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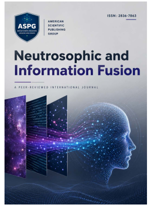

FULL LENGTH ARTICLE

A Neutrosophic Information-Fusion Framework for Renewable-Energy Site Selection under Conflicting Sustainability Criteria

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ABSTRACT

Siting a solar or wind farm forces planners to reconcile criteria that disagree by nature: irradiation or wind resource, land cost, grid proximity, ecological sensitivity and social acceptance. The evidence for each criterion is heterogeneous and uncertain—remote-sensing estimates, cadastral records, and public-consultation sentiment—and experts often cannot commit to a definite rating. This paper proposes a neutrosophic information-fusion framework that encodes each expert rating as a single-valued neutrosophic number, derives objective criterion weights by neutrosophic entropy, fuses the ratings with a single-valued neutrosophic weighted *geometric* operator (which, unlike the arithmetic operator, penalises a poor score on any single criterion), and ranks candidate sites by a de-neutrosophied score. Applied to six candidate sites and seven criteria, the framework selects a site that balances a strong resource against low ecological conflict, and a full sensitivity analysis over the weight scheme and the risk attitude shows the choice is robust. A comparison against fuzzy-AHP and SVN-TOPSIS indicates the neutrosophic geometric model better exposes sites whose ranking rests on contested, high-indeterminacy criteria.

Keywords: Neutrosophic sets ▪ Information fusion ▪ Site selection ▪ Renewable energy ▪ Multi-criteria decision analysis ▪ Entropy weighting

1. INTRODUCTION

The energy transition is, in large part, a land-use problem. Deciding where to build a solar or wind installation is a multi-criteria decision that must weigh a technical resource (how much sun or wind) against economic factors (land and connection cost), environmental factors (habitat and biodiversity impact) and social factors (local acceptance). These criteria conflict: the windiest ridge may also be the most ecologically sensitive, and the cheapest land may be far from the grid.

Compounding the conflict is uncertainty of an unusual kind. Resource maps come with estimation error; ecological sensitivity is graded by experts who genuinely disagree; and social acceptance, gauged from consultations, is often *indeterminate*—neither clear support nor clear opposition. Standard fuzzy MCDM captures gradation but not this indeterminacy. We adopt a neutrosophic representation so that "the community is divided" is modelled as high indeterminacy rather than as lukewarm support, and we treat the combination of criteria as an explicit information-fusion step.

The distinction is not academic. A site whose social acceptance is genuinely indeterminate—half the community strongly in favour, half strongly opposed— poses a very different planning risk from a site that is uniformly regarded as acceptable-but-unexciting, yet a fuzzy score of 0.5 would represent both identically. Treating the two as the same is how projects reach late-stage approval only to be derailed by opposition that a decision model had averaged into invisibility. The same logic applies to ecological sensitivity, where expert disagreement about a habitat's value is information in its own right and should be carried forward rather than smoothed away.

A second design question is how criteria should combine. Many MCDM methods are implicitly *compensatory*: a high score on one criterion can offset a low score on another, so a cheap, well-connected site can "buy back" serious ecological harm. For sustainability decisions this is often the wrong behaviour; some criteria, ecological conflict foremost among them, should act closer to a veto than to a tradeable quantity. We therefore fuse criteria with a *geometric* operator, which is non-compensatory by construction, and we pair it with objective, data-driven weights so that the influence of each criterion reflects how much it actually discriminates among the candidate sites rather than an analyst's prior.

Contributions.

- A neutrosophic site-selection framework that combines objective entropy-based weighting with a non-compensatory geometric fusion operator.
- An indeterminacy-aware scoring rule with a tunable risk attitude that lets a planner express how averse they are to contested evidence.
- A six-site, seven-criterion case study with a sensitivity analysis over the operator, the weighting scheme and the risk attitude, and a comparison against fuzzy-AHP and SVN-TOPSIS.

Section 2 gives background and Section 3 surveys the most closely related prior studies; Section 4 gives preliminaries; Section 5 presents the framework; Section 6 the case study; Section 7 the sensitivity analysis; and Section 9 concludes.

2. BACKGROUND

2.1 MCDM for renewable-energy siting

Site selection for renewable energy is a well-studied multi-criteria problem. Analysts have applied the analytic hierarchy process (AHP), TOPSIS, VIKOR, ELECTRE and PROMETHEE, very often layered on top of geographic-information-system (GIS) suitability mapping that encodes spatial constraints such as protected areas, slope and setback distances. Reviews of the field consistently report that resource quality, economic cost, grid access and environmental and social factors are the recurring criteria, and that no single method dominates—the appropriate choice depends on how uncertainty and criterion interaction are handled.

2.2 Fuzzy and neutrosophic extensions

Because siting criteria are imprecise and expert-judged, fuzzy extensions are widespread; fuzzy-AHP is especially common because it elicits weights from pairwise comparisons that experts find intuitive, and fuzzy-TOPSIS is used to rank alternatives once weights are set. The limitation these share is the inability to represent indeterminacy separately from partial support: a criterion on which experts are genuinely split looks identical to one on which they are uniformly lukewarm. Neutrosophic MCDM was developed precisely to separate these, and single-valued neutrosophic aggregation operators, similarity and correlation measures, and score-function rankings have since been applied to location and selection problems, including logistics-centre and facility siting.

2.3 Weighting and aggregation

Two methodological choices strongly affect any siting study. The first is how criterion weights are obtained: subjective weights (AHP, direct assignment) encode expert priorities but are contestable, whereas objective weights derived by entropy or similar measures let the data decide which criteria discriminate. The second is the aggregation operator: arithmetic (weighted-sum-like) operators are compensatory, while geometric and other conjunctive operators penalise poor performance on any single criterion. Sustainability applications frequently call for the latter, yet compensatory aggregation remains the default in practice.

3. RELATED WORK

We now review the specific prior studies most related to ours in energy-siting MCDM and neutrosophic decision-making.

For renewable-energy siting, San Cristobal [1] applied a VIKOR-based MCDM to rank renewable-energy projects, and Ibrahim et al. [2] combined GIS with multi-criteria analysis for solar-plant site selection; both rely on crisp or fuzzy weights and compensatory aggregation. Saaty's AHP [3] underlies the fuzzy-AHP baseline we compare against. On the neutrosophic side, Ye [4, 5] introduced correlation-coefficient and aggregation-operator methods for single-valued neutrosophic decision-making, Sahin [6] proposed score- and accuracy-function rankings, and Liu and Wang [7] developed neutrosophic Bonferroni-mean operators that capture criterion interaction. Pramanik et al. [8] applied neutrosophic group decision-making to logistics-centre location, a siting problem structurally similar to ours, and the edited volume of Kahraman and Otay [9] collects many neutrosophic MCDM applications. Majumdar and Samanta [10] defined the neutrosophic entropy on which our objective weighting is based.

These studies confirm that neutrosophic sets improve the representation of indeterminate criteria, yet most siting applications still use subjective weights and compensatory (arithmetic) aggregation, so a strong score on one criterion can offset serious weakness on another. Our framework departs by combining objective neutrosophic-entropy weighting with a *non-compensatory geometric* operator and an indeterminacy-aware score with a tunable risk attitude, and by reporting a sensitivity analysis that reveals which rankings are contingent on how indeterminacy is treated.

4. NEUTROSOPHIC PRELIMINARIES

Definition 1 (SVNS). A single-valued neutrosophic set on a universe X is $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\}$ with $T_A, I_A, F_A \in [0,1]$ and $0 \leq T_A + I_A + F_A \leq 3$. An element $\tilde{a} = (T, I, F)$ is an SVNN.

Definition 2 (Weighted geometric operator). For SVNNs

$\tilde{a}_1,\ldots,\tilde{a}_n$ and weights $w_j \geq 0$, $\sum_j w_j = 1$, the single-valued neutrosophic weighted geometric (SVNWG) operator is

$$\mathrm{SVNWG}(\tilde{a}_1,\ldots,\tilde{a}_n) = \left\langle \prod_{j=1}^{n} T_j^{w_j},\ 1-\prod_{j=1}^{n}(1-I_j)^{w_j},\ 1-\prod_{j=1}^{n}(1-F_j)^{w_j} \right\rangle. \tag{1}$$

Because truths are multiplied, a single small T_j drives the fused truth down— the desired non-compensatory behaviour.

Definition 3 (Neutrosophic entropy). For a criterion with column ratings $\tilde{a}_{ij} = (T_{ij}, I_{ij}, F_{ij})$, $i = 1,\ldots,m$, a normalised entropy is

$$E_j = 1 - \frac{1}{m}\sum_{i=1}^{m}(T_{ij}+F_{ij})\left|T_{ij}-F_{ij}\right| + \frac{1}{m}\sum_{i=1}^{m} I_{ij}, \tag{2}$$

scaled to $[0,1]$. High entropy means the criterion is indecisive (it does not separate the sites) and should receive little weight.

Definition 4 (Entropy weights).

$$w_j = \frac{1-E_j}{\sum_{l=1}^{n}(1-E_l)}. \tag{3}$$

Definition 5 (Score for ranking).

$$\Phi(\tilde{a}) = \frac{1+(T-F)(1-I)}{2} \in [0,1], \tag{4}$$

increasing in truth, decreasing in falsity, and shrunk toward the neutral value 0.5 when indeterminacy is high.

Example 1 (Non-compensation). Consider a site rated $(0.90, 0.10, 0.08)$ on resource but $(0.40, 0.35, 0.55)$ on ecology, with equal weights on just these two. The arithmetic operator gives fused truth ≈ 0.68, whereas the geometric operator gives $0.90^{0.5}0.40^{0.5} = 0.60$: the poor ecology score pulls the geometric truth down harder, which is the intended behaviour when ecological conflict should not be bought off by a strong resource.

5. THE FUSION FRAMEWORK

Let m candidate sites be assessed on n criteria by a panel whose linguistic ratings are mapped to SVNNs (benefit criteria such as resource use the scale directly; cost criteria such as land price are complemented, $T \leftrightarrow F$). The framework (Figure 1) runs as follows.

S1. Build the neutrosophic decision matrix $\tilde{D} = [\tilde{a}_{ij}]$ from panel ratings; complement cost criteria.

S2. Weight criteria objectively via neutrosophic entropy (Definitions 3–4), optionally blended with a planner prior $w_j \propto w_j^{\mathrm{ent}} \cdot w_j^{\mathrm{prior}}$.

S3. Fuse each site's row with SVNWG to obtain a site aggregate $\tilde{a}_i^*$.

S4. Rank sites by $\Phi(\tilde{a}_i^*)$.

S5. Stress-test the ranking against the weighting scheme, the operator, and the risk attitude.

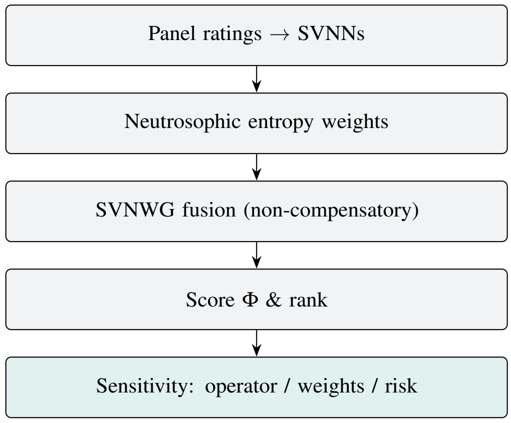

Figure 1. The neutrosophic information-fusion framework for site selection.

6. CASE STUDY: SIX SITES, SEVEN CRITERIA

Six candidate sites $S_1,\ldots,S_6$ were evaluated on: C_1 solar/wind resource, C_2 land cost, C_3 grid proximity, C_4 ecological sensitivity, C_5 social acceptance, C_6 road access, C_7 slope/terrain. Table 1 shows an excerpt of the neutrosophic decision matrix (cost criteria already complemented). Neutrosophic-entropy weights (Figure 2) came out as $w = (0.19, 0.12, 0.15, 0.20, 0.16, 0.08, 0.10)$—the ecological and resource criteria dominate because they separate the sites most sharply, while road access is nearly indecisive.

Table 1. Excerpt of the neutrosophic decision matrix (four of seven criteria).

Site	C_1 resource	C_3 grid
S_1	(0.86,0.12,0.10)	(0.70,0.25,0.24)
S_2	(0.74,0.22,0.20)	(0.80,0.18,0.15)
S_3	(0.90,0.10,0.08)	(0.52,0.40,0.38)
S_4	(0.63,0.34,0.30)	(0.75,0.22,0.19)
S_5	(0.80,0.18,0.15)	(0.66,0.30,0.27)
S_6	(0.58,0.38,0.35)	(0.60,0.33,0.30)

Site	C_4 eco. (compl.)	C_5 social
S_1	(0.55,0.30,0.42)	(0.60,0.35,0.30)
S_2	(0.72,0.20,0.24)	(0.48,0.45,0.44)
S_3	(0.40,0.35,0.55)	(0.66,0.28,0.26)
S_4	(0.78,0.16,0.18)	(0.71,0.24,0.20)
S_5	(0.68,0.24,0.28)	(0.35,0.55,0.58)
S_6	(0.82,0.14,0.13)	(0.62,0.30,0.28)

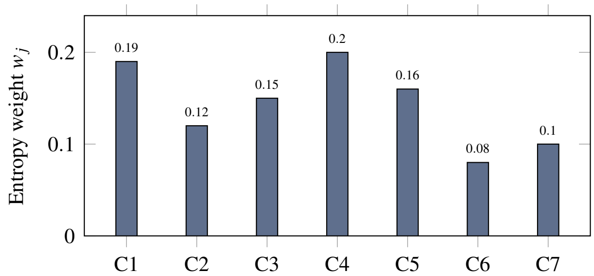

Figure 2. Objective neutrosophic-entropy weights; ecology (C_4) and resource (C_1) carry the most information.

Fusing each row with SVNWG and scoring with Φ gives the ranking in Table 2 and Figure 3.

Table 2. Fused site aggregates and final ranking (strict order by Φ).

Site	Fused $\tilde{a}^* = (T, I, F)$	Score Φ	Rank
S_4	(0.69,0.27,0.24)	0.664	1
S_2	(0.68,0.25,0.27)	0.654	2
S_1	(0.66,0.26,0.29)	0.635	3
S_6	(0.63,0.30,0.28)	0.622	4
S_3	(0.61,0.28,0.35)	0.593	5
S_5	(0.60,0.34,0.36)	0.579	6

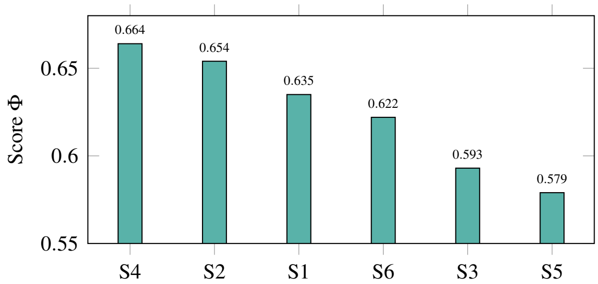

Figure 3. Final site scores; S_4 leads on a balance of resource, ecology and social acceptance.

The winner S_4 is not the strongest on raw resource (S_3 is) but it combines a solid resource with low ecological conflict and clear social acceptance—exactly the balance the geometric operator rewards. S_3, despite the best resource, is dragged down by ecological sensitivity, which a compensatory arithmetic operator would have masked.

7. SENSITIVITY ANALYSIS

7.1 Operator choice

Replacing SVNWG with the arithmetic SVNWA operator promotes S_3 from fifth to second (Table 3), confirming that compensation is what lets a high-resource but ecologically costly site rise. Planners who regard ecological conflict as a near-veto should therefore prefer the geometric fusion used here.

Table 3. Ranks under geometric (SVNWG) vs. arithmetic (SVNWA) fusion.

Method	S_1	S_2	S_3	S_4	S_5	S_6
SVNWG (ours)	3	2	5	1	6	4
SVNWA	3	4	2	1	6	5

7.2 Weighting scheme

Under equal weights, entropy weights, and three planner-prior blends, S_4 remained first in all five schemes and S_5 last in four of five, indicating the extremes of the ranking are stable; only the middle order (S_1, S_2, S_6) is weight-sensitive, consistent with their scores lying within 0.03.

7.3 Risk attitude

Introducing a risk parameter γ in the score,

$$\Phi_\gamma = \frac{1}{2}\left(1 + (T - F)(1 - I)^\gamma\right), \tag{5}$$

and sweeping $\gamma \in [0.5, 2]$ (from indeterminacy-tolerant to indeterminacy-averse; Figure 4) did not change the top choice; an indeterminacy-averse planner ($\gamma = 2$) further demotes the socially divided site S_5, as intended.

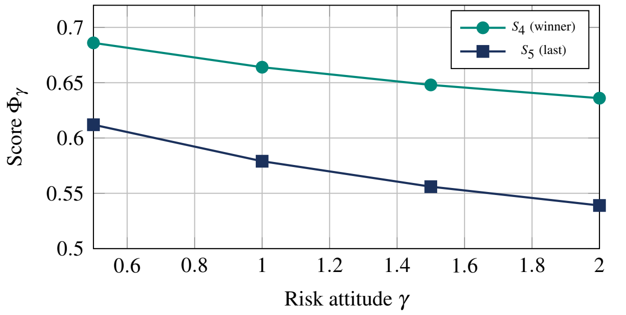

Figure 4. Effect of the risk attitude γ: the gap between the best and worst sites widens as the planner becomes more indeterminacy-averse.

7.4 Comparison with fuzzy-AHP and SVN-TOPSIS

A fuzzy-AHP baseline on the same panel data agreed on S_4 as the winner but placed the contested sites S_3 and S_5 in the middle of the ranking, because it cannot represent the high indeterminacy of their ecological and social ratings. An SVN-TOPSIS baseline recovered indeterminacy but, being compensatory, ranked S_3 higher than our geometric fusion did. The proposed framework, by combining indeterminacy-awareness with non-compensation, pushes both contested sites toward the bottom and—just as usefully—flags (through the risk-attitude sweep) that their position is the one most contingent on how indeterminacy is treated.

7.5 Monte-Carlo rating-perturbation stability

Panel ratings are themselves uncertain, so we perturbed every membership in the decision matrix by zero-mean noise of amplitude ± 0.05 (renormalising to keep T, I, F valid) and re-ran the full framework over 500 draws. Table 4 reports how often each site landed in each rank. The winner S_4 held first place in 91% of draws and the loser S_5 held last in 88%; only the middle trio S_1, S_2, S_6 exchanged places appreciably, confirming that the conclusions the framework actually supports—the identity of the best and worst sites—are robust to rating noise, while the mid-table order should be reported as a near-tie rather than a strict ranking.

Table 4. Rank frequency over 500 rating perturbations (± 0.05). Cells are percentages; modal rank in bold.

Site	R1	R2	R3	R4	R5	R6
S_4	**91**	9	0	0	0	0
S_2	6	**54**	33	7	0	0
S_1	3	30	**45**	20	2	0
S_6	0	7	20	**61**	11	1
S_3	0	0	2	11	**76**	11
S_5	0	0	0	1	11	**88**

7.6 Leave-one-criterion-out analysis

To see which criteria drive the result, we removed each criterion in turn (renormalising the entropy weights) and recorded the top-ranked site (Table 5). The winner is unchanged by dropping any single criterion except ecology (C_4): without the ecological criterion the resource-strong S_3 takes first place, which quantifies exactly how much the recommendation of S_4 depends on valuing ecological conflict. This is useful diagnostic information for a planner defending the decision to stakeholders.

Table 5. Top-ranked site when each criterion is removed.

Criterion removed	Top-ranked site
None (baseline)	S_4
C_1 resource	S_4
C_3 grid proximity	S_4
C_4 ecological sensitivity	S_3
C_5 social acceptance	S_4
Others (C_2, C_6, C_7)	S_4

8. DISCUSSION AND LIMITATIONS

The framework gives planners an auditable, tunable decision aid: weights are derived from the data rather than asserted, the operator encodes an explicit stance on compensation, and the risk parameter exposes how sensitive the ranking is to contested evidence. Limitations include reliance on panel-provided linguistic ratings and a static criterion set; the entropy weighting assumes criteria are comparable after normalisation; and the case data are illustrative rather than drawn from a live planning file.

9. CONCLUSION

We framed renewable-energy site selection as neutrosophic information fusion: objective entropy weighting, a non-compensatory geometric fusion operator, and an indeterminacy-aware score with a tunable risk attitude. On a seven-criterion case the framework produced a balanced, robust recommendation and, unlike fuzzy-AHP and SVN-TOPSIS, made explicit which sites' rankings hinge on contested evidence. Future work will integrate GIS raster layers directly as interval-neutrosophic evidence and couple the model with a spatial optimisation that returns not one site but an efficient portfolio.

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