and shading losses) and the crop microclimate/light regime (via PAR attenuation and spatial distribution) [7]. Some reviews available in the current scientific literature have catalogued many agrivoltaic design options (e.g., row spacing, tilt, canopy/pergola structures, and semi-transparent modules), emphasizing that optimality is often dependent on site and crop variables [8–10]. In Mediterranean and warm-temperate climates, high summer irradiance can push open-sky daily light integral (DLI) well above the optimal range for some leafy crops, motivating shading as a functional light management tool rather than simply a yield penalty [11–13].

Selecting a rooftop agrivoltaic configuration should be therefore considered as a complex decision problem with conflicting criteria and the presence of several uncertainties in both climate and agronomic response evaluation. For this reason, multi-criteria planning is often needed to balance energy yield, economics, constructability, and social/environmental impacts when deploying rooftop PV at scale [14]. Multi-criteria decision analysis (MCDA) has been widely applied in sustainable energy problems precisely because it can combine heterogeneous indicators and support transparent trade-off reasoning [15, 16]. In this context, objective weighting methods such as CRITIC quantify the informativeness of criteria based on contrast intensity and inter-criterion conflict, reducing reliance on subjective weights when preference elicitation is difficult [17].

However, standard crisp MCDA often under-represents indeterminacy when solving these design problems. Indeed, often expert judgments may be incomplete, and the performance metrics can depend upon the scenario under which are evaluated and may vary substantially across crop profiles or climate perturbations. Neutrosophic sets and their single-valued forms defined single-valued neutrosophic sets (SVNS) have been used in MCDM to represent truth, indeterminacy, and falsity simultaneously, improving robustness when the data of the decision problem considered are vague or partially contradictory [18, 19]. In parallel, the MAIRCA method is increasingly employed as a ranking approach in applied engineering decision problems and can be implemented with repeatable steps using normalized and weighted matrices [20–22].

This paper provides a neutrosophic decision framework tailored to rooftop agrivoltaics in a warm-temperate Mediterranean context, with three specific novelty aspects:

1. Seasonal dynamic weighting: objective weights are computed separately for Spring–Summer and Autumn–Winter to reflect seasonal priorities (crop performance emphasized in Spring–Summer; PV output emphasized in Autumn–Winter).
2. Scenario-driven SVNS construction: climate and crop scenarios drive indeterminacy directly from performance dispersion rather than relying solely on linguistic expert uncertainty.
3. Robust ranking diagnostics: MAIRCA is executed scenario-wise and supplemented with rank-stability metrics (Top-1/Top-3 frequency; Kendall's τ; Spearman's ρ) to quantify rank reversals and robustness.

2 Materials and methods

2.1 Case study, climate and crop scenarios

The case study analysed in this research considers a warm-temperate Mediterranean rooftop context in Naples, a city located in Southern Italy. For the analyses hourly meteorological boundary conditions are considered and the data are taken from a typical year EPW weather file. In particular, a set of seven rooftop agrivoltaic layout alternatives (A1–A7) is evaluated, representing distinct PV–crop co-location geometries (e.g., dense and sparse PV row arrangements, elevated/pergola configurations, and East–West layouts). The evaluated alternatives are defined as follows: A1 = Dense PV rows; A2 = Medium-spacing rows (balanced PV–crop); A3 = Sparse PV rows (high-light crop preference); A4 = Elevated/pergola-type PV canopy (more uniform shading); A5 = Intermediate canopy/row configuration (balanced shading and PV); A6 = East–West PV layout; A7 = Pergola canopy - reinforced structure. Crop cultivation is assumed to occur over the entire cultivable roof surface, including both inter-row areas and areas beneath PV modules, so that shading affects crop-light conditions across the full planting area.

The host building is assumed to be a representative mid-rise urban building with a flat roof suitable for PV installation and rooftop cultivation. The roof is modelled as a planar horizontal surface with unobstructed sky exposure (i.e., no parapet-induced shading and no neighbouring-building shading), so that incident irradiance and the resulting PV/crop shading are governed only by the agrivoltaic geometry of each alternative (Figure 1).

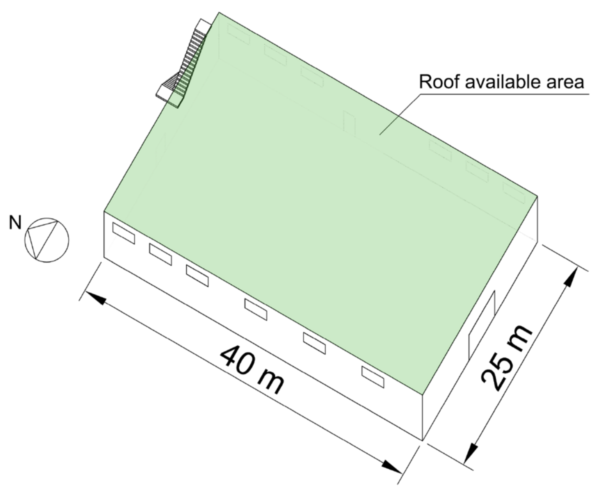

Fig. 1. Case study building

To reflect seasonal operational priorities, two evaluation windows are defined: Spring–Summer (SS, April–September) and Autumn–Winter (AW, October–March). The MCDM weighting and ranking are performed separately for SS and AW and then aggregated to obtain an overall (combined) decision outcome.

Uncertainty is represented using a discrete scenario set formed by combining three climate cases and three crop groups, yielding nine crop–climate scenarios:

Climate cases (weather variants): typical meteorological year (W0), hot-summer perturbation (W1), and cloudy-winter perturbation (W2).

Crop groups: leafy crops (G1), herbs (G2), and fruiting crops (G3), each characterized by a crop-specific target DLI band $[DLI_{\min}, DLI_{\max}]$ and an excess-light cap PAR_{cap} used to identify potentially stressful high-light exposure.

For each scenario $s \in \{1, \ldots, 9\}$, a crisp decision matrix $X^{(s)} = [x_{a,j}^{(s)}]$ is computed, where a indexes alternatives and j indexes criteria.

The criterion set includes PV, crop-light, economic, and feasibility dimensions and is defined as: C1 = PV Summer energy (MWh); C2 = PV Winter energy (MWh); C3 = PV shading loss (%); C4 = CAPEX (EUR/kWp); C5 = DLI days in target (%); C6 = Mean DLI shortfall (mol/m^2 per day); C7 = Excess-PAR exposure (hours); C8 = Cultivable area fraction (-); C9 = O&M complexity (1–5, cost); C10 = Irrigation/drainage benefit (1–5, benefit); C11 = Structural risk (1–5, cost); C12 = Acceptance (1–5, benefit).

2.2 Hourly PV electricity modelling and crop-light indicators

PV electricity generation is computed at hourly resolution using EPW irradiance and temperature variables [23] and a temperature-dependent module performance formulation [24]. Layout-specific shading and self-shading effects are accounted for in PV yield via the geometric configuration of each alternative. Seasonal PV energy indicators are then derived for SS (April–September) and AW (October–March) and used in the decision matrix.

Hourly crop-plane photosynthetically photon flux density is expressed as PPFD [μmol/(m^{2}s)], obtained by combining EPW irradiance with a layout-dependent shading model consistent with each rooftop geometry. Daily Light Integral (DLI) for each day d is computed as:

$$DLI(d) = \sum_{t \in d} \frac{PPFD(t) \cdot \Delta t}{10^6} [\mathrm{mol/m^2}\ per\ day] \tag{1}$$

Using $DLI(d)$ and $PPFD(t)$, three crop-light criteria are evaluated over SS (April–September), reflecting the main growing season:

C5 (Days-in-target DLI, %)

$$C5 = 100 \times \frac{|\{d: DLI_{\min} \leq DLI(d) \leq DLI_{\max}\}|}{|SS|} \tag{2}$$

C6 (Mean DLI shortfall, mol/m^2 per day)

$$Shortfall(d) = \max\big(0, DLI_{\min} - DLI(d)\big),\ C6 = \frac{1}{|SS|} \sum_{d \in SS} Shortfall(d) \tag{3}$$

C7 (Excess-light exposure, hours)

$$C7 = \big|\{t \in SS: PPFD(t) > PPFD_{\mathrm{cap}}\}\big| \tag{4}$$

where $PPFD_{\mathrm{cap}}$ is crop-group dependent (lower for leafy/herbs and higher for fruiting crops).

Each alternative is evaluated across PV, crop-light, economic, and feasibility criteria. Criteria are classified as benefit-type (to be maximized) or cost-type (to be minimized). The crisp decision matrices were recomputed to ensure crop-light indicators account for cultivation both between rows and under PV modules for the relevant alternatives.

To harmonize heterogeneous criteria, each scenario matrix $X^{(s)}$ is transformed into a scenario-wise desirability matrix $P^{(s)} = [p_{a,j}^{(s)}]$, with $p_{a,j}^{(s)} \in [0,1]$, using min–max normalization across alternatives. For a benefit criterion:

$$p_{a,j}^{(s)} = \frac{x_{a,j}^{(s)} - \min_a x_{a,j}^{(s)}}{\max_a x_{a,j}^{(s)} - \min_a x_{a,j}^{(s)} + \varepsilon} \tag{5}$$

For a cost criterion:

$$p_{a,j}^{(s)} = \frac{\max_a x_{a,j}^{(s)} - x_{a,j}^{(s)}}{\max_a x_{a,j}^{(s)} - \min_a x_{a,j}^{(s)} + \varepsilon} \tag{6}$$

where ε is a small constant used to avoid division by zero when the range is null.

2.3 Neutrosophic decision matrix (T–I–F) from scenario dispersion and expert uncertainty

For each alternative a and criterion j, the set $\{p_{a,j}^{(s)}\}_{s=1}^{9}$ is aggregated into a single-valued neutrosophic triple $(T_{a,j}, I_{a,j}, F_{a,j})$ as follows.

Truth (central tendency):

$$T_{a,j} = \text{median}_s\left(p_{a,j}^{(s)}\right) \tag{7}$$

Indeterminacy (scenario dispersion):

$$I_{a,j} = Q_{0.90}\left(p_{a,j}^{(s)}\right) - Q_{0.10}\left(p_{a,j}^{(s)}\right) \tag{8}$$

Falsity (complement):

$$F_{a,j} = 1 - T_{a,j} \tag{9}$$

For qualitative criteria elicited on a 1–5 scale, uncertainty in expert assessment is represented by a small discrete set $\{r-1, r, r+1\}$ (restricted to $[1,5]$), mapped to desirability and propagated into the neutrosophic representation. The judgement-driven indeterminacy is combined with scenario-driven indeterminacy using a conservative operator (maximum), so that both scenario dispersion and expert ambiguity contribute to $I_{a,j}$. A robust scalar score is then obtained as $p_{a,j}^{*} = T_{a,j} - \lambda I_{a,j}$ (with $\lambda = 0.5$) and used for objective weighting.

2.4 Objective weighting using CRITIC with seasonal emphasis

CRITIC weights are computed separately for SS and AW from the robust matrix P^{*}. For each criterion j, the CRITIC information content is:

$$C_j = \sigma_j \sum_{k=1}^{m} (1 - r_{jk}) \tag{10}$$

where σ_j is the standard deviation of criterion j across alternatives and r_{jk} is the Pearson correlation between criteria $j$and k. Weights are then:

$$w_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{11}$$

Seasonal differentiation is introduced through an explicit seasonal emphasis factor applied to CRITIC weights. Differently from the previous version, both PV criteria (C1 and C2) are retained in both seasons, but they receive season-dependent emphasis:

SS: crop-light criteria (C5–C7) multiplied by 1.8; C1 (PV Apr–Sep) multiplied by 1.8; C2 (PV Oct–Mar) multiplied by 0.6; PV shading loss (C3) multiplied by 0.8; other criteria unchanged.

AW: crop-light criteria (C5–C7) multiplied by 0.8; C2 (PV Oct–Mar) multiplied by 1.8; C1 (PV Apr–Sep) multiplied by 0.6; PV shading loss (C3) multiplied by 1.8; other criteria unchanged.

After applying emphasis factors, weights are renormalized to sum to one. This approach preserves CRITIC's objective treatment of contrast and conflict while encoding seasonal planning priorities in a transparent, reproducible manner.

2.5 MAIRCA ranking and robustness assessment

For each season and scenario, MAIRCA is applied using normalized performance metrics and seasonal weights. MAIRCA constructs a theoretical preference matrix T based on equiprobable alternatives and a real preference matrix R based on weighted performances. For a given scenario, the theoretical element is:

$$t_{a,j} = \frac{1}{n} w_j \tag{12}$$

where n is the number of alternatives. The real preference is:

$$r_{a,j} = t_{a,j} \cdot p_{a,j} \tag{13}$$

and the gap is:

$$g_{a,j} = t_{a,j} - r_{a,j} = t_{a,j}(1 - p_{a,j}) \tag{14}$$

The total gap for alternative a is:

$$Q_a = \sum_{j=1}^{m} g_{a,j} \tag{15}$$

Alternatives are ranked by ascending Q_a (lower gap indicates better alignment with the theoretical preference).

Seasonal aggregation is obtained using a combined objective:

$$Q_{\mathrm{comb}} = 0.6 \cdot Q_{\mathrm{SS}} + 0.4 \cdot Q_{\mathrm{AW}} \tag{16}$$

and ranked analogously.

Robustness across the nine scenarios is quantified using: Top-1 and Top-3 frequencies, rank dispersion (mean and standard deviation), and pairwise Kendall's τ and Spearman's ρ correlations between scenario-specific rankings.

3 Results

3.1 Decision matrix and neutrosophic CRITIC weights under seasonal prioritization

The raw (non-normalized) decision matrix for the reference scenario (G1–W0: leafy crop group under typical climate) is reported in Table 1. The other matrices are not reported for brevity. The matrix lists the performance of each rooftop agrivoltaic layout (A1–A7) against the full set of criteria (C1–C12).

Table 1. G1–W0: leafy crop group under typical climate decision matrix.

Alt.	C1 (MWh)	C2 (MWh)	C3 (%)	C4 (EUR/kWp)	C5 (%)	C6 (mol/m² per day)	C7 (h)	C8 (–)	C9 (1–5)	C10 (1–5)	C11 (1–5)	C12 (1–5)
A1	109.631	52.958	0.415	1100	15	1.309	0	0.2	4	2	3	3
A2	70.439	33.721	0.76	1250	11.7	0.059	0	0.45	3	4	3	4
A3	46.990	22.740	0.346	1300	6	0	82	0.6	2	4	2	4
A4	75.312	34.600	0	1700	19.4	0.371	0	0.9	3	4	4	4
A5	105.437	48.440	0	2300	18	0.07	2	0.9	4	4	4	4
A6	85.973	36.930	5.022	1350	22.7	0.565	0	0.3	3	4	3	4
A7	75.332	34.609	0	1850	19.4	0.371	0	0.9	4	4	4	4

The final seasonal CRITIC weights (Table 2) indicate a pronounced shift in criterion importance between Spring–Summer (SS) and Autumn–Winter (AW), consistent with the adopted seasonal priority structure. In SS, the PV component linked to the cultivation season becomes explicitly dominant among PV indicators: C1 (PV energy Apr–Sep) has weight 0.132, while C2 (PV energy Oct–Mar) is retained but down-weighted (0.043). In SS, crop-light indicators remain influential (C5–C7 sum ≈ 0.309), with C6 (mean DLI shortfall) 0.116 and C7 (excess-PAR hours) 0.105 carrying substantial weight, confirming that crop suitability still provides major discrimination among alternatives.

In AW, PV-related criteria dominate: C3 (PV shading loss) reaches 0.150 and C2 (PV energy Oct–Mar) reaches 0.143, whereas C1 (PV energy Apr–Sep) is retained but secondary (0.049). Crop-light criteria receive lower AW weights (C5–C7 sum ≈ 0.152), implying that AW rankings are primarily governed by winter electricity output and PV-related penalties. Feasibility-related qualitative criteria (e.g., O&M complexity and structural risk) remain moderate and relatively stable across seasons, reflecting their secondary but non-negligible role as discriminators.

Table 2. Final neutrosophic CRITIC weights by season.

Criterion	w_{SS}	w_{AW}
C1 - PV energy Apr–Sep (MWh)	0.132	0.048
C2 - PV energy Oct–Mar (MWh)	0.043	0.143
C3 - PV shading loss (%)	0.060	0.150
C4 - CAPEX (EUR/kWp)	0.080	0.089
C5 - DLI days in target (%)	0.087	0.043
C6 - Mean DLI shortfall (mol/m² per day)	0.115	0.057
C7 - Excess-PAR exposure (hours)	0.105	0.051
C8 - Cultivable area fraction (–)	0.080	0.089
C9 - O&M complexity (1–5)	0.076	0.084
C10 - Irrigation/drainage benefit (1–5)	0.067	0.075
C11 - Structural risk (1–5)	0.082	0.091
C12 - Social acceptance (1–5)	0.067	0.075

3.2 Scenario-wise MAIRCA rankings and robustness

Scenario-wise neutrosophic MAIRCA rankings were computed for the nine crop–climate scenarios in each season and for the combined objective ($Q_{\mathrm{comb}} = 0.6 \cdot Q_{\mathrm{SS}} + 0.4 \cdot Q_{\mathrm{AW}}$). Robustness summaries are reported in Tables 3–5.

Under SS, A5 becomes the dominant Top-1 alternative with 6/9 scenario wins, while A2 wins the remaining 3/9 scenarios (Table 3). Importantly, both A5 and A2 remain Top-3 in 9/9 scenarios, indicating robust performance under cultivation-season priorities when both PV seasonal components are retained. Under AW, A5 again dominates with 6/9 Top-1 wins, while A3 achieves 3/9 Top-1 wins (Table 4). This indicates that under winter electricity priorities, the best-performing configuration is most frequently A5, but a subset of scenarios favours A3 as the most competitive alternative under PV-weighted trade-offs.

For the combined objective, A5 remains Top-1 in 6/9 scenarios and A2 is Top-1 in 3/9 scenarios (Table 5), confirming that A5 provides the most robust aggregated performance under the adopted seasonal aggregation, while A2 becomes optimal for a subset of crop-driven scenarios.

Table 3. MAIRCA robustness - Spring–Summer (Apr–Sep), 9 scenarios.

Alternative	Top-1	Top-3	Mean rank	Std dev
A5	6	9	1.333	0.471
A2	3	9	2.000	0.816
A4	0	3	3.333	0.943
A6	0	3	4.333	1.247
A3	0	3	5.000	1.414
A7	0	0	5.000	0
A1	0	0	7.000	0

Stability (SS): mean Kendall $\tau \approx 0.667$; mean Spearman $\rho \approx 0.786$; distinct Top-1 winners = 2.

Table 4. MAIRCA robustness - Autumn–Winter (PV-priority), 9 scenarios.

Alternative	Top-1	Top-3	Mean rank	Std dev
A5	6	9	1.333	0.471
A4	0	6	2.667	0.943
A2	0	9	3.000	0
A3	3	3	3.000	1.414
A7	0	0	5.000	0
A6	0	0	6.333	0.471
A1	0	0	6.667	0.471

Stability (AW): mean Kendall $\tau \approx 0.762$; mean Spearman $\rho \approx 0.857$; distinct Top-1 winners = 2.

Table 5. MAIRCA robustness - Combined objective (0.6 SS + 0.4 AW), 9 scenarios.

Alternative	Top-1	Top-3	Mean rank	Std dev
A5	6	9	1.333	0.471
A2	3	9	2.000	0.816
A4	0	6	3.000	0.816
A7	0	0	4.667	0.471
A6	0	0	5.000	0.816
A3	0	3	5.000	1.414
A1	0	0	7.000	0

3.3 Scenario-wise ranks

Table 6 and Figure 2 report the scenario-wise MAIRCA ranks for the combined objective across the 3×3 scenario set (crop group × climate case). Using the scenario notation (G1–G3 for crop groups and W0–W2 for climate cases), the combined ranking shows that A5 is top-ranked for G1 (leafy) and G2 (herbs) under all climate cases, whereas A2 is top-ranked for G3 (fruiting) under all climate cases. This indicates that, within the current scenario parameterization, crop group remains the primary driver of rank differentiation, whereas the climate perturbations do not produce rank reversals for a fixed crop group.

Table 6. Scenario-wise MAIRCA ranks - Combined objective (0.6 SS + 0.4 AW).

Alternative	G1–W0	G1–W1	G1–W2	G2–W0	G2–W1	G2–W2	G3–W0	G3–W1	G3–W2
A1	7	7	7	7	7	7	7	7	7
A2	3	3	3	2	2	2	1	1	1
A3	6	6	6	6	6	6	3	3	3
A4	2	2	2	3	3	3	4	4	4
A5	1	1	1	1	1	1	2	2	2
A6	5	5	5	4	4	4	6	6	6
A7	4	4	4	5	5	5	5	5	5

The absence of rank changes across climate variants within each crop group is consistent with the adopted indicator definitions and scenario construction. Specifically, crop-light indicators (C5–C7) are evaluated over SS (Apr–Sep) and are therefore weakly coupled to a cloudy-winter perturbation; moreover, the present dataset yields largely common-mode PV impacts across alternatives under the selected climate perturbations. Consequently, climate scenarios contribute more to the dispersion captured in neutrosophic indeterminacy than to changes in rank ordering.

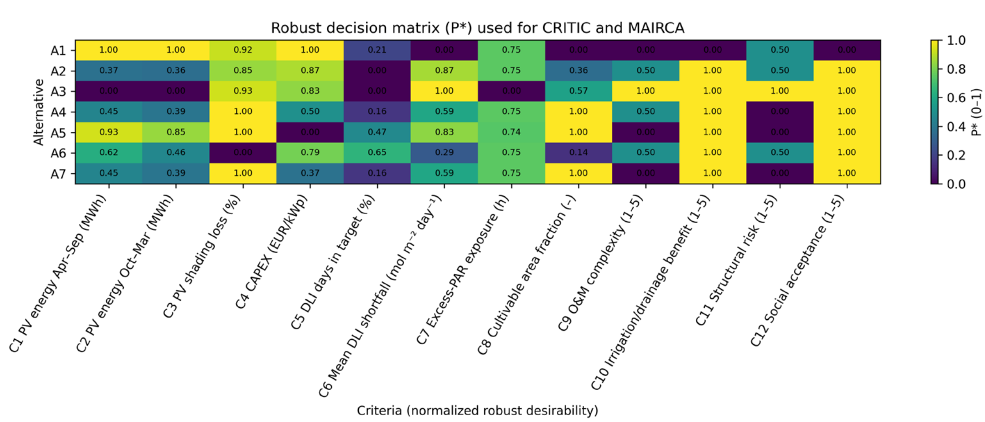

Fig. 2. Heatmap of MAIRCA ranks across scenarios

3.4 Rank stability statistics

Rank-stability statistics, computed from the set of scenario-wise rankings, are summarized here for completeness. In SS, the average pairwise rank agreement is moderate-to-high (mean Kendall's $\tau = 0.667$; mean Spearman's $\rho = 0.786$), and only two distinct Top-1 winners occur (A5 and A2). In AW, rank agreement increases (mean $\tau = 0.762$; mean $\rho = 0.857$) and two distinct Top-1 winners occur (A5 and A3), indicating stronger ordering consistency under PV-priority evaluation. For the combined objective, agreement remains high (mean $\tau = 0.714$; mean $\rho = 0.821$), while only two distinct Top-1 winners occur (A5 and A2).

4 Discussion

4.1 Seasonal prioritization and implications for criterion structure

The seasonal weighting strategy produces two distinct evaluation regimes. In Spring–Summer (SS), the final CRITIC weights assign high importance to crop-light compatibility indicators (C5–C7) while explicitly prioritizing the PV component relevant to the cultivation season (C1: PV Apr–Sep). In Autumn–Winter (AW), the weights shift toward PV-oriented indicators with emphasis on winter PV output (C2: PV Oct–Mar) and PV shading loss (C3) (Table 2). This seasonal divergence is consistent with a Mediterranean rooftop context in which cultivation performance is most relevant during the main growing period, while PV electricity production becomes relatively more decisive in the low-irradiance season. Importantly, the seasonal weighting affects not only the magnitude of weights but also the relative contribution of trade-off criteria (e.g., PV shading loss versus crop-light shortfall), thereby modifying the effective decision structure of the MCDM problem.

4.2 Scenario-wise ranking and crop-dependent optima

Scenario-wise neutrosophic MAIRCA ranks (Table 5) indicate that the preferred layout depends on crop group, while climate variants do not induce rank reversals in the present uncertainty set. Under the combined objective ($0.6 \cdot SS + 0.4 \cdot AW$), A5 is consistently top-ranked for G1 (leafy) and G2 (herbs) across all climate cases, whereas G3 (fruiting) consistently favours A2 as the Top-1 alternative. This pattern suggests that, within the current formulation, crop-light requirements drive a small set of stable optima, rather than yielding a unique globally optimal solution across all crop groups.

At the same time, robustness summaries across the nine scenarios (Tables 3–5) show that A5 exhibits the strongest scenario-wide performance as a low-regret candidate (Top-3 in 9/9 scenarios in SS, AW, and combined, and Top-1 in 6/9 scenarios in SS, AW, and combined). A2 emerges as the most competitive alternative for high-light (fruiting) crop scenarios in the combined objective, consistent with a design that offers a favourable balance between crop-light adequacy and PV penalties under the adopted weights.

4.3 Rank stability and the role of uncertainty

Rank-stability metrics quantify the sensitivity of the ordering to scenario changes. Both SS and AW exhibit only two Top-1 winners and higher agreement (SS mean $\tau \approx 0.667$; AW mean $\tau \approx 0.762$). Within each crop group, the ordering does not change across the three climate variants (W0–W2) (Table 6). This behaviour follows from the present definition and propagation of scenario uncertainty. Specifically, the crop-light criteria C5–C7 are evaluated over Apr–Sep and are therefore not directly affected by the cloudy-winter perturbation;

moreover, the PV perturbations implemented here do not alter the relative performance ordering among alternatives (i.e., they act approximately as common-mode shifts rather than geometry-dependent changes). Consequently, climate scenarios contribute primarily to the dispersion captured in the neutrosophic indeterminacy component rather than inducing rank reversals.

4.4 Limitations and recommended extensions

The crop module uses light-based proxies (DLI-target compliance, mean shortfall, excess-PAR hours) rather than a mechanistic yield/quality model. These indicators are suitable for early-stage screening and comparative decision support, but subsequent design stages should incorporate crop growth response models or empirical calibration to translate PAR regimes into yield and quality metrics. In addition, economic estimates (CAPEX) and feasibility criteria could be refined through local market quotations and structural verification, while expert-judgement criteria could be elicited from multiple stakeholder groups.

5 Conclusions

This work proposed a neutrosophic multi-criteria decision framework for rooftop agrivoltaic layout selection in a warm-temperate Mediterranean context (Naples, Italy), using hourly climate data (taken from EPW weather files) and integrating PV simulation, rooftop shading/PAR assessment, neutrosophic uncertainty modelling (based on the Truth-Indeterminacy-Falsity paradigm), objective CRITIC weighting, and MAIRCA ranking with scenario-based stability metrics. The final crisp decision matrix assumes cultivation both between PV rows and under PV modules for the relevant alternatives, ensuring consistent accounting of crop-plane light availability across the whole cultivable surface.

In the analyses, a seasonal prioritization was implemented by computing seasonal weight structures and applying an explicit seasonal weighting, leading to a weighting regime dominated by crop light in Spring–Summer and by PV production in Autumn–Winter. Scenario-wise MAIRCA rankings under the combined objective ($0.6 \cdot \mathrm{SS} + 0.4 \cdot \mathrm{AW}$) indicated the following crop-dependent optima: A5 displays the most consistent high performance as a robust Top-3 alternative, supporting its interpretation as a low-regret choice when crop selection is uncertain, while A2 remains a robust Top-3 option and becomes optimal for fruiting-crop scenarios.

A rank-stability analysis performed on the results indicates moderate-to-high robustness overall, with higher stability under PV-priority conditions and lower stability under crop-priority conditions, consistent with crop profile being the dominant driver of ranking variability in the analyzed setup. Climate variants did not induce rank reversals within crop groups under the current perturbation assumptions, suggesting that future work should incorporate irradiance-component and geometry-sensitive climate perturbations to better resolve climate-driven differences among rooftop layouts. Overall, the proposed framework provides an uncertainty-aware decision support tool for designing and selecting efficient dual-use rooftop agrivoltaic systems in warm-temperate climates.

Nomenclature

Indices and sets

a: alternative index (rooftop layout), $a \in \{A1, \dots, A7\}$
j: criterion index, $j \in \{1, \dots, 12\}$

k: criterion index used for correlation calculations
s: scenario index (crop–climate combination), $s \in \{1, \dots, 9\}$
t: hourly time-step index within a day/season
d: day index within the evaluation season
SS: Spring–Summer period (Apr–Sep)
AW: Autumn–Winter period (Oct–Mar)
$|SS|$: number of days in SS (cardinality of the SS day set)

Decision matrix and normalization

$X^{(s)}$: non-normalized decision matrix for scenario s
$x_{a,j}^{(s)}$: performance value of alternative a under criterion j in scenario s
$P^{(s)}$: normalized desirability matrix for scenario s
$p_{a,j}^{(s)}$: normalized desirability of $x_{a,j}^{(s)}$, $p_{a,j}^{(s)} \in [0,1]$
ε: small constant to avoid division by zero in normalization

Neutrosophic aggregation

$T_{a,j}$: truth-membership component for alternative a, criterion j
$I_{a,j}$: indeterminacy component for a, j
$F_{a,j}$: falsity component for a, j
λ: indeterminacy penalty parameter used to obtain a robust scalar score
$p_{a,j}^{*}$: robust scalar performance used for weighting/ranking

CRITIC weighting

m: number of criteria
σ_j: standard deviation of criterion j across alternatives
$r_{j,k}$: Pearson correlation coefficient between criteria j and k
C_j: CRITIC information content of criterion j
w_j: CRITIC weight of criterion j
$w_{j,SS}$, $w_{j,AW}$: seasonal weights for SS and AW after applying seasonal emphasis factors and renormalization

MAIRCA ranking

n: number of alternatives
$t_{a,j}$: theoretical preference element for alternative a, criterion j
$r_{a,j}$: real preference element for alternative a, criterion j
$g_{a,j}$: gap element between theoretical and real preference
Q_a: total gap score for alternative a
Q_{SS}, Q_{AW}: seasonal MAIRCA total gaps for SS and AW
Q_{comb}: combined objective

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