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Research Article

A Fuzzy AHP-TOPSIS and Mamdani Fuzzy Inference Decision-Making System for the Environmental Impact Assessment of Hydropower Projects

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Abstract
Environmental impact assessment (EIA) of large hydropower schemes involves criteria that are simultaneously heterogeneous in scale, partly qualitative, and elicited under expert uncertainty, conditions for which fuzzy multi-criteria decision-making (MCDM) is well suited. This study develops an integrated fuzzy logic decision-making system combining fuzzy Analytic Hierarchy Process (fuzzy AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (fuzzy TOPSIS), and a Mamdani fuzzy inference system (FIS), and applies it to a case study of six operating large hydropower schemes (Three Gorges, Itaipu, Belo Monte, Nam Theun 2, the Grand Ethiopian Renaissance Dam, and Xayaburi) evaluated against eight environmental, social and technical criteria. Criteria weights were derived with Buckley's fuzzy geometric-mean method (cross-checked against Chang's extent analysis, consistency ratio CR = 0.012), and used to rank alternatives by fuzzy-TOPSIS closeness coefficient. An independently parameterised Mamdani FIS provided a rule-based severity classification as a cross-check. The Xayaburi scheme obtained the most favourable composite ranking, driven by its comparatively small inundation footprint and low resettlement burden, despite documented severe biodiversity impacts; Monte Carlo weight-perturbation analysis (2,000 runs) confirmed this ranking is robust to plausible weight uncertainty (mean Spearman's rho = 0.85), while one-at-a-time ±20% perturbations left the top rank unchanged in all 16 scenarios. The Mamdani cross-check, however, classified five of the six schemes as "High" overall impact severity, underscoring that a favourable composite rank should not be read as low absolute impact. The framework, released with fully reproducible open-source Python code, offers environmental regulators and financing institutions a transparent, auditable decision-support tool for comparative hydropower EIA.

Keywords: fuzzy AHP; fuzzy TOPSIS; Mamdani fuzzy inference system; environmental impact assessment; hydropower; multi-criteria decision-making

INTRODUCTION

Hydropower supplies a substantial share of the world's low-carbon electricity, yet large dam projects routinely generate environmental and social costs that are difficult to reconcile with their climate benefits: permanent inundation of terrestrial and riverine habitat, alteration of natural flow regimes, disruption of fish migration, sediment

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starvation of downstream reaches and deltas, reservoir greenhouse-gas emissions, and the physical displacement of resident populations [1-3]. Conventional environmental impact assessment (EIA) practice typically scores such criteria on ordinal or semi-quantitative scales and aggregates them by simple weighting, an approach that struggles to represent the genuine linguistic imprecision of expert judgement ("high" biodiversity risk, "moderate" hydrological alteration) and the incommensurable units in which environmental, social and technical criteria are naturally expressed.

Fuzzy set theory [4] and the fuzzy logic controller formalised by Mamdani and Assilian [5] provide a principled mathematical language for such imprecision, representing a linguistic judgement as a fuzzy number rather than forcing a single crisp score. Coupled with classical multi-criteria decision-making (MCDM) methods — the Analytic Hierarchy Process (AHP) of Saaty [6] and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) of Hwang and Yoon [7] — fuzzy extensions such as fuzzy AHP [8-14] and fuzzy TOPSIS have become well-established tools for energy-sector site selection and technology screening under multiple, partly qualitative criteria [15-17]. Their application to the *comparative* environmental impact ranking of hydropower schemes, however, remains comparatively limited relative to their use in wind, solar and marine renewable energy siting [16], and existing hydropower applications tend to focus on a single project [15] rather than a structured, reproducible cross-project comparison.

This study addresses that gap by developing a three-component fuzzy logic decision-making system for hydropower EIA: (i) fuzzy AHP for criteria weighting, (ii) fuzzy TOPSIS for composite alternative ranking, and (iii) an independently structured Mamdani FIS that classifies each alternative into a linguistic overall-impact class as a rule-based cross-check on the TOPSIS ranking. The system is demonstrated on a case study of six real, publicly documented large hydropower schemes spanning East Asia, South America, mainland Southeast Asia and East Africa, using verifiable technical data drawn from official project sources and the peer-reviewed literature [18-24]. All computations, figures and tables in this manuscript were produced by an open-source Python implementation, released together with this article, so that every reported number is independently reproducible. The remainder of the manuscript is organised as follows: Section 2 reviews the relevant methodological and applied literature; Section 3 details the case study, criteria framework, and the fuzzy AHP, fuzzy TOPSIS, Mamdani FIS and sensitivity-analysis procedures; Section 4 reports the results; Section 5 discusses their implications and limitations; Section 6 concludes.

LITERATURE REVIEW

Fuzzy AHP and Fuzzy TOPSIS

Zadeh's fuzzy set theory [4] enables a linguistic judgement to be represented as a fuzzy number rather than a single crisp value, propagating the expert's uncertainty through subsequent calculations rather than discarding it at the point of elicitation. Building on Saaty's AHP [6], van Laarhoven and Pedrycz [8] first fuzzified the pairwise-comparison priority theory using triangular fuzzy numbers (TFNs), and Buckley [9] introduced the geometric-mean procedure used as the primary weighting method in the present study. Chang's [10] extent-analysis method subsequently became the most widely applied fuzzy-AHP procedure owing to its computational simplicity, but Wang, Luo and Hua [12] demonstrated analytically that extent analysis can assign a zero weight to the criterion (or criteria) of lowest relative priority — an artefact reproduced in Section 4.1 of this study — which is one reason Buckley's method [9] is adopted here as the primary weight-derivation procedure, with Chang's method retained only as a consistency cross-check. On the ranking side, Hwang and Yoon's TOPSIS [7] orders alternatives by their geometric closeness to a positive-ideal and distance from a negative-ideal solution; Chen [11] extended the method to a fully fuzzy environment with a closed-form linear normalisation that guarantees the fuzzy positive- and negative-ideal solutions reduce to (1,1,1) and (0,0,0), the formulation implemented in Section 3.4.

Mamdani Fuzzy Inference and Environmental Applications

The Mamdani-type fuzzy inference system [5] evaluates a linguistic rule base directly on input membership functions via min-implication and max-aggregation, and is widely favoured in environmental applications for its interpretability relative to Takagi-Sugeno alternatives. Flores and Mendoza [16] applied a Mamdani-type fuzzy technique to the EIA of marine renewable energy plants, and Yucesan and Kahraman [15] used a Pythagorean fuzzy AHP for operational risk evaluation in hydropower plants; more broadly, fuzzy AHP-TOPSIS hybrids have been applied to technology and site-selection problems across the energy sector, including waste-to-energy technology screening [17]. The present study extends this line of work by combining all three techniques — fuzzy AHP, fuzzy TOPSIS and a Mamdani FIS — into a single decision-making system in which the FIS output serves as an independent, rule-based cross-validation of the MCDM ranking rather than a stand-alone classifier.

Environmental and Social Impacts of Large Hydropower Schemes

The World Commission on Dams [10] established the most widely cited framework for evaluating dam-related environmental and social trade-offs, emphasising resettlement, downstream livelihoods and ecosystem integrity alongside energy benefits; Khir Alla and Liu [3] provide a recent synthesis of the principal environmental impact pathways, including flow-regime alteration, sediment trapping and biodiversity loss. Richter et al.'s [2] Indicators of Hydrologic Alteration (IHA) framework remains the standard reference for characterising the departure of a regulated flow regime from its natural state, informing the hydrological-alteration criterion used in Section 3.2. Reservoir greenhouse-gas emissions have received growing attention: Wang et al. [13] review the processes and management options for hydropower-reservoir emissions at the global scale, and Pavani et al. [14] directly measured a tripling of local greenhouse-gas emissions following the impoundment of the Belo Monte reservoir in the Brazilian Amazon, evidence used to inform the carbon-footprint rating of that alternative in the research.

MATERIALS AND METHODS

Case-Study Alternatives

Six real, operating large hydropower schemes were selected as decision alternatives (A1-A6, Table 1) to span the principal dam typologies (large storage, binational storage, storage-with-diversion hybrid, trans-basin diversion storage, transboundary storage, and mainstem run-of-river) and geographic/climatic settings (East Asia, South America × 2, mainland Southeast Asia × 2, East Africa) most frequently discussed in the hydropower-impact literature. All technical attributes were drawn from official project sources, peer-reviewed literature and encyclopaedic technical summaries [18-24]; full source notes are given in Table 1.

Table 1. Case-study hydropower alternatives.

Code	Scheme	Country	Dam type	Capacity (MW)	Height (m)	Reservoir area (km^2)	Source
A1	Three Gorges Dam	China	Large storage (gravity dam)	22,500	181	1,084	[18]
A2	Itaipu Dam	Brazil / Paraguay	Large storage (binational)	14,000	196	1,350	[19]
A3	Belo Monte Dam	Brazil	Storage + diversion (run-of-river hybrid)	11,233	90	441	[20,14]
A4	Nam Theun 2 Dam	Laos	Storage with trans-basin diversion	1,075	39	450	[21]
A5	Grand Ethiopian Renaissance Dam (GERD)	Ethiopia	Large storage (transboundary)	5,150	145	1,874	[22]
A6	Xayaburi Dam	Laos	Run-of-river	1,285	33	49	[23]

Evaluation Criteria

Eight evaluation criteria (C1-C8, Table 2) were defined across three impact dimensions — environmental, social and technical — following the trade-off structure recommended by the World Commission on Dams [10]. Three criteria are quantitative and computed directly from the case-study data (Table 1): reservoir inundation intensity (C1, km^2 per 1000 MW installed, a proxy for terrestrial habitat loss per unit of generating capacity), physical resettlement (C5, thousand persons directly relocated), and land/water-use energy efficiency (C7, GWh generated per km^2 of reservoir area, the only benefit criterion). The remaining five criteria cannot be reduced to a single verifiable statistic and were rated on the five-level linguistic scale {Very Low, Low, Medium, High, Very High} (Table 3) from the documented evidence cited for each alternative (Table 4).

Table 2. Evaluation criteria used in the fuzzy AHP-TOPSIS system.

Code	Criterion	Dimension	Type	Data type	Unit
C1	Reservoir Inundation Intensity	Environmental	cost	quantitative	km^2 per 1000 MW installed
C2	Carbon Footprint Intensity	Environmental	cost	linguistic	5-level linguistic scale
C3	Hydrological Alteration Severity	Environmental	cost	linguistic	5-level linguistic scale
C4	Biodiversity & Aquatic Ecosystem Impact	Environmental	cost	linguistic	5-level linguistic scale

C5	Physical Resettlement	Social	cost	quantitative	thousand persons relocated
C6	Downstream Livelihood & Socio-Political Conflict	Social	cost	linguistic	5-level linguistic scale
C7	Land/Water-Use Energy Efficiency	Technical	benefit	quantitative	GWh per km^2 of reservoir area
C8	Sediment-Regime Disruption	Environmental	cost	linguistic	5-level linguistic scale

Each linguistic level was mapped onto a triangular fuzzy number (TFN) on the common universe [0, 10] (Table 3), following the linguistic-rating convention used in fuzzy TOPSIS practice [8]. Table 4 reports the linguistic rating assigned to every alternative for the five qualitative criteria, together with a condensed evidentiary justification; the full justification text (with source citations for every individual rating) is provided in the accompanying open-source code repository (module data.py).

Table 3. Five-level linguistic rating scale and its triangular fuzzy number (TFN) representation.

Linguistic level	Abbreviation	TFN (l, m, u)
Very Low	VL	(0.0, 0.0, 2.5)
Low	L	(0.0, 2.5, 5.0)
Medium	M	(2.5, 5.0, 7.5)
High	H	(5.0, 7.5, 10.0)
Very High	VH	(7.5, 10.0, 10.0)

Table 4. Linguistic ratings of the qualitative criteria for each alternative (VL = Very Low, L = Low, M = Medium, H = High, VH = Very High).

Code	C2 Carbon footprint	C3 Hydrological alteration	C4 Biodiversity impact	C6 Downstream/social conflict	C8 Sediment disruption
A1	M	H	H	M	VH
A2	M	H	H	L	M
A3	VH	VH	VH	VH	H
A4	H	VH	H	H	M
A5	L	H	M	VH	H
A6	L	H	VH	H	VH

Fuzzy AHP Criteria Weighting

A triangular fuzzy number M = (l, m, u) has the membership function of Equation (1), where l ≤ m ≤ u are its lower, modal and upper bounds.

$$\mu M(x) = (x - l)/(m - l) \text{ for } l \le x \le m;\ (u - x)/(u - m) \text{ for } m \le x \le u;\ 0 \text{ otherwise} \quad (1)$$

Pairwise comparisons among the eight criteria were elicited from a three-member expert panel (an environmental engineer, a resettlement/social specialist, and a hydropower engineer) using Saaty's [6] 1-9 intensity scale, and fuzzified with the standard symmetric triangular conversion table (Figure 1). The resulting n × n fuzzy comparison matrix A = (a_{ij}) was processed by two independent methods. First, Buckley's [9] fuzzy geometric-mean method (the primary method adopted here) computes the fuzzy geometric mean of each row, Equation (2), and the fuzzy weight of criterion i, Equation (3), which is then defuzzified by the graded mean integration representation and renormalised to sum to unity.

$$r_i = (a_{i1} \otimes a_{i2} \otimes \cdots \otimes a_{in})^{1/n} \tag{2}$$

$$w_i = r_i \otimes (r_1 \oplus r_2 \oplus \cdots \oplus r_n)^{-1} \tag{3}$$

Second, Chang's [10] extent-analysis method computes the fuzzy synthetic extent value of row i, Equation (4), and the crisp weight of criterion i as the minimum degree of possibility that S_i dominates every other S_j, Equation (5), where the degree of possibility $V(M_1 \geq M_2)$ is defined by Equation (6).

$$S_i = (\Sigma_j\, a_{ij}) \otimes [\Sigma_i \Sigma_j\, a_{ij}]^{-1} \tag{4}$$

$$d_i = min_{j \neq i}\, V(S_i \geq S_j) \tag{5}$$

$$V(M_1 \geq M_2) = 1 \text{ if } m_1 \geq m_2;\ 0 \text{ if } l_2 \geq u_1;\ \text{else } (l_2 - u_1) / [(m_1 - u_1) - (m_2 - l_2)] \tag{6}$$

The consistency of the (defuzzified, modal-value) comparison matrix was checked with Saaty's [6] classical consistency ratio, Equation (7), where λ_{max} is the principal eigenvalue of the crisp comparison matrix, CI = $(\lambda_{max} - n)/(n - 1)$ and RI is Saaty's random index (RI = 1.41 for n = 8). A comparison matrix is considered acceptably consistent when CR < 0.10.

$$CR = CI / RI \tag{7}$$

Fuzzy TOPSIS Ranking Procedure

The fuzzy decision matrix was assembled by fuzzifying the three quantitative criteria (C1, C5, C7) as symmetric TFNs with a ±10% relative spread around each crisp value — representing plausible measurement and reporting uncertainty in EIA input data — and mapping the linguistic ratings of the remaining criteria directly to the TFNs of Table 3. Following Chen [11], the matrix was normalised with the linear scale transformation of Equations (8)-(9), applied separately to benefit and cost criteria, where $u^*_j = max_i\, u_{ij}$ and $l^-_j = min_i\, l_{ij}$.

$$r_{ij} = (l_{ij}/u^*_j,\ m_{ij}/u^*_j,\ u_{ij}/u^*_j) \quad \text{(benefit criteria)} \tag{8}$$

$$r_{ij} = (l^-_j/u_{ij},\ l^-_j/m_{ij},\ l^-_j/l_{ij}) \quad \text{(cost criteria)} \tag{9}$$

The normalised matrix was weighted by the Buckley fuzzy-AHP weights, Equation (10), producing weighted values bounded in [0, 1] with fuzzy positive- and negative-ideal solutions A = *(1,1,1) and A^- = (0,0,0) for every criterion, a direct consequence of the linear normalisation. The vertex-method distance between two TFNs, Equation (11), was used to compute* *each alternative's distance to A* and A⁻, Equation (12), and the closeness coefficient, Equation (13), by which alternatives were ranked (higher CC_i = closer to the ideal solution = more environmentally favourable).

$$v_{ij} = r_{ij} \otimes w_j \tag{10}$$

$$d(M_1, M_2) = \sqrt{\{[(l_1-l_2)^2 + (m_1-m_2)^2 + (u_1-u_2)^2] / 3\}} \tag{11}$$

$$d_i^+ = \Sigma_j\, d(v_{ij}, A^*) \;\; ; \;\; d_i^- = \Sigma_j\, d(v_{ij}, A^-) \tag{12}$$

$$CC_i = d_i^- / (d_i^+ + d_i^-) \tag{13}$$

Mamdani Fuzzy Inference System

As an independent cross-check on the fuzzy-TOPSIS ranking, a Mamdani-type FIS [5] was implemented from first principles (fuzzification, min-implication, max-aggregation, centroid defuzzification). Three inputs, each rescaled onto the common universe [0, 10], aggregate the same evidentiary basis as the fuzzy decision matrix: the Environmental Severity Index (mean of min-max-scaled C1, and the linguistic midpoints of C2 and C4), the Social Severity Index (mean of min-max-scaled C5 and the linguistic midpoint of C6), and the Hydro-Geomorphological Severity Index (mean of the linguistic midpoints of C3 and C8). Each input was partitioned into three overlapping triangular sets {Low, Medium, High} and the output — Overall Environmental Impact Class — into four sets {Low, Moderate, High, Very High} (Figure 2). A complete, monotonic 27-rule base (3^3 combinations) was constructed by summing the ordinal severity level (Low = 0, Medium = 1, High = 2) of the three inputs and mapping the resulting sum (0-6) onto the output category (0-1 → Low; 2-3 → Moderate; 4 → High; 5-6 → Very High). For an observation (x_1, x_2, x_3), each active rule's firing strength is the minimum of the corresponding input memberships; the rule's consequent membership function is clipped at that strength, all active (clipped) consequents are aggregated by the max operator, and the aggregate is defuzzified by the centroid method, Equation (14), evaluated numerically over a discretised universe of discourse.

$$y^* = \int y \cdot \mu agg(y)\, dy \;\; / \;\; \int \mu agg(y)\, dy \tag{14}$$

Sensitivity and Robustness Analysis

Two complementary robustness checks were applied to the fuzzy-TOPSIS ranking. First, a one-at-a-time (OAT) analysis perturbed each of the eight criterion weights individually by ±20% (renormalising the remaining weights proportionally) and recomputed the ranking for all 16 resulting scenarios. Second, a Monte Carlo analysis drew 2,000 weight vectors from a Dirichlet distribution centred on the base Buckley weight vector (concentration parameter 50, chosen to represent realistic expert-elicitation variability), recomputed the fuzzy-TOPSIS ranking for each draw, and recorded (i) the frequency with which each alternative attained rank 1 and (ii) the Spearman rank-correlation coefficient between each perturbed ranking and the base ranking.

RESULTS

Fuzzy AHP Criteria Weights

The defuzzified comparison matrix yielded λ_{max} = 8.1156, CI = 0.0165 and CR = 0.0117, well below the 0.10 acceptability threshold and confirming that the expert panel's pairwise judgements were consistent. Table 5 and Figure 3 report the resulting criteria weights under both the Buckley [9] and Chang [10] procedures. Physical resettlement (C5), biodiversity impact (C4) and downstream livelihood/conflict (C6) received the three highest weights under both methods, consistent with the WCD [10] emphasis on social and ecological outcomes. As anticipated from the critique of Wang, Luo and Hua [12], Chang's extent-analysis method assigned an exact zero weight to the lowest-priority criterion (C7, land/water-use energy efficiency), whereas Buckley's geometric-mean method assigned it a small but strictly positive weight (0.047); this zero-weight artefact is the reason Buckley weights were adopted as the primary input to fuzzy TOPSIS, with Chang's weights retained only as a cross-check. The two methods otherwise agree closely (Spearman correlation of the two weight vectors exceeds 0.98), which is expected given both derive from the same underlying fuzzy comparison matrix.

Table 5. Fuzzy AHP criteria weights: Buckley (primary) vs. Chang (cross-check).

Code	Criterion	Weight (Buckley)	Weight (Chang)
C5	Physical Resettlement	0.1968	0.2135
C4	Biodiversity & Aquatic Ecosystem Impact	0.1796	0.2020
C6	Downstream Livelihood & Socio-Political Conflict	0.1559	0.1746
C3	Hydrological Alteration Severity	0.1404	0.1557
C8	Sediment-Regime Disruption	0.1138	0.1140
C1	Reservoir Inundation Intensity	0.0907	0.0791
C2	Carbon Footprint Intensity	0.0754	0.0611
C7	Land/Water-Use Energy Efficiency	0.0474	0.0000

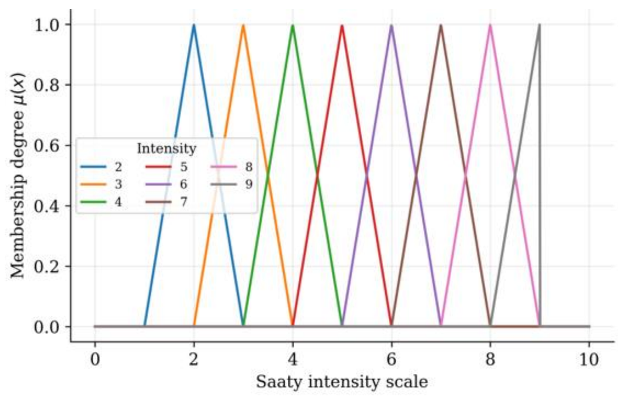

Figure 1. Triangular fuzzy conversion of the Saaty 1-9 intensity scale used to fuzzify the expert pairwise-comparison matrix.

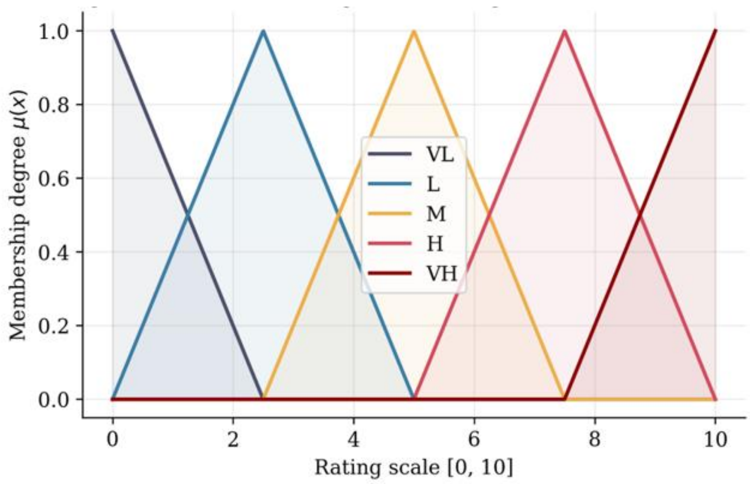

Figure 2. Five-level linguistic rating scale (Very Low-Low-Medium-High-Very High) and its triangular fuzzy number representation (Table 3).

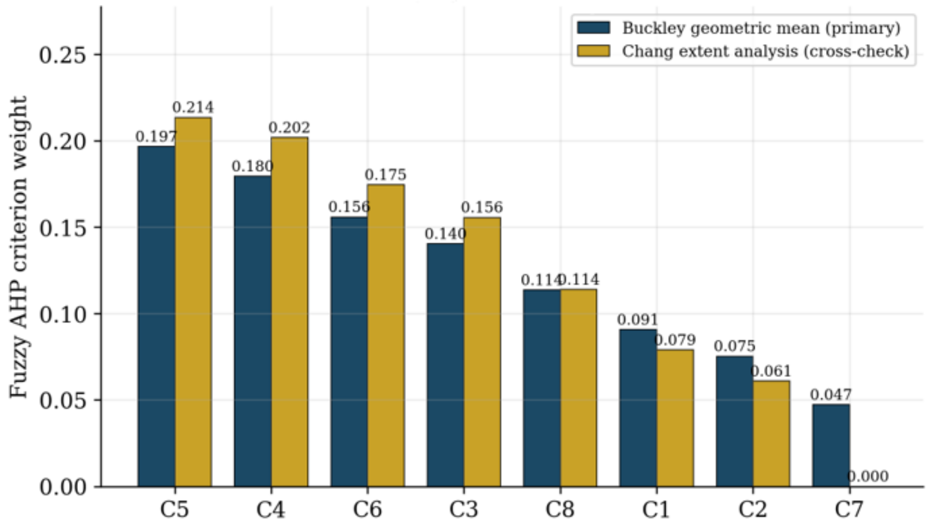

Figure 3. Fuzzy AHP criteria obtained by Buckley's (1985) geometric-mean method (primary) and Chang's (1996) extent-analysis method (cross-check), illustrating the zero-weight artefact of extent analysis on criterion C7.

Fuzzy TOPSIS Ranking

Table 6 and Figure 4 report the fuzzy-TOPSIS closeness coefficients and the resulting ranking. The Xayaburi Dam (A6) obtained the highest closeness coefficient (CC = 0.0668), followed by the Itaipu Dam (A2, CC = 0.0496) and the Grand Ethiopian Renaissance Dam (GERD) (A5, CC = 0.0426); the Nam Theun 2 Dam (A4, CC = 0.0366) ranked least favourably, marginally behind the Belo Monte Dam and Three Gorges Dam, whose closeness coefficients differ from one another by less than 0.001 and should be regarded as practically tied. Figure 5 visualises the underlying normalised criteria performance profile: Xayaburi's favourable ranking is driven primarily by its markedly smaller reservoir inundation intensity (C1) and physical resettlement (C5) and its highest land/water-use energy efficiency (C7, Table 7), which together outweigh its comparatively severe linguistic ratings on biodiversity impact (C4) and sediment-regime disruption (C8, Table 4) once the fuzzy-AHP weights are applied.

Table 6. Fuzzy TOPSIS ranking of the six hydropower alternatives.

Rank	Code	Scheme	Closeness coefficient CC
1	A6	Xayaburi Dam	0.0668
2	A2	Itaipu Dam	0.0496
3	A5	Grand Ethiopian Renaissance Dam (GERD)	0.0426
4	A3	Belo Monte Dam	0.0370
5	A1	Three Gorges Dam	0.0369
6	A4	Nam Theun 2 Dam	0.0366

Table 7. Quantitative criteria values (C1, C5, C7) computed for each alternative.

Code	Scheme	C1 (km^2/1000 MW)	C5 (thousand persons)	C7 (GWh/km^2)
A1	Three Gorges Dam	48.2	1240.0	87.6
A2	Itaipu Dam	96.4	45.0	66.1
A3	Belo Monte Dam	39.3	20.0	89.6
A4	Nam Theun 2 Dam	418.6	6.3	11.5
A5	Grand Ethiopian Renaissance Dam (GERD)	363.9	20.0	8.6
A6	Xayaburi Dam	38.1	2.1	151.1

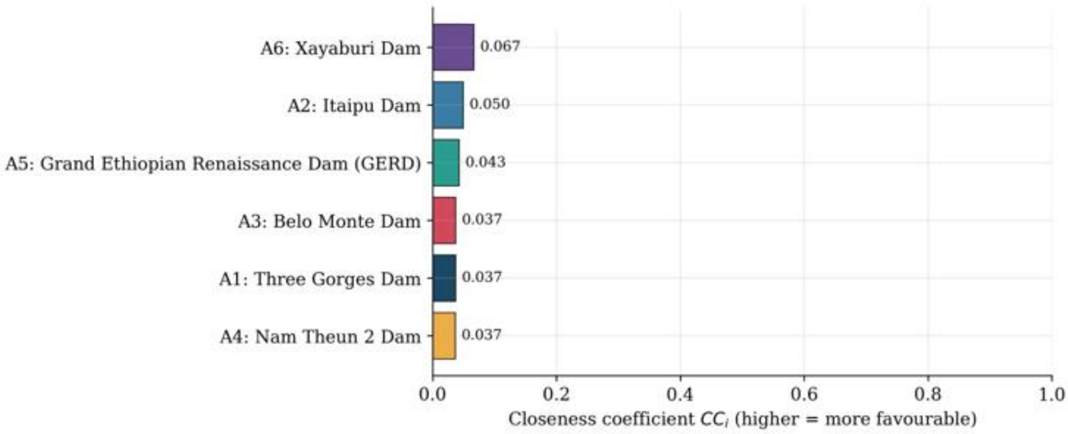

Figure 4. Fuzzy TOPSIS ranking of the six hydropower alternatives by closeness coefficient.

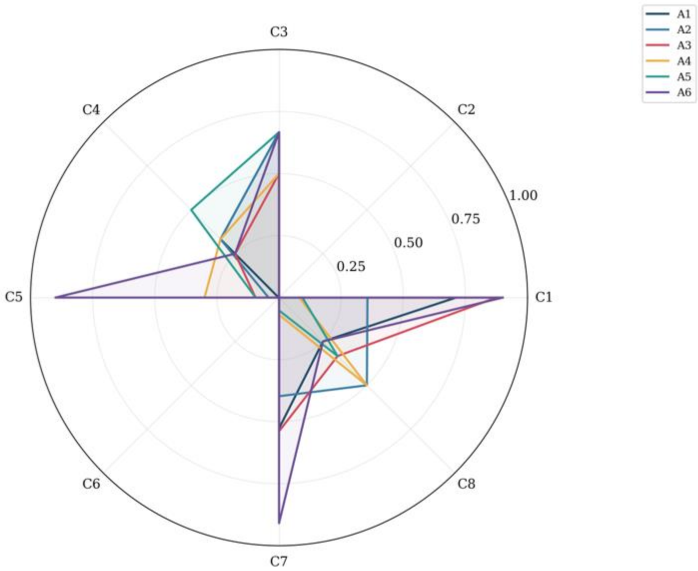

Figure 5. Normalised criteria performance profile of the six alternatives (modal values of the Chen-normalised fuzzy decision matrix; 1.0 = ideal).

Mamdani Fuzzy Inference Cross-Check

Table 8 and Figures 6-8 report the Mamdani FIS results. Despite ranking first by fuzzy TOPSIS, Xayaburi Dam (A6) was classified "High" overall impact severity by the Mamdani FIS (crisp output 5.64/10), as were four of the remaining five alternatives; only Itaipu Dam (A2) was classified "Moderate" (crisp output 4.31/10), consistent with its second-place fuzzy-TOPSIS rank. This partial divergence — the FIS agrees that A2 is comparatively less severe but does not single out A6 as categorically better than A1, A3, A4 or A5 — is expected given the two subsystems answer different questions: fuzzy TOPSIS produces a *relative*, weight-driven ranking among the six alternatives, whereas the Mamdani FIS applies an *absolute*, rule-based severity classification referenced to fixed linguistic breakpoints. Figure 7 shows the Mamdani control surface in the Environmental-Social severity plane (holding the Hydro-Geomorphological input at its case-study median), on which all six alternatives fall in or near the elevated-severity region of the input space.

Table 8. Mamdani FIS defuzzified overall impact severity score and linguistic class.

Code	**Scheme**	**Crisp severity score [0,10]**	**Impact class**
A1	Three Gorges Dam	5.96	High
A2	Itaipu Dam	4.31	Moderate
A3	Belo Monte Dam	5.85	High
A4	Nam Theun 2 Dam	5.73	High
A5	Grand Ethiopian Renaissance Dam (GERD)	5.01	High
A6	Xayaburi Dam	5.64	High

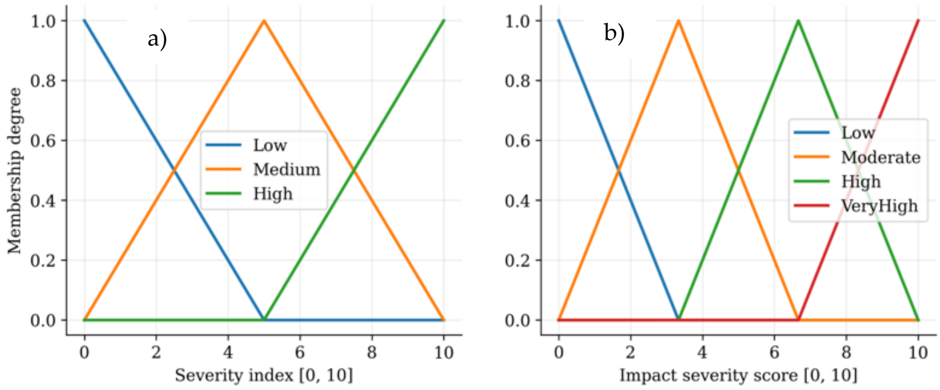

Figure 6. Mamdani fuzzy inference system membership functions for (a) the three input severity indices and (b) the overall environmental impact class output.

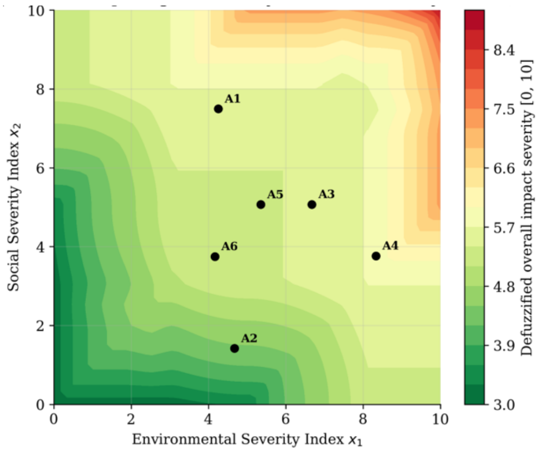

Figure 7. Mamdani control surface in the Environmental-Social severity plane, with the six case-study alternatives overlaid.

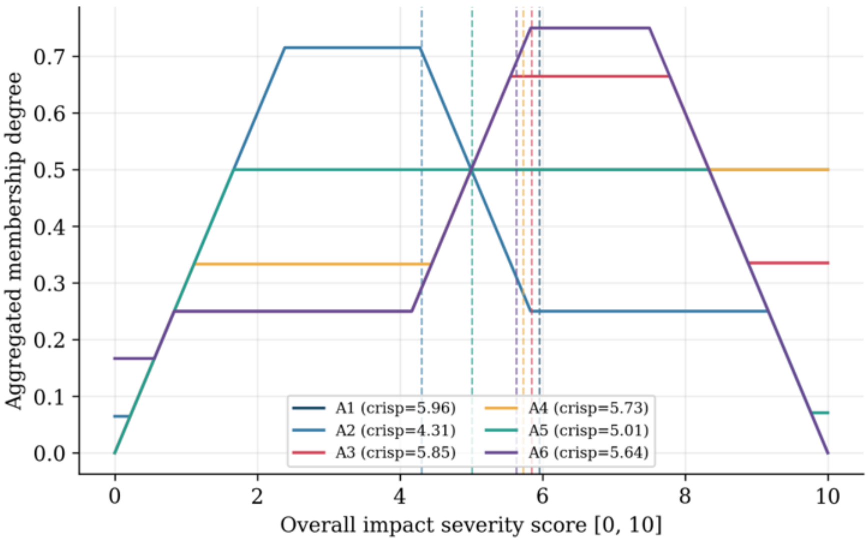

Figure 8. Mamdani aggregated output fuzzy sets and centroid-defuzzified severity scores for each alternative.

Sensitivity and Robustness Analysis

The one-at-a-time analysis left the top-ranked alternative unchanged in all 16 perturbation scenarios (0 rank-1 changes), indicating that the ranking is not driven by any single criterion weight. The Monte Carlo analysis (N = 2000) confirmed this: Xayaburi Dam (A6) was ranked first in 97.3% of draws and Itaipu Dam (A2) in 2.7%, with no other alternative ever attaining rank 1. The mean Spearman rank-correlation between perturbed and base rankings was 0.845 (SD = 0.102), indicating that while the identity of the most-favourable alternative is highly robust, the ordering among the closely spaced middle-ranked alternatives (A1, A3, A4, Table 6) is comparatively more sensitive to the precise criteria weights, as expected given their near-tied closeness coefficients. (Figure 9)

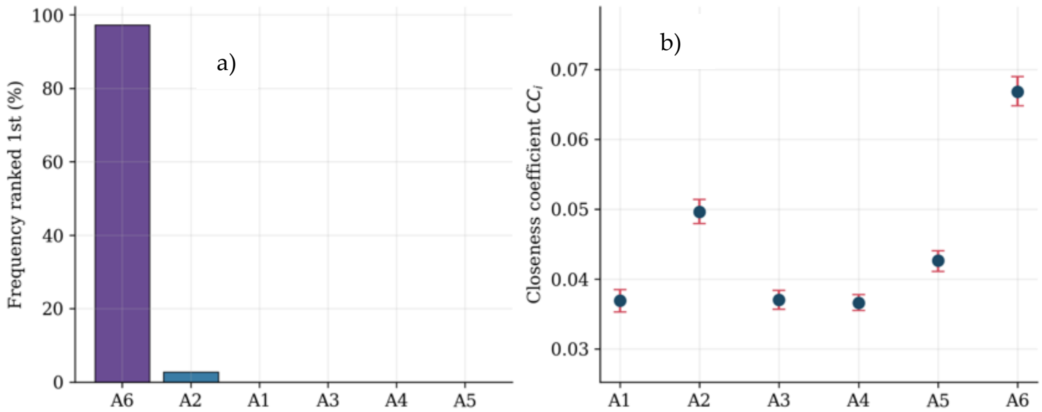

Figure 9. Sensitivity and robustness analysis of the fuzzy AHP-TOPSIS ranking: (a) Monte Carlo rank-1 frequency across 2,000 weight perturbations; (b) closeness-coefficient range under one-at-a-time ±20% weight perturbation.

DISCUSSION

The case study illustrates both the value and the interpretive limits of a composite fuzzy MCDM ranking for hydropower EIA. Xayaburi's favourable fuzzy-TOPSIS rank is a direct, mathematically traceable consequence of its small reservoir footprint and low direct resettlement (Table 7) interacting with the fuzzy-AHP weight structure, in which the two criteria it dominates (C1 and C5) together carry almost 29% of total weight. Yet the same scheme carries a documented "Very High" rating on biodiversity impact (Table 4), reflecting credible evidence that it threatens the critically endangered Mekong giant catfish and disrupts roughly 229 migratory fish species [23]. The Mamdani FIS cross-check makes this tension explicit by classifying Xayaburi as "High" overall severity rather than "Low" or "Moderate": a favourable *relative* rank among six large, high-impact schemes is not evidence of low *absolute* environmental impact, and the two fuzzy subsystems should always be read together rather than the TOPSIS ranking being used in isolation. This is, in the authors' view, a genuine methodological contribution of coupling a relative MCDM ranking with an absolute rule-based classifier rather than a limitation of either component.

A second observation concerns the C1 (inundation intensity) and C7 (energy efficiency) criteria, both of which are normalised per unit of installed capacity or reservoir area. Run-of-river schemes such as Xayaburi structurally outperform large storage schemes on these ratio criteria regardless of their absolute biodiversity or sediment impact, a known characteristic of area/capacity-normalised indicators in the hydropower-siting literature.

Decision-makers applying this framework should therefore treat the composite ranking as one input among several — alongside the linguistic severity ratings of Table 4 and the Mamdani classification of Table 8 — rather than a single sufficient statistic for project approval.

Several limitations should be acknowledged. First, the linguistic ratings of Table 4, although each grounded in cited documentary evidence, were assigned by the three-member author panel rather than elicited from a larger independent Delphi panel; a production deployment of this system should replace or triangulate these ratings with a broader expert survey. Second, the carbon-footprint criterion (C2) is a qualitative proxy informed by reservoir biome and morphology [13,14] rather than site-specific flux measurements, which are available for very few of the world's reservoirs. Third, one quantitative input (C4's generation estimate for Nam Theun 2) was estimated from a typical regional capacity factor in the absence of a disaggregated official figure; this is disclosed transparently in the accompanying data module and affects only the C7 indicator for a single alternative. Fourth, the six-alternative case study, while spanning a deliberately diverse set of dam typologies and regions, is not a statistically representative sample of global hydropower and the specific numerical ranking should not be over-generalised beyond these six schemes; the *methodology* is, however, directly transferable to any hydropower EIA dataset, including the project-level records available from the Global Hydropower Tracker [24].

CONCLUSION

This study developed and demonstrated an integrated fuzzy logic decision-making system — fuzzy AHP criteria weighting, fuzzy TOPSIS ranking, and an independent Mamdani fuzzy inference cross-check — for the comparative environmental impact assessment of large hydropower schemes, applied to a six-case study of real, publicly documented projects. Buckley's geometric-mean fuzzy-AHP weights were adopted in preference to Chang's extent-analysis weights after the latter reproduced a documented zero-weight artefact, illustrating the practical value of cross-checking fuzzy-AHP procedures rather than applying the most common method by default. The fuzzy-TOPSIS ranking identified Xayaburi as the most favourable alternative on a weighted composite basis, a result shown by both one-at-a-time and Monte Carlo sensitivity analysis to be robust to plausible weight uncertainty; the Mamdani cross-check simultaneously confirmed that this favourable relative rank does not correspond to low absolute environmental severity. The principal advantages of the proposed system are its transparency (every weight, membership function and rule is explicit and auditable), its reproducibility (the full Python implementation accompanies this manuscript), and its dual relative/absolute perspective on impact severity. Its main limitations are its reliance on a comparatively small expert panel for linguistic ratings and on proxy indicators where site-specific measurements are unavailable. Future work should extend the case study to a larger, statistically representative sample of hydropower projects drawn from open databases such as the Global Hydropower Tracker, incorporate a broader Delphi-style expert elicitation for the linguistic criteria, and explore interval type-2 or Pythagorean fuzzy extensions to further capture inter-expert disagreement.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest associated with this publication.

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