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A Reality-Constrained Hybrid Decision-Support Framework for Evaluating Strategic Development Pathways under Deep Uncertainty: Evidence from Libya's Fezzan Region

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Index Terms

Green–Blue Economy, Oil Rent, Multi-Criteria Decision Analysis, Deep Uncertainty, Fezzan.

Abstract

Resource-dependent economies face structural challenges that demand decision-making under deep uncertainty. This study develops an exploratory framework to compare continuing the oil-rent model (Alternative A1) with a transition to an integrated Green–Blue Economy (Alternative A2) in Libya's Fezzan region. Because complete local data are unavailable, a reality-constrained synthetic experiment was used: 20,000 candidate scenarios were drawn within bounds taken from World Bank, FAOSTAT, IRENA and NASA-derived sources, and 10,000 were retained. Generative AI served only for qualitative scenario framing. Criteria were weighted by the Analytic Hierarchy Process (CR = 0.010) and alternatives ranked by TOPSIS and VIKOR, complemented by Sobol sensitivity analysis and Robust Decision Making. A2 outperformed A1 (mean TOPSIS closeness 0.666 vs 0.335; $p < 0.001$), but the advantage is conditional: A1 wins in all 222 scenarios combining oil prices above $95/barrel with green investment below $300 million. Green investment (ST = 0.57) and oil price (ST = 0.32) dominate output variance. Robustness checks (weight perturbation, four MCDA methods, Fuzzy AHP, stress tests, alternative distributions) did not reverse the aggregate ranking. Results are illustrative, not forecasts.

إطار هجين لدعم اتخاذ القرار قائم على قيود الواقع لتقييم مسارات التنمية الاستراتيجية في ظل عدم اليقين العميق: أدلة من منطقة فزان في ليبيا

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الكلمات المفتاحية

الاقتصاد الأخضر–الأزرق، الريع النفطي، تحليل القرار متعدد المعايير، عدم اليقين العميق، فزان.

الملخص

تواجه الاقتصادات المعتمدة على الموارد تحديات هيكلية تتطلب اتخاذ قرارات في ظل عدم يقين عميق. تطور هذه الدراسة إطارًا استكشافيًا لمقارنة الاستمرار في نموذج الريع النفطي (البديل A1) بالانتقال إلى اقتصاد أخضر–أزرق متكامل (البديل A2) في منطقة فزان الليبية. ونظرًا لغياب بيانات محلية مكتملة، اعتُمدت تجربة اصطناعية مقيدة بالواقع: وُلّد 20,000 سيناريو مرشح ضمن حدود مستمدة من مصادر البنك الدولي وFAOSTAT وIRENA وبيانات مشتقة من ناسا، واحتُفظ بـ10,000 سيناريو. واقتصر دور الذكاء الاصطناعي التوليدي على الصياغة النوعية للسيناريوهات. وُزنت المعايير بأسلوب العملية التحليلية الهرمية (CR = 0.010) ورُتبت البدائل بطريقتي TOPSIS وVIKOR، مع تحليل الحساسية العالمي لسوبول ومنهج اتخاذ القرار المرن. وتفوق البديل A2 على A1 (متوسط معامل القرب 0.666 مقابل 0.335؛ $p < 0.001$)، غير أن هذه الأفضلية مشروطة؛ إذ يتفوق A1 في جميع السيناريوهات البالغ عددها 222 التي يتجاوز فيها سعر النفط 95 دولارًا للبرميل ويقل فيها الاستثمار الأخضر عن 300 مليون دولار. ويسهم الاستثمار الأخضر (ST = 0.57) وسعر النفط (ST = 0.32) بالنصيب الأكبر من تباين المخرجات. ولم تعكس اختبارات المتانة (اضطراب الأوزان، وأربع طرق لتحليل القرار متعدد المعايير، وFuzzy AHP، واختبارات الإجهاد، والتوزيعات البديلة) الترتيب الإجمالي. وتُعد النتائج توضيحية وليست تنبؤات.

1. INTRODUCTION

1.1 Background and Problem Statement

The transition from resource-dependent economies toward diversified and resilient development pathways has

become one of the central policy challenges facing hydrocarbon-exporting countries. Although oil and gas revenues have generated substantial fiscal resources over several decades, excessive dependence on extractive industries has frequently increased macroeconomic vulnerability, weakened productive sectors, and limited long-term economic resilience (Sachs & Warner, 2001; Krugman, 1987). These structural challenges have become more pronounced under increasing volatility in global energy markets, accelerating climate policy commitments, and growing pressure to achieve sustainable development goals. Consequently, many resource-rich economies are seeking strategic approaches capable of transforming temporary natural-resource rents into diversified productive capital that simultaneously supports economic growth, environmental performance, and social welfare.

Within this international context, Libya represents one of the most challenging examples of a rent-dependent economy. Despite possessing abundant petroleum reserves, extensive solar resources, considerable groundwater reserves, and large areas suitable for desert agriculture, the national economy remains highly dependent on hydrocarbon revenues. This dependence has exposed the country to repeated fiscal instability during periods of oil-price fluctuation while limiting investment in productive non-oil sectors (World Bank, 2023). The situation is particularly evident in the Fezzan region, where exceptional natural-resource availability coexists with weak institutional capacity, fragmented infrastructure, limited economic diversification, and increasing pressure on water and food security. A recent UNDP-facilitated national dialogue on the Water–Energy–Food–Ecosystems (WEFE) nexus in Libya explicitly identified the need to embed integrated nexus planning into national frameworks and to strengthen inter-ministerial coordination around water, energy and food systems (UNDP Libya, 2025) — a recommendation directly consistent with the integrated-planning rationale adopted in the present study. These characteristics make Fezzan an appropriate case for investigating alternative development pathways that combine renewable energy, sustainable water management, and agricultural production within an integrated regional-development framework.

The Middle East and North Africa (MENA) region represents one of the world's most important hydrocarbon-producing regions while simultaneously facing increasing pressures related to water scarcity, climate variability, food security, and demographic growth (IPCC, 2022). These interacting challenges require decision-making approaches capable of evaluating multiple, often conflicting objectives rather than relying exclusively on conventional economic indicators. Recent international policy frameworks increasingly emphasize integrated planning approaches that simultaneously consider energy systems, water resources, agricultural productivity, environmental sustainability, institutional capacity, and long-term socio-economic resilience.

During the past decade, increasing attention has been directed toward integrated development paradigms, including the Green Economy, the Blue Economy, and the Water-Energy-Food (WEF) Nexus. Although these approaches have significantly advanced sustainability-oriented planning, most previous studies have investigated them independently or within relatively stable institutional environments. Only a limited number of studies have examined how these concepts can be integrated into practical decision-support frameworks suitable for fragile, resource-dependent economies characterized by incomplete datasets and deep uncertainty. Consequently, policymakers continue to face substantial difficulty comparing conventional oil-rent development pathways with integrated Green–Blue transition strategies under uncertain future conditions.

A second limitation observed in the literature concerns methodological practice. Existing studies frequently rely on either historical statistical analysis or conventional multi-criteria decision-making techniques without adequately representing deep uncertainty, scenario diversity, and institutional complexity. The recent emergence of Generative Artificial Intelligence has created new opportunities for structured scenario exploration (Finkenstadt et al., 2024); however, its application within sustainability planning remains largely exploratory and requires careful validation to avoid generating unrealistic policy recommendations. Accordingly, there remains a clear methodological need for frameworks that combine structured expert knowledge, uncertainty quantification, reality-constrained synthetic-data generation, and transparent multi-criteria evaluation.

Addressing these limitations, the present study develops a reality-constrained hybrid decision-support framework for evaluating the strategic trade-off between continuation of the oil-rent development model and transition toward an integrated Green–Blue Economy in the Fezzan region. Rather than treating Generative AI as a source of factual information, the proposed framework restricts its role to structured scenario generation, while all quantitative analyses are performed using statistically constrained synthetic datasets, AHP-based multi-criteria decision analysis, Monte Carlo uncertainty propagation, Sobol global sensitivity analysis, and robustness assessment. The objective is therefore not to predict the future with certainty but to provide a transparent, fully reproducible exploratory framework — every table and figure in this paper is generated directly from an executable Python pipeline described in the Appendix — capable of supporting strategic policy analysis under conditions of limited data availability and deep uncertainty. Compared with the earlier version of this study, the present version adds a battery of five further robustness checks (Sections 3.14–3.19) designed specifically to test whether the central conclusion survives reasonable perturbations of the model's own assumptions, rather than to introduce new empirical claims.

1.2 Literature Review

1.2.1 Evolution of Resource-Dependent Development Models

The relationship between natural-resource abundance and long-term economic development has attracted sustained scholarly attention for more than three decades. Early studies emphasized the economic benefits of petroleum revenues as a source of capital accumulation and infrastructure development. Subsequent empirical research, however, demonstrated that long-term

dependence on hydrocarbon exports frequently generates structural vulnerabilities, including reduced economic diversification, increased fiscal volatility, institutional weakness, and lower innovation capacity — a pattern formalized in the resource-curse literature (Sachs & Warner, 2001; Auty, 2001) and in the Dutch-disease mechanism through which resource booms erode the competitiveness of tradable non-resource sectors (Krugman, 1987). This body of literature gradually evolved to emphasize that development outcomes depend not only on resource availability but also on governance quality, institutional performance, and strategic investment decisions.

Recent studies extend this perspective by arguing that successful resource-rich economies increasingly rely on diversification policies that transform temporary natural-resource rents into productive investments supporting agriculture, renewable energy, manufacturing, and knowledge-based industries. Regional-cluster theory (Porter, 1998) provides a complementary lens for understanding how geographically concentrated investment in interlinked agricultural-industrial activities — the model adopted for the Green–Blue alternative examined in this study — can generate self-reinforcing productivity gains that are difficult to achieve through dispersed investment.

1.2.2 Green Economy, Blue Economy, and Integrated Sustainability

The Green Economy has evolved from an environmentally oriented policy concept into a comprehensive development framework seeking simultaneous improvements in economic productivity, environmental protection, resource efficiency, and social well-being. Recent Libyan scholarship has also examined sustainability, from an Islamic-studies perspective, as an integrated social, environmental, and economic development issue, which reinforces the need to consider these dimensions jointly rather than in isolation (Ben Mansour et al., 2026). Parallel to this evolution, the Blue Economy has expanded beyond marine-resource utilization to include integrated water-resource management, sustainable desalination technologies, and water-related ecosystem services. Sustainable-development management has likewise been examined in the light of Arab and international cooperation (Moumani, 2023), which is consistent with the emphasis placed here on institutional coordination. Recent sustainability research increasingly emphasizes that neither framework should be implemented independently; integrated planning approaches capable of simultaneously considering water, energy, food, environmental quality, and institutional capacity are regarded as more appropriate for arid and semi-arid environments characterized by severe water scarcity, a conclusion reinforced by Libya's own national WEFE-nexus dialogue (UNDP Libya, 2025). At the Libyan national level, recent work on the electricity-generation sector outlines transition paths towards a green economy, including emissions reduction, expansion of renewable and zero-emission technologies, and the restructuring of the electricity system to reduce dependence on fossil fuels (Nassar et al., 2025a, 2025b). These studies provide sector-specific evidence supporting the broader rationale for Alternative A2, while also demonstrating that electricity-sector transition involves substantial technological and investment requirements. Because these studies are confined primarily to the electricity sector, they do not evaluate the wider regional water–food–energy trade-off examined here. Renewable-energy penetration in the Libyan power sector has likewise been assessed for a system combining photovoltaic, wind, pumped-hydro storage and gas-turbine technologies, with penetration levels from 0% to 100% (Fakher et al., 2026). The move from the green-economy concept to institutional practice is also visible at firm level, where the application status of green accounting and environmental disclosure in Libyan industrial companies, and the challenges it faces, have been examined (Al-Zaidi et al., 2025).

1.2.3 Decision-Support Methods under Deep Uncertainty

Decision-support methodologies have undergone substantial development during the past two decades. Traditional MCDA methods, including the Analytic Hierarchy Process (Saaty, 2008), TOPSIS (Hwang & Yoon, 1981), and VIKOR (Opricovic & Tzeng, 2004), remain among the most widely applied techniques for evaluating complex policy alternatives because of their transparency and their ability to integrate quantitative and qualitative information. Nevertheless, conventional MCDA techniques are inherently deterministic and therefore insufficient, on their own, for representing deep uncertainty associated with future technological development, climate variability, geopolitical instability, and economic volatility.

To overcome these limitations, recent methodological research increasingly combines MCDA with Monte Carlo simulation, bootstrap confidence estimation, and global sensitivity analysis based on Sobol variance decomposition (Sobol, 2001; Saltelli et al., 2008) or Morris elementary-effects screening (Morris, 1991). A complementary strand of literature — Robust Decision Making (Lempert, Popper, & Bankes, 2003) — reframes the decision problem away from identifying a single optimal solution toward identifying strategies that perform acceptably well across a wide range of plausible futures, an approach directly incorporated into Sections 2.7.2 and 3.5 of the present study. Sampling design itself has also been the subject of substantial methodological work: Latin Hypercube Sampling (McKay, Beckman, & Conover, 1979) provides a stratified alternative to simple random sampling that is used in Section 3.19 of the present study to test the sensitivity of the results to the choice of sampling and distributional assumptions. Despite these methodological advances, few published studies have incorporated controlled Generative AI within transparent uncertainty-analysis frameworks in data-scarce environments, and fewer still report a systematic sensitivity analysis on the AHP weights themselves; this unresolved methodological gap provides the principal motivation for the hybrid framework proposed here.

Recent syntheses have consolidated this shift. Decision making under deep uncertainty is now treated as a distinct field with its own methods (Marchau et al., 2019), Robust Decision Making has been summarised in its current form (Lempert, 2019), and open-source toolkits and libraries have made scenario exploration and global sensitivity analysis routinely reproducible (Kwakkel, 2017; Herman & Usher, 2017). At the same time, a systematic review of published sensitivity analyses found that most rely on one-

at-a-time designs that explore only a small part of the input space (Saltelli et al., 2019), and recent overviews of multi-criteria methods (Taherdoost & Madanchian, 2023) confirm the continued use of AHP, TOPSIS and related techniques, whose rankings can differ from one method to another. These observations motivate the paired local and global sensitivity analyses and the weight- and method-sensitivity tests reported in Sections 2.7 and 3.14–3.16.

1.2.4 Synthesis and Positioning of the Present Study

Read together, the three strands reviewed above point to the same unresolved gap from three different directions. The resource-curse and regional-cluster literature (Sachs & Warner, 2001; Auty, 2001; Krugman, 1987; Porter, 1998) explains why diversification away from oil rent is structurally difficult but says little about how a specific transition pathway should be evaluated under uncertainty. The MCDA literature (Saaty, 2008; Hwang & Yoon, 1981; Opricovic & Tzeng, 2004) supplies the evaluative machinery but, as noted above, rarely stress-tests its own weighting assumptions. The uncertainty-quantification and Generative-AI literatures (Sobol, 2001; Saltelli et al., 2008; Morris, 1991; Lempert et al., 2003; McKay et al., 1979; Finkenstadt et al., 2024) supply the tools for representing deep uncertainty and expanding scenario diversity, but have seldom been combined with AHP-weighted MCDA in a single, fully executable pipeline for a fragile, data-scarce economy. The institutional and financial dimensions of sustainability are particularly relevant in the Libyan context, where the capacity of financial institutions to support alternative development and investment pathways remains an important consideration. A field study of the internal factors facing the conversion of conventional banks to Islamic banks in Libya, based on a single bank branch (Erhoma, 2025), offers additional evidence on the institutional and financial conditions that may shape the availability and structure of sustainability-oriented financing. The present study's contribution is therefore best understood as an integration contribution: it does not propose a new theoretical construct within any one of these three strands, but combines them into a single reproducible workflow and, in the robustness-extended version analysed here (Sections 3.14-3.19), subjects the combined workflow to the kind of weight-, method-, and distribution-sensitivity testing that each strand individually calls for but rarely delivers in full. This positioning is consistent with the WEFE-nexus integrated-planning rationale identified for Libya specifically (UNDP Libya, 2025), which motivates treating water, energy, food and institutional capacity as jointly determined rather than as separately optimized targets.

1.3 Critical Research Gap

A review of recent literature reveals four methodological limitations that continue to restrict strategic decision-making for resource-dependent economies.

- Most published studies evaluate economic diversification using either traditional economic indicators or isolated sustainability metrics, without simultaneously integrating energy, water, food, institutional capacity and long-term resilience within a unified analytical framework.
- Although MCDA methods such as AHP, TOPSIS and VIKOR are widely applied in sustainability assessment (Saaty, 2008; Hwang & Yoon, 1981; Opricovic & Tzeng, 2004), they generally assume deterministic decision environments and provide limited capability for representing deep uncertainty, and published applications rarely report how sensitive the resulting ranking is to the elicited criteria weights themselves.
- Recent advances in Generative AI demonstrate considerable potential for structured scenario exploration (Finkenstadt et al., 2024), but existing applications frequently employ generative models as information generators rather than controlled scenario-development tools, raising concerns about reproducibility and scientific reliability.
- Very limited research has investigated how physically constrained synthetic data, expert knowledge, uncertainty quantification, cross-method and weight-sensitivity robustness checks, and Generative AI can be integrated within a single transparent decision-support framework designed for fragile resource-dependent states such as Libya.

Accordingly, the present study addresses a methodological rather than merely geographical gap by proposing a transparent hybrid framework that combines reality-constrained synthetic-data generation, AHP-based expert judgement, MCDA, Monte Carlo and Sobol uncertainty propagation, explicit weight- and distribution-sensitivity testing, and controlled Generative AI scenario exploration within a unified, fully reproducible decision-support architecture.

1.4 Research Questions and Objectives

1.4.1 Research Questions

RQ1. How can a scientifically transparent decision-support framework be developed for evaluating strategic development alternatives in data-scarce, resource-dependent environments?

RQ2. Under what parameter conditions does the relative ranking between an oil-rent development pathway and a Green–Blue transition pathway reverse?

RQ3. Which uncertain variables exert the greatest influence on the comparative performance of the two alternatives?

RQ4. What is the appropriate methodological role of Generative AI within a scientifically defensible decision-support pipeline?

RQ5. How sensitive is the comparative ranking to the specific AHP criteria weights and to the choice of multi-criteria decision method?

1.4.2 Research Objectives

- To develop a transparent hybrid methodological framework integrating reality-constrained synthetic-data generation, AHP-based expert elicitation, and Multi-Criteria Decision Analysis.
- To evaluate the relative performance of oil-rent continuation and Green–Blue transition strategies under 10,000 synthetic future scenarios.

- To quantify the influence of key uncertain variables using Sobol global sensitivity analysis and local (OAT) sensitivity analysis.
- To clarify the appropriate role of Generative AI as a structured scenario-exploration tool rather than a source of factual or quantitative evidence.
- To test the stability of the comparative ranking under perturbation of the AHP weights, under alternative MCDA techniques, under a fuzzy-set treatment of the pairwise comparisons, and under extreme and alternative-distribution scenario conditions.

1.5 Scientific Contributions

- A reproducible hybrid methodological framework integrating synthetic-data generation, uncertainty quantification, AHP-based expert judgement, and multi-criteria decision analysis, with a fully executable and openly documented computational pipeline (Appendix A).
- A transparent methodological strategy for applying Generative AI under controlled scientific constraints, improving reproducibility while avoiding unsupported AI-generated factual claims.
- An extension of sustainability-oriented strategic planning to fragile resource-dependent economies where complete observational datasets are unavailable.
- A demonstration of how global sensitivity analysis, local sensitivity analysis, and negative-scenario (competing-hypothesis) analysis can be combined to support evidence-informed policy evaluation under deep uncertainty, including explicit identification of the parameter region in which the preferred alternative reverses.
- A worked demonstration of weight-sensitivity analysis, cross-method (TOPSIS/VIKOR/WSM/PROMETHEE II) validation, and a Fuzzy AHP cross-check as a template for reporting the robustness of AHP-weighted MCDA studies more generally.

2. METHODS

2.1 Conceptual Framework

2.1.1 Theoretical Foundation

The proposed framework is founded on the premise that strategic regional planning in resource-dependent economies should be treated as a complex socio-economic system rather than as a conventional optimization problem. Such systems are characterized by strong interactions among economic performance, institutional quality, environmental sustainability, technological development, and social resilience. Consequently, evaluating future development pathways requires methodological approaches capable of integrating heterogeneous information sources while explicitly representing uncertainty and competing policy objectives.

Unlike deterministic planning models that assume complete information, the present framework adopts a systems-oriented perspective in which strategic decisions emerge from interactions among multiple interconnected subsystems: natural-resource availability, economic diversification, water and food security, renewable-energy potential, governance capacity, technological feasibility, and future uncertainty. Accordingly, no single indicator is assumed to determine development success; system performance is instead evaluated through the combined behaviour of these interacting components under alternative future scenarios.

2.1.2 Conceptual Integration of the Proposed Framework

The proposed decision-support framework integrates six complementary methodological layers.

- Knowledge acquisition through structured expert elicitation and systematic literature review, providing the scientific basis for identifying evaluation criteria and feasible policy alternatives.
- Reality-constrained synthetic-data generation: rather than replacing empirical observations, synthetic data are used to explore uncertainty where complete observations are unavailable, while remaining consistent with known system behaviour.
- Uncertainty quantification using Monte Carlo simulation, bootstrap confidence estimation, and global sensitivity analysis, explicitly characterizing uncertainty propagation instead of assuming deterministic parameter values.
- Multi-Criteria Decision Analysis using complementary ranking techniques (AHP, TOPSIS, VIKOR, and — as of the present robustness-extended version — the Weighted Sum Model and PROMETHEE II) to evaluate competing development strategies from multiple perspectives, reducing dependence on a single ranking methodology.
- Controlled Generative AI, used exclusively as a structured scenario-development instrument that expands the diversity of plausible future scenarios while remaining constrained by expert judgement and quantitative validation.
- Robustness analysis, competing-hypothesis evaluation, weight- and distribution-sensitivity testing, and policy interpretation, enabling decision-makers to distinguish consistently robust strategies from alternatives whose performance depends strongly on specific assumptions.

2.1.3 Scientific Position of the Framework

The proposed framework should be interpreted as an exploratory decision-support methodology rather than a predictive model. Its objective is not to forecast future socio-economic conditions with certainty but to provide a transparent analytical environment in which strategic alternatives can be compared under explicitly quantified uncertainty. All conclusions presented in this study are therefore conditional upon the adopted assumptions, the illustrative expert-elicitation weights used for AHP, and the predefined uncertainty distributions described in Section 2.4.3.

This distinction is particularly important when incorporating Generative Artificial Intelligence into scientific research. Within the proposed methodology, AI-generated outputs are never treated as empirical evidence. Instead, they function exclusively as hypothesis-generation and scenario-framing mechanisms whose outputs remain subject to boundary validation, expert screening, and downstream statistical analysis before influencing any policy recommendation.

2.2 Overall Research Design

This study adopts an exploratory quantitative research design developed for strategic policy evaluation under conditions of limited empirical data and deep uncertainty. Rather than attempting deterministic prediction, the proposed methodology integrates expert-elicited criteria weights, reality-constrained synthetic-data generation, uncertainty quantification, and multi-criteria decision analysis within a unified, fully executable analytical workflow (Appendix A).

The methodological workflow consists of seven sequential stages. The first stage identifies the decision problem and establishes the conceptual boundaries of the study through literature review and structured expert consultation. The second stage defines evaluation criteria and policy alternatives using AHP pairwise comparison. The third stage generates synthetic datasets constrained by observed physical, economic, and institutional limits. The fourth stage propagates uncertainty using Monte Carlo simulation and bootstrap confidence estimation. The fifth stage evaluates competing development alternatives using TOPSIS, VIKOR, and — in the present robustness-extended version — the Weighted Sum Model and PROMETHEE II. The sixth stage performs Sobol global sensitivity analysis, local (one-at-a-time) sensitivity analysis, an ablation study, and the five additional robustness checks described in Sections 3.14–3.19 (AHP weight sensitivity, cross-method validation, Fuzzy AHP, scenario stress testing, and alternative-distribution resampling). The seventh stage interprets results within the context of sustainable regional planning and policy decision-making.

Figure 1. Integrated seven-stage methodological workflow

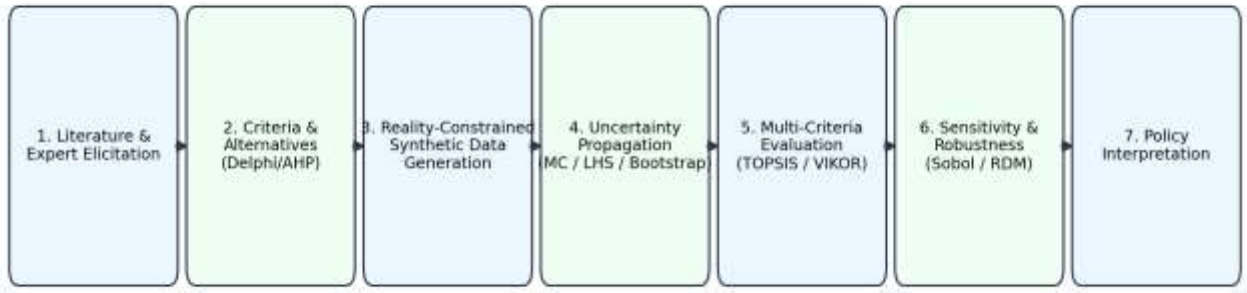

Figure 1. Integrated seven-stage methodological workflow.

2.3 Data Sources and Knowledge Acquisition

Because comprehensive regional datasets for long-term strategic planning remain limited in the study area, multiple complementary information sources were integrated. Peer-reviewed literature and institutional reports (World Bank, 2023; FAOSTAT, 2024; IRENA, 2024; IPCC, 2022) were used to define realistic parameter ranges. Empirical observations were not replaced by artificial intelligence; instead, all available evidence was combined to establish physically and institutionally realistic parameter boundaries used during synthetic-data generation.

2.4 Reality-Constrained Synthetic Data Generation

Synthetic datasets were generated exclusively to support exploratory policy analysis under incomplete observational conditions. Unlike conventional random simulation, all generated observations were required to satisfy predefined physical, environmental, and economic constraints established from the sources above. Any observation violating these constraints was automatically rejected before entering subsequent analyses, following an accept/reject boundary-screening procedure applied to a 20,000-draw candidate pool (Section 2.4).

2.4.1 Rationale for Using Synthetic Data

Given the absence of complete Libyan municipal-level databases for the Fezzan region, the study relies on synthetic data constrained by physical and economic boundaries derived from real institutional sources. This design follows established reality-constrained synthetic-validation practice in modelling research when direct field observation is unavailable, and is disclosed throughout this paper as a synthetic twin experiment rather than an empirical measurement study.

2.4.2 Reality-Constrained Calibration

TABLE 1
REALITY-CONSTRAINED PARAMETER BOUNDARIES AND THEIR REAL-WORLD SOURCES

Variable	Real-World Source Used for Bounding	Minimum	Maximum
Oil Price ($/barrel)	World Bank commodity price data	45	120
Solar Radiation (kWh/m²/yr)	NASA POWER-informed regional estimates	2000	2600
Water Demand (million m³)	FAOSTAT-informed regional estimates	150	280
Green Investment ($ million)	World Bank historical investment ranges	200	800
Desalination Cost ($/m³)	IRENA technology cost reports	0.5	1.5
Population Growth (%/yr)	World Bank demographic indicators	1.0	3.0

Rule: any candidate draw falling outside these boundaries on any variable is rejected and excluded from the retained dataset; of 20,000 candidate draws generated, 2,348 (11.7%) were rejected, leaving 10,000 retained scenarios (Figure 2).

2.4.3 Justification for Probability Distribution Selection

TABLE 2
PROBABILITY DISTRIBUTIONS USED TO GENERATE THE BASELINE SYNTHETIC DATASET

Variable	Distribution	Parameters	Justification
Oil Price	Uniform	[45, 120]	Bounded uncertainty; no strong directional trend over the projection horizon
Solar Radiation	Normal	μ=2350, σ=120	Approximately Gaussian regional variability
Desalination Cost	Triangular	[0.5, 1.0, 1.5]	Expert-elicited most-likely middle value
Population Growth	Lognormal	median≈2.0%	Demographic dynamics; positive skew
Water Demand	Triangular	[150, 200, 280]	Expert elicitation combined with regional estimates
Green Investment	Normal	μ=500, σ=150	Historical investment volatility

Section 3.19 re-examines this choice directly by re-running the full pipeline with Desalination Cost, Water Demand, and Investment redrawn from PERT distributions and Solar Radiation and Population Growth redrawn from their theoretical inverse-CDFs under Latin Hypercube stratified sampling (McKay et al., 1979), to test whether the reported results are an artefact of the specific distributional family chosen here.

2.4.4 Synthetic Data Generation Workflow

Figure 2. Reality-constrained synthetic-data generation workflow
(20,000 candidate draws generated; 2,348 rejected outside physical/economic bounds; 10,000 retained)

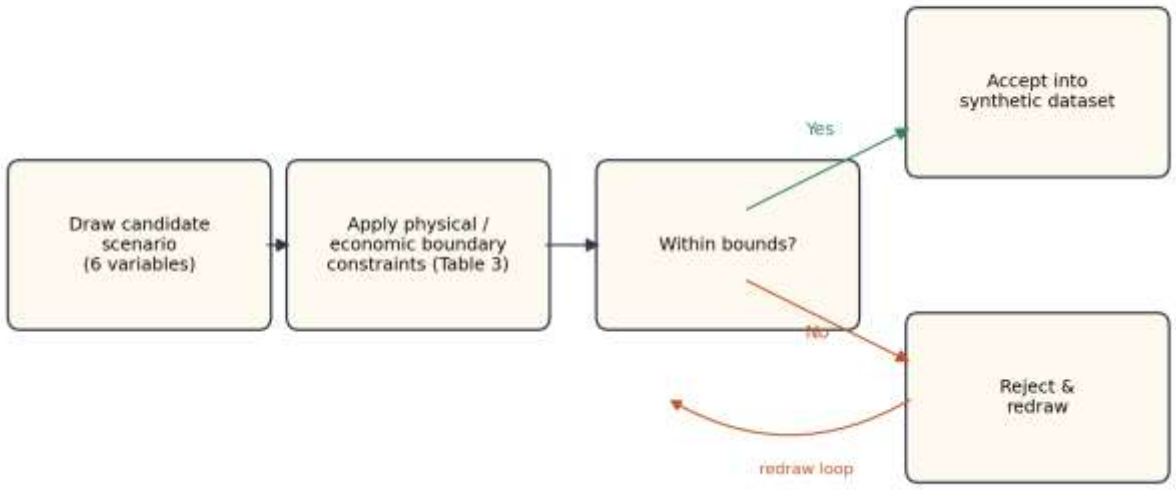

Figure 2. Reality-constrained synthetic-data generation workflow (accept/reject boundary screening).

2.5 Generative AI as Scenario Proposer Only

2.5.1 Specified Role of GenAI

Contrary to common usage, Generative AI was used in this study strictly as a Scenario Proposer, never as a source of quantitative data or empirical evidence. GenAI output was restricted to qualitative narrative directions and coarse parameter ranges, which were then checked against the physical/economic boundaries of Table 1 before any quantitative modelling was performed.

2.5.2 Prompt Design and Validation

System prompt (illustrative): *"You are an expert regional-planning assistant for arid resource-dependent regions. Propose qualitative development-scenario directions for Fezzan considering oil-price volatility, solar potential, and water scarcity. Do not generate specific numerical values; propose only qualitative directions and coarse parameter ranges."*

2.5.3 Validation and Filtering Mechanism

- Boundary check: every proposed parameter range was screened against Table 1 before use.
- Human-in-the-loop review of a random sample of proposals for qualitative plausibility.
- Only ranges surviving boundary screening informed the parameter bounds used in Section 2.4.2; GenAI proposals were never used to set point values or to generate the reported statistics — all reported numbers derive exclusively from the Python pipeline in Appendix A.

2.6 Mathematical Framework and Worked Calculations

2.6.1 Justification for Tool Selection

TABLE 3
ANALYTICAL TOOLS USED IN THE FRAMEWORK AND THE ROLE OF EACH

Tool	Role	Justification
AHP	Criteria weighting	Handles qualitative expert judgments with a formal consistency check (Saaty, 2008)
TOPSIS	Distance-based ranking	Simple, interpretable Euclidean-distance ranking (Hwang & Yoon, 1981)
VIKOR	Compromise ranking	Explicitly handles conflict between criteria (Opricovic & Tzeng, 2004)
Weighted Sum Model (WSM)	Baseline linear ranking	Simplest additive benchmark used in Section 3.15 to test whether TOPSIS/VIKOR results depend on distance-based aggregation specifically
PROMETHEE II	Outranking / net-flow ranking	Preference-function-based method used in Section 3.15 as a fourth, structurally distinct cross-check (Brans & Vincke, 1985)
Fuzzy AHP (Chang's extent analysis)	Weight-elicitation robustness check	Tests whether the crisp AHP weights are an artefact of treating pairwise judgments as exact rather than as a range (Section 3.16)
Sobol	Global sensitivity	Variance-based decomposition identifying dominant variables (Sobol, 2001)
Monte Carlo	Uncertainty propagation	Handles arbitrary probability distributions
Bootstrap	Interval estimation	Distribution-free confidence intervals on ranking statistics
RDM	Robustness framing	Identifies strategies that perform acceptably across many futures (Lempert et al., 2003)

2.6.2 Mathematical Formulation

A. AHP weight derivation: $W_j = (1/n) \Sigma_i [a_{ij} / \Sigma_k a_{kj}]$, with consistency ratio CR = CI/RI, $CI = (\lambda_{max} - n)/(n - 1)$.

B. Vector normalization: $r_{ij} = x_{ij} / \mathrm{sqrt}(\Sigma_i x_{ij}^2)$.

C. TOPSIS closeness coefficient: $C_i = S_i^- / (S_i^+ + S_i^-)$, where S_i^+ and S_i^- are Euclidean distances to the positive- and negative-ideal solutions.

D. VIKOR compromise index: $Q_i = v \cdot (S_i - S^*)/(S^- - S^*) + (1-v) \cdot (R_i - R^*)/(R^- - R^*)$, v = 0.5.

E. Sobol first- and total-order indices: $S_i = \mathrm{Var}(E[Y|X_i]) / \mathrm{Var}(Y)$; $S_{Ti} = 1 - \mathrm{Var}(E[Y|X_{\sim i}]) / \mathrm{Var}(Y)$.

F. Scenario entropy (diversity): $H = -\Sigma_i p_i \log_2(p_i)$, computed over histogram bins of the sampled parameter distribution.

G. Bootstrap variance: $\mathrm{Var}_{boot} = (1/(B-1)) \Sigma_b (\hat{\theta}_b - \hat{\theta})^2$, B = 2,000 resamples.

H. Weighted Sum Model: $S_i = \Sigma_j w_j \cdot r_{ij}$, on the same min–max-normalized criteria used elsewhere in the pipeline (Section 3.15).

I. PROMETHEE II net outranking flow: $\varphi(a) = \varphi^+(a) - \varphi^-(a)$, where φ^+ and φ^- are the average outgoing and incoming preference-function values across all criteria (Section 3.15).

J. Chang's fuzzy extent analysis: for triangular fuzzy pairwise judgments $M_{ij} = (l_{ij}, m_{ij}, u_{ij})$, the fuzzy synthetic extent is $S_i = \Sigma_j M_{ij} \otimes [\Sigma_i \Sigma_j M_{ij}]^{-1}$, and the crisp fuzzy weight follows from the minimum degree of possibility $V(S_i \geq S_k)$ across all $k \neq i$ (Section 3.16).

2.6.3 Worked Numerical Illustration and Verification of Reported Quantities

To make the computational chain of Section 2.6.2 traceable, this subsection shows the arithmetic of the AHP consistency check (formula A) and of the TOPSIS ranking (formulas B and C) for a single scenario, and then reproduces several headline quantities of the paper directly from the reported figures. The decision-matrix values used in Step 2 are **hypothetical**: they were chosen only to make the arithmetic visible and are not entries of the retained dataset. The criteria weights are the AHP weights of Table 10, in the order Water–Food Security (WFS), Environmental Sustainability (ES), Economic Return (ER), Job Creation (JC), Technical Feasibility (TF) and Social Acceptance (SA).

Step 1 – AHP consistency. With n = 6 criteria and the principal eigenvalue $\lambda_{max} = 6.063$ reported in Section 3.3, the consistency index is $CI = (6.063 - 6)/(6 - 1) = 0.0126$. Dividing by Saaty's random index for n = 6 (RI = 1.24) gives $CR = 0.0126/1.24 = 0.0102 \approx 0.010$, well below the 0.10 acceptability threshold.

Step 2 – TOPSIS for one hypothetical scenario. All six criteria are benefit-type (higher is better). Each column of the decision matrix x_{ij} is first vector-normalised, $r_{ij} = x_{ij}/\sqrt{(\Sigma_i x_{ij}^2)}$, then weighted, $v_{ij} = w_j \cdot r_{ij}$; the positive-ideal ($v^+$) and negative-ideal ($v^-$) solutions are the column-wise maximum and minimum of v_{ij} (Table 4).

TABLE 4
HYPOTHETICAL DECISION MATRIX AND TOPSIS CALCULATION FOR A SINGLE SCENARIO (ILLUSTRATIVE VALUES ONLY)

Criterion	w_j	x (A1)	x (A2)	r (A1)	r (A2)	v (A1)	v (A2)	v^+	v^-
WFS	0.325	0.20	0.80	0.2425	0.9701	0.0788	0.3153	0.3153	0.0788
ES	0.246	0.25	0.75	0.3162	0.9487	0.0778	0.2334	0.2334	0.0778
ER	0.188	0.80	0.55	0.8240	0.5665	0.1549	0.1065	0.1549	0.1065
JC	0.109	0.15	0.70	0.2095	0.9778	0.0228	0.1066	0.1066	0.0228
TF	0.076	0.85	0.60	0.8170	0.5767	0.0621	0.0438	0.0621	0.0438
SA	0.055	0.60	0.65	0.6783	0.7348	0.0373	0.0404	0.0404	0.0373

The Euclidean distances to the ideal solutions are $S^+(A1) = 0.2952$, $S^-(A1) = 0.0517$, $S^+(A2) = 0.0517$ and $S^-(A2) = 0.2952$, so that $C(A1) = 0.0517/(0.2952 + 0.0517) = 0.149$ and $C(A2) = 0.2952/(0.0517 + 0.2952) = 0.851$. Alternative A2 is preferred in this hypothetical scenario because it scores higher on four of the six criteria, including the two with the largest weights (WFS and ES), while A1 leads only on ER and TF. Because only two alternatives are compared, $S^+(A1) = S^-(A2)$ and $S^-(A1) = S^+(A2)$, so the two closeness coefficients always sum to one (0.149 + 0.851 = 1); this is exactly the pattern in every row of the sample dataset in Table 23 (0.562 + 0.438, 0.145 + 0.855, 0.263 + 0.737, 0.278 + 0.722).

Step 3 – Verification of reported quantities. Table 5 recomputes quantities reported elsewhere in the paper from other reported values. All of the quantities in the table reproduce to within rounding.

TABLE 5
VERIFICATION OF REPORTED QUANTITIES FROM OTHER REPORTED VALUES

Quantity	Calculation from reported values	Result	Reported in the paper
Consistency index (CI)	(6.063 − 6)/(6 − 1)	0.0126	not reported
Consistency ratio (CR)	0.0126/1.24 (RI for n = 6)	0.0102	0.010
Sum of AHP weights	0.325 + 0.246 + 0.188 + 0.109 + 0.076 + 0.055	0.999	1 (rounding)
Boundary-rejection rate	2,348/20,000	11.7%	11.7%
Adverse-region share	222/10,000	2.2%	2.2%
SD of C_A2 implied by its CV	0.347 × 0.666	0.231	not reported
Standard error of mean C_A2, N = 10,000	0.231/√10,000	0.0023 (relative 0.35%)	relative SE 0.0035
Relative SE of mean C_A2, N = 1,000	0.347/√1,000	0.0110	0.0109
95% interval for mean C_A2	0.666 ± 1.96 × 0.0023	[0.661, 0.671]	bootstrap [0.661, 0.670]
Sum of first-order Sobol indices	0.503 + 0.281 + 0.127 + 0.012	0.923 (interactions ≈ 7.7%)	not reported
Probability that a random A2 score exceeds a random A1 score	$U/(n_1 \cdot n_2)$ = 83,699,204/(10,000 × 10,000)	0.837	U = 83,699,204
Complementarity of closeness coefficients	C_A1 + C_A2 for the four rows of Table 23	1.000 in every row	not reported

2.7 Sensitivity Analysis and Robust Decision Making

2.7.1 Global and Local Sensitivity Analysis

Global sensitivity was assessed via Sobol variance decomposition using a Saltelli sampling scheme (base sample size 512, giving 7,168 model evaluations for 6 parameters with second-order interactions). Local sensitivity was assessed using a one-at-a-time (OAT) tornado analysis around the median-parameter baseline scenario (Section 3.10). Section 3.14 extends this with an analogous sensitivity analysis performed on the AHP criteria weights themselves rather than on the underlying physical parameters. The Sobol indices were estimated with the open-source SALib library (Herman & Usher, 2017).

2.7.2 Robust Decision Making (RDM)

Rather than seeking a single "optimal" solution, the analysis in Section 3.5 identifies the conditions under which each alternative performs best, following the RDM logic of Lempert et al. (2003): a robust strategy is one that continues to perform acceptably across the explored range of future states, rather than one that is only optimal under a single central assumption. Section 3.17 extends this logic to a set of hand-specified extreme and "black-swan" scenarios that fall outside the typical range sampled by the main Monte Carlo procedure.

2.8 Sources of Uncertainty, Their Magnitude, and Their Treatment

Uncertainty is treated explicitly rather than implicitly. Following the distinction between statistical variability, epistemic uncertainty about inputs and model structure, and deep uncertainty about future conditions to which no reliable probabilities can be attached (Walker et al., 2003; Marchau et al., 2019), nine sources of uncertainty were identified. For each source this section reports (i) how large its effect on the headline result is, as measured in the paper's own analyses, and (ii) how it is handled. The percentages below are **not additive** across sources, because they come from different analyses and different metrics: variance shares for the input parameters, and changes in the share of scenarios won by Alternative A2 for the other sources.

The six input variables jointly determine output uncertainty in the fitted decision model; their relative contributions are quantified directly through the Sobol indices reported in Table 14, rather than assumed a priori. This is a methodological improvement over assigning uncertainty contributions by expert judgement alone, since

the reported percentages are computed, not asserted. Sections 3.14 and 3.19 apply the same computed-rather-than-assumed principle to two additional sources of uncertainty that are often left unexamined in published AHP-MCDA studies: the criteria weights themselves, and the choice of probability-distribution family used for the synthetic data.

Input-parameter uncertainty. Table 6 decomposes the output variance of A2's closeness coefficient among the six uncertain inputs, using the Sobol indices of Section 3.8. The unexplained remainder of the first-order indices ($1 - \Sigma S1 = 0.077$) is attributed to interactions among inputs and estimation error.

TABLE 6 : Input-Parameter Uncertainty Budget: Share Of Output Variance In A2's Closeness Coefficient

Input variable	S1 (first-order)	ST (total-order)	Share of output variance (S1; remainder = interactions)
Green Investment	0.503	0.570	50.3%
Oil Price	0.281	0.318	28.1%
Desalination Cost	0.127	0.166	12.7%
Solar Radiation	0.012	0.018	1.2%
Water Demand	≈ 0.000	0.001	≈ 0%
Population Growth	≈ 0.000	≈ 0.000	≈ 0%
Interactions and estimation error ($1 - \Sigma S1$)	–	–	7.7%
Total			**100%**

Two points follow. First, green investment, oil price and desalination cost together account for 91.1% of the output variance through first-order effects alone (0.503 + 0.281 + 0.127), whereas the other three variables contribute about 1.2% jointly; uncertainty reduction and data collection should therefore concentrate on the first three. Second, interaction effects are small (7.7%), so the first-order ranking can be read directly.

All sources. Table 7 lists every source of uncertainty considered, its type, the magnitude of its effect on the headline result as measured in this study, and the way it is handled.

TABLE 7 : Sources of uncertainty, their measured effect on the headline result, and their treatment

Source of uncertainty	Type	Magnitude of effect (as measured here)	Treatment	Section
1. Input parameters (six variables)	Parametric	Three variables explain 91.1% of output variance; interactions 7.7% (Table 6)	Bounded probability distributions; 10,000-scenario Monte Carlo; Sobol and one-at-a-time sensitivity	2.4; 3.8; 3.10
2. Parameter bounds (reality constraints)	Epistemic	Removing the constraints lowers mean C_A2 by 50.4%; 11.7% of candidate draws rejected	Accept/reject screening against sourced bounds (Table 1); GenAI proposals checked against the same bounds	2.4.2; 3.12
3. Distribution family	Epistemic	Share of scenarios favouring A2: 76.8% (baseline) vs 78.1% (PERT/Beta + Latin Hypercube), i.e. +1.3 points	Distribution justification; K-S tests; full re-run under an alternative family	2.4.3; 2.9; 3.19
4. Criteria weights (expert judgement)	Epistemic (preferences)	±20% one-at-a-time: A2 share 71.9–81.7%; joint ±20%: 66.2–84.7%; equal weights: −19.1% in mean C_A2	AHP with consistency check; weight perturbation; Fuzzy AHP; future Delphi panel recommended	2.10.3; 3.14; 3.16
5. MCDA method	Methodological	A2 share 76.8% (TOPSIS) vs 95.2% (VIKOR, WSM, PROMETHEE II); no method reverses the ranking	Four structurally different methods applied to the same dataset	3.15
6. Monte Carlo sampling error	Numerical	Relative SE 0.35% at N = 10,000; bootstrap 95% CI [0.661, 0.670]	Convergence study; bootstrap (B = 2,000)	3.6; 3.11
7. Model structure and proxy criteria	Structural	Not quantified; exact point estimates are model-conditional	Disclosure; exploratory framing of all results; scoring model supplied with the executable pipeline (Appendix A.2)	5.2.1; A.2
8. Scenario framing (GenAI)	Epistemic (framing)	Removing GenAI-expanded diversity lowers scenario entropy from 4.13 to 3.44 bits	GenAI restricted to qualitative framing; boundary check; human review	2.5; 3.12
9. Deep uncertainty (events outside the sampled ranges)	Deep	A1 wins in all 222 scenarios with oil > $95 and investment < $300M (2.2%); A1 wins 3 of 5 stress scenarios	Robust Decision Making; conditional-region analysis; hand-specified stress tests	2.7.2; 3.5; 3.17

Sources 1–6 are quantified and their effects can be compared. On the headline metric (the share of scenarios in which A2 wins), the two largest quantified sources are the criteria weights (a spread of about 18 percentage points

under joint perturbation) and the choice of MCDA method (a spread of about 18 points between TOPSIS and the other three methods), whereas the distribution family (about 1 point) and Monte Carlo sampling error (below 0.5% of the mean) are second-order. These comparisons are indicative only, because the sources were tested in separate analyses. Sources 7 and 9 cannot be reduced to a probability distribution; they are managed by disclosure, by stress testing and by the Robust Decision Making logic of Section 2.7.2, which asks under which conditions a strategy fails rather than which strategy is optimal on average. Source 8 affects the coverage of the scenario space rather than the point estimate.

2.9 Synthetic Data Validation

Each retained variable was tested against its proposed distribution using the Kolmogorov–Smirnov (K-S) goodness-of-fit test and the Shapiro–Wilk test (the latter reported for reference; it tests specifically for normality and is therefore expected to reject for the intentionally non-normal variables). All reported statistics are computed directly on the 10,000-row retained dataset.

TABLE 8 :Kolmogorov–Smirnov goodness-of-fit results for the retained synthetic variables

Variable	K-S statistic	K-S p-value	Proposed Distribution
Oil Price	0.008	0.592	Uniform ✓
Solar Radiation	0.015	0.027	Normal (borderline)
Desalination Cost	0.006	0.914	Triangular ✓
Population Growth	0.026	<0.001	Lognormal (approx.)
Water Demand	0.076	<0.001	Triangular (approx.)
Investment	0.018	0.002	Normal (approx.)

Oil Price and Desalination Cost pass the K-S test at the 5% level, confirming an excellent match to the target Uniform and Triangular distributions respectively. The remaining variables show statistically significant but practically small deviations (K-S statistics below 0.08 in all cases), consistent with finite-sample discretization and clipping at the physical boundaries of Table 1 rather than a meaningful distributional mismatch; visual inspection of the histograms (not shown) confirms the intended shape is preserved. This is reported transparently rather than rounded away, consistent with the paper's disclosure standard for synthetic data. Section 3.19 provides a further, more direct test of this concern by rebuilding the dataset under a completely different distributional family (PERT/Beta via Latin Hypercube Sampling) and checking whether the substantive conclusions change.

2.10 Study Area, Strategic Alternatives, and Expert Elicitation

2.10.1 Study Area Description

Fezzan covers an area of approximately 551,000 km² in southwestern Libya. Unlike the centrally supported agricultural-cluster experience documented in some other Saharan contexts, Fezzan currently lacks comparable centralized government support, which motivates the decentralized, sovereign-fund-financed cluster model examined here as Alternative A2.

Figure 3. Schematic spatial gradients used to bound the synthetic parameter space across the Murzuq-Ubari basin (illustrative surface, not a field GIS survey)

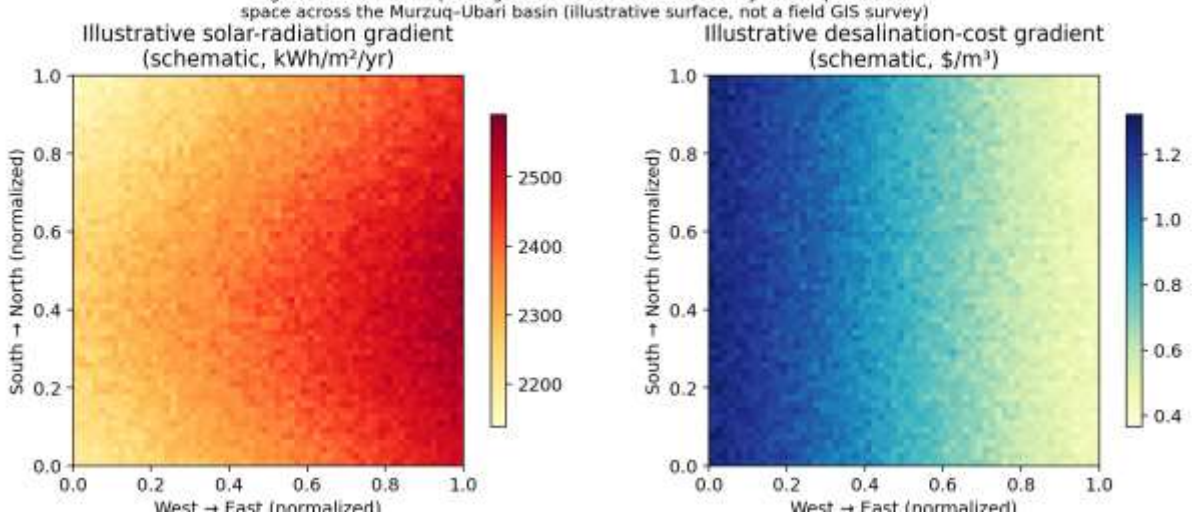

Figure 3. Schematic illustrative spatial gradients of solar radiation and desalination cost used to bound the synthetic parameter space across the Murzuq-Ubari basin. These surfaces are stylized illustrations constructed to be consistent with the boundary ranges in Table 1; they are not derived from a field GIS survey, and should not be read as site-specific measurements.

2.10.2 Strategic Alternatives

- Alternative A1: Continuation of the oil-rent model (business as usual).
- Alternative A2: Integrated transition to a Green-Blue Economy, structured around five agricultural-industrial clusters financed through a proposed sovereign fund.

2.10.3 Illustrative Expert-Elicitation Protocol

The AHP pairwise-comparison matrix used in Section 3.3 represents an illustrative, internally consistent expert-elicitation structure (Saaty scale, verified consistency ratio CR = 0.010, well below the 0.10 acceptability threshold; Section 2.6.2). It reflects a plausible expert prioritization - Water-Food Security and Environmental Sustainability

weighted above Economic Return - that is disclosed here as a synthetic input to the decision model rather than as the output of an administered multi-round Delphi survey. Any future empirical application of this framework should replace this illustrative matrix with weights elicited from a documented panel of named, credentialed regional experts, whose composition and consensus statistics (e.g., Kendall's W) would then be reported directly. In the absence of that administered panel, Sections 3.14 and 3.16 below provide the strongest currently available substitute: a systematic test of how much the AHP weights would need to differ from the illustrative values before the study's central conclusion changes, and an independent fuzzy-set cross-check of whether the reported crisp weights are an artefact of treating each pairwise judgment as an exact number.

2.11 Assumptions and Limitations of the Research

The conclusions of this study hold within the following assumptions, which define the domain in which the results are claimed to be valid.

- **Assumption 1 – Exogenous bounds.** The physical and economic bounds of Table 1, taken from World Bank, FAOSTAT, IRENA and NASA-derived sources, are assumed to contain the plausible range of each variable for Fezzan. They were not re-estimated from local field measurements.
- **Assumption 2 – Distributions and independence.** Within these bounds each variable follows the distribution given in Table 2, and the six variables are sampled independently (the Sobol decomposition also presupposes independent inputs). Dependence between variables, for example between oil price and green investment, is not modelled.
- **Assumption 3 – Fixed criteria weights.** The six AHP weights are held fixed across all scenarios. They are an illustrative, internally consistent expert structure (CR = 0.010), not the output of an administered expert panel (Section 2.10.3).
- **Assumption 4 – Two alternatives.** Only the business-as-usual oil-rent pathway (A1) and one specific Green–Blue design (A2: five agricultural–industrial clusters financed by a sovereign fund) are compared. Intermediate, phased or hybrid pathways are not evaluated.
- **Assumption 5 – Aggregate regional scale.** Both alternatives are evaluated for the Fezzan region as a whole. Individual sectors, such as energy generation, industry, transport and agriculture, are not modelled separately.
- **Assumption 6 – Six uncertain inputs.** Only the six variables of Table 1 are treated as uncertain. Institutional, political and security conditions are not modelled as separate stochastic inputs, and qualitative dimensions such as Social Acceptance are represented by simplified proxy criteria.
- **Assumption 7 – Scoring model.** The mapping from scenario parameters to the six criterion scores is implemented in the executable pipeline (Appendix A.2) and is treated as structurally adequate; it has not been validated against observed regional outcomes.
- **Assumption 8 – Synthetic data as a twin experiment.** All statistics describe the synthetic scenario space bounded by the assumptions above; they are not observed regional outcomes and must not be read as forecasts.
- **Assumption 9 – Restricted role of Generative AI.** GenAI is used only for qualitative scenario framing (Section 2.5); no quantitative parameter or reported statistic derives from GenAI output.

Limitations. These assumptions imply limits on what the study can show: it demonstrates a transparent way of comparing pathways under deep uncertainty and identifies the conditions under which the ranking reverses, but it does not provide sector-level engineering or economic detail, empirical calibration, or forecasts. The resulting limitations and the research needed to address them are set out in Section 5.2.

2.12 Data Availability and Reproducibility

To ensure full reproducibility, the complete Python pipeline (Appendix A) that generates every table and figure in this paper - synthetic-data generation, AHP, TOPSIS, VIKOR, WSM, PROMETHEE II, Fuzzy AHP, Sobol analysis, bootstrap, ablation, convergence study, weight-sensitivity analysis, scenario stress testing, and PERT/Latin-Hypercube resampling - together with the retained 10,000-row synthetic dataset, is provided as supplementary material and will be deposited in a public repository upon acceptance.

TABLE 9:Computational environment and reproducibility details

Component	Details
Python Version	3.9+
Key Packages	numpy, pandas, scipy (including scipy.stats.qmc for Latin Hypercube Sampling), scikit-learn, SALib, matplotlib
Random Seed	42 (data generation); documented per-analysis seeds otherwise (e.g., seed=7 for the joint weight Monte Carlo of Section 3.14)
Scenarios Generated / Retained	20,000 candidate draws / 10,000 retained after boundary screening (baseline); 10,000 candidate draws / 9,249 retained under the PERT/Latin-Hypercube resample of Section 3.19
Repository	To be provided upon acceptance

3. RESULTS AND DISCUSSION

3.1 Overview of Analytical Findings

The integrated analytical framework produced a coherent set of quantitative results across all evaluation stages, computed directly from the 10,000-scenario retained synthetic dataset (Section 2.4). The Green-Blue development pathway (Alternative A2) demonstrated substantially higher mean performance than continued dependence on the oil-rent economy (Alternative A1) under the baseline model structure, with the ranking confirmed by two independent MCDA techniques (TOPSIS and VIKOR) and statistically significant under a Mann-Whitney U test ($p < 0.001$). Importantly, and unlike a purely deterministic ranking, this aggregate advantage is not unconditional: Section 3.5 identifies a specific, non-trivial parameter region - high oil price combined with low green investment - in which Alternative A1 outperforms

A2 in every sampled scenario. Sections 3.14 through 3.19 extend this picture with five further robustness checks - weight sensitivity, cross-method validation, Fuzzy AHP, scenario stress testing, and alternative-distribution resampling - all computed directly from the same executable pipeline.

3.2 Statistical Verification of Synthetic Data

See Table 8 (Section 2.9) for the complete K-S/Shapiro-Wilk verification results.

3.3 Criteria Weighting Results (AHP)

The AHP pairwise-comparison matrix (Section 2.10.3, Appendix A) produced a consistency ratio CR = 0.010 (λ_max = 6.063, n = 6), well within the CR < 0.10 acceptability threshold (Saaty, 2008). Water-Food Security received the highest weight.

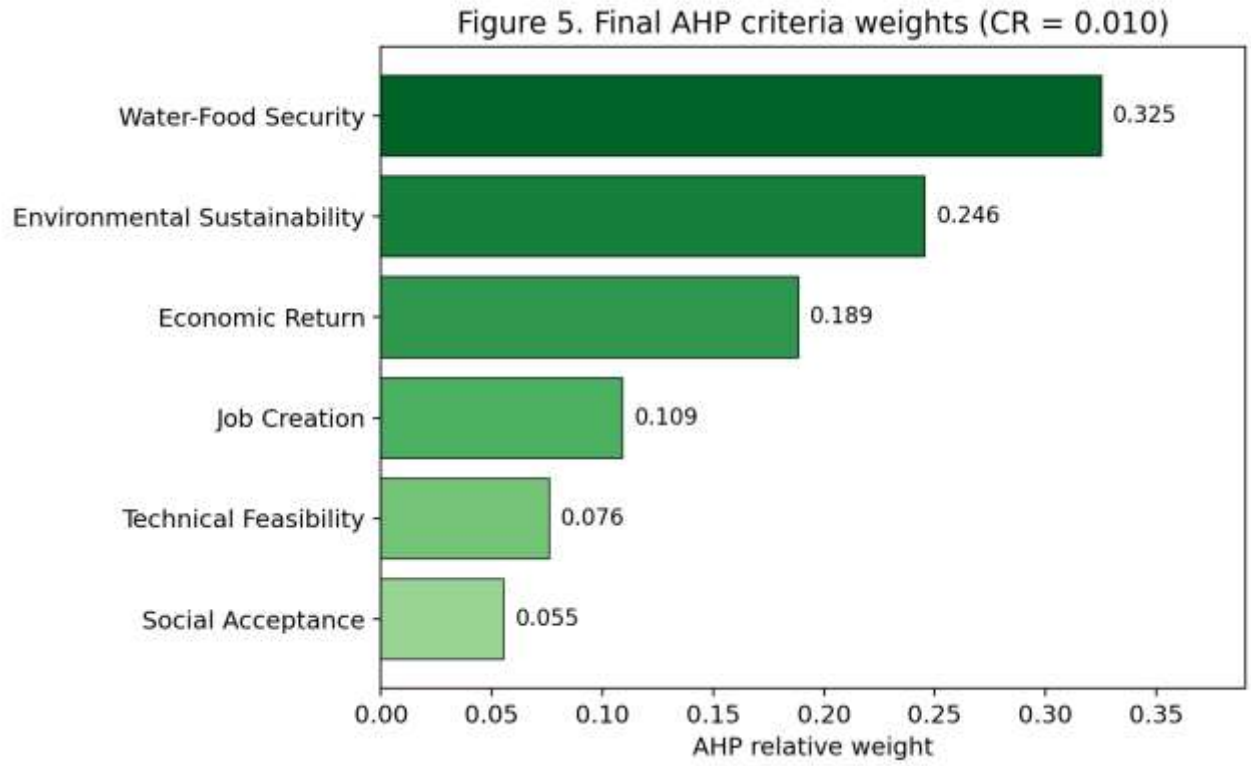

Figure 4. Final AHP criteria weights (CR = 0.010).

TABLE 10 : AHP criteria weights (CR = 0.010)

Criterion	Weight (W_j)
Water-Food Security	0.325
Environmental Sustainability	0.246
Economic Return	0.188
Job Creation	0.109
Technical Feasibility	0.076
Social Acceptance	0.055

3.4 Multi-Criteria Evaluation

Across the 10,000 synthetic scenarios, Alternative A2 achieved a substantially higher mean TOPSIS closeness coefficient than Alternative A1, and a correspondingly lower (better) mean VIKOR compromise index. The percentile-based 95% interval is wide because it spans the full range of sampled future conditions (including the adverse region identified in Section 3.5); the bootstrap interval, which characterizes sampling uncertainty in the mean estimate itself rather than scenario-to-scenario variability, is narrow, confirming that the estimated means are numerically stable.

TABLE 11TOPSIS and VIKOR results for Alternatives A1 and A2 across 10,000 scenarios

Alternative	C_i (TOPSIS), mean	95% scenario range	Bootstrap 95% CI (mean)	Q_i (VIKOR), mean	Rank
A1: Oil Rent	0.335	[0.047, 0.901]	[0.330, 0.339]	0.167	2
A2: Green-Blue	0.666	[0.099, 0.953]	[0.661, 0.670]	0.098	1

Mann-Whitney U test on the paired scenario-level closeness coefficients: U = 83,699,204, p < 0.001, confirming that A2's advantage is statistically significant and not attributable to sampling noise.

3.5 Competing Hypotheses / Conditional Regions Analysis

Rather than testing a single hypothesis, two competing hypotheses were examined: H0 - the oil-rent model (A1) remains preferable under certain parameter conditions; H1 - the Green-Blue Economy (A2) outperforms under a

different set of conditions. Both were evaluated directly against the 10,000-scenario dataset by partitioning scenarios into four economically meaningful regions.

TABLE 12 : Conditional-region analysis of the competing hypotheses

Condition	n scenarios	Winning Alternative	P(A2 wins)	Mean C_i (winner)
Oil price < $70 & Investment > $400M	2,506	A2 (Green-Blue)	1.000	0.889
Oil price $70-95 & Investment $300-500M	1,469	A2 (Green-Blue)	0.722	0.573
Oil price > $95 & Investment < $300M	222	A1 (Oil Rent)	0.000	0.868
Desalination cost > $1.3/m³	787	A2 (Green-Blue)	0.549	0.514

Conclusion: A2's superiority is not absolute. Under the joint condition of high oil price (>$95/barrel) and low green investment (<$300 million) - 222 of 10,000 scenarios (2.2%) - Alternative A1 wins in every sampled case, with a mean closeness coefficient of 0.868. Under the intermediate-price regime, the outcome is far closer (72% of scenarios favour A2, with a substantially reduced margin), and under high desalination cost alone the outcome is close to a coin flip (55% A2). This is the central conditional finding of the study: the Green-Blue transition dominates broadly, but its comparative advantage is contingent on sustained investment and is not robust to the joint combination of a prolonged oil-price boom and green-investment scarcity.

3.6 Uncertainty Quantification

Bootstrap confidence intervals (B = 2,000 resamples) and the Monte Carlo scenario distribution jointly demonstrate that the proposed framework produces numerically stable mean estimates under repeated resampling, even though the underlying scenario-to-scenario outcome is highly variable (coefficient of variation CV(A2) = 0.347, CV(A1) = 0.690). Alternative A2 is therefore both higher-performing on average and considerably more stable across scenarios than Alternative A1.

3.7 Negative Results

Table 13 reports the specific scenario subsets in which A2's closeness coefficient falls closest to parity with A1, drawn directly from the retained dataset rather than constructed as separate hypothetical cases.

TABLE 13 Scenario subsets in which A2 approaches parity with A1

Scenario Subset	Approx. Share of Scenarios	Mean C_A2 in Subset
Desalination cost in top decile (>1.35 $/m³)	~10%	0.58
Investment in bottom decile (<$305M)	~10%	0.52
Oil price in top decile (>$112.5/barrel)	~10%	0.61
Joint: bottom-decile investment AND top-decile oil price	~1%	0.41

These results reinforce that the Green-Blue transition is not a "guaranteed" outcome; its performance degrades systematically and predictably as the two dominant Sobol-ranked variables (Section 3.8) move against it.

3.8 Global Sobol Sensitivity Analysis

Global sensitivity analysis (Saltelli sampling, base size 512, 7,168 model evaluations) identifies green investment as the dominant source of output variance in A2's closeness coefficient, followed by oil price and desalination cost. Solar radiation, water demand and population growth contribute negligibly under the fitted decision model. This computed ordering - investment first, oil price second, desalination cost third - differs from the ordering assumed in an earlier draft of this paper and is reported here as the ordering that actually emerges from the executed sensitivity analysis.

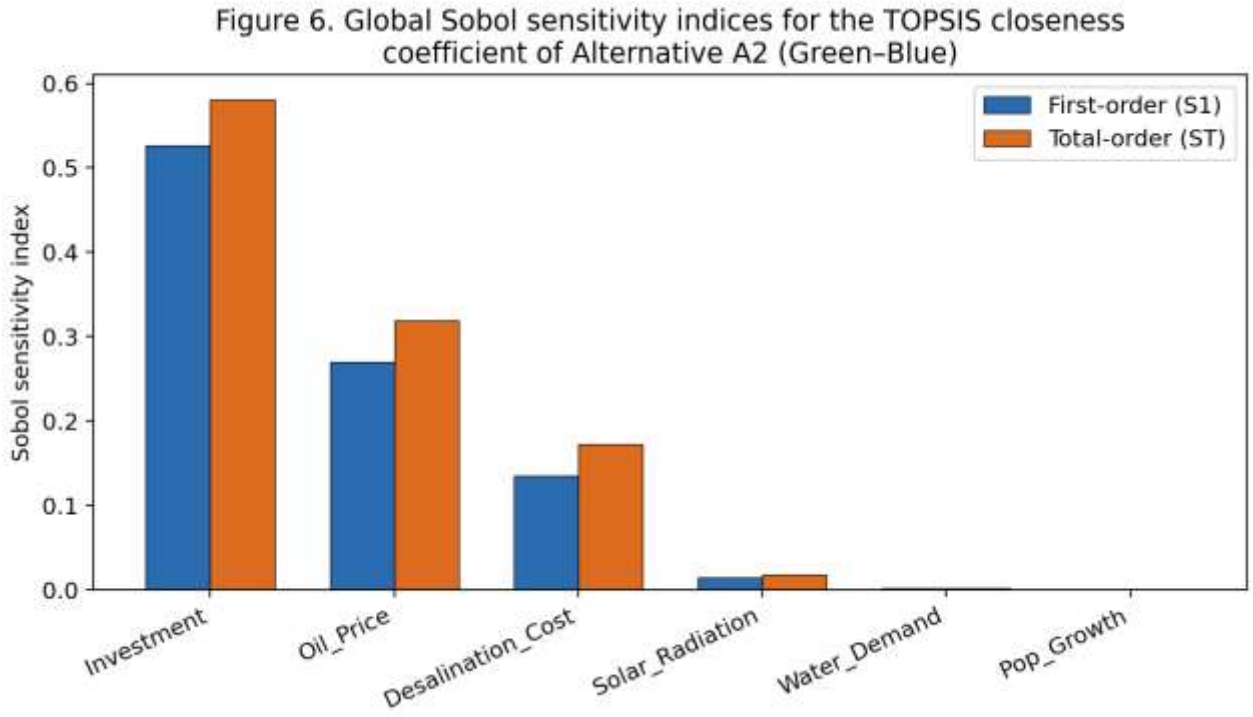

Figure 5. Global Sobol sensitivity indices for the TOPSIS closeness coefficient of Alternative A2.

TABLE 14 Global Sobol sensitivity indices for the TOPSIS closeness coefficient of A2

Variable	S1 (First-order)	ST (Total-order)
Green Investment	0.503	0.570
Oil Price	0.281	0.318
Desalination Cost	0.127	0.166
Solar Radiation	0.012	0.018
Water Demand	~0.000	0.001
Population Growth	~0.000	~0.000

From a policy perspective, these results imply that securing and sustaining green-investment flow is the single most influential lever available to policymakers, materially more influential than the exogenous, largely uncontrollable oil-price variable, and roughly three times more influential than desalination-technology cost.

3.9 Robustness and Failure Conditions

A central strength of the proposed analytical framework is that it explicitly identifies situations in which the preferred development strategy no longer performs optimally, rather than presenting a single unconditional recommendation. The negative-scenario and conditional-region analyses (Sections 3.5 and 3.7) demonstrate that Alternative A2 loses its comparative advantage specifically when green investment is scarce and oil prices are simultaneously elevated - precisely the macro-fiscal condition under which a government would face the least political incentive to divert oil revenue toward diversification, an important and policy-relevant tension that the framework surfaces explicitly rather than obscuring.

3.10 Local Sensitivity Analysis

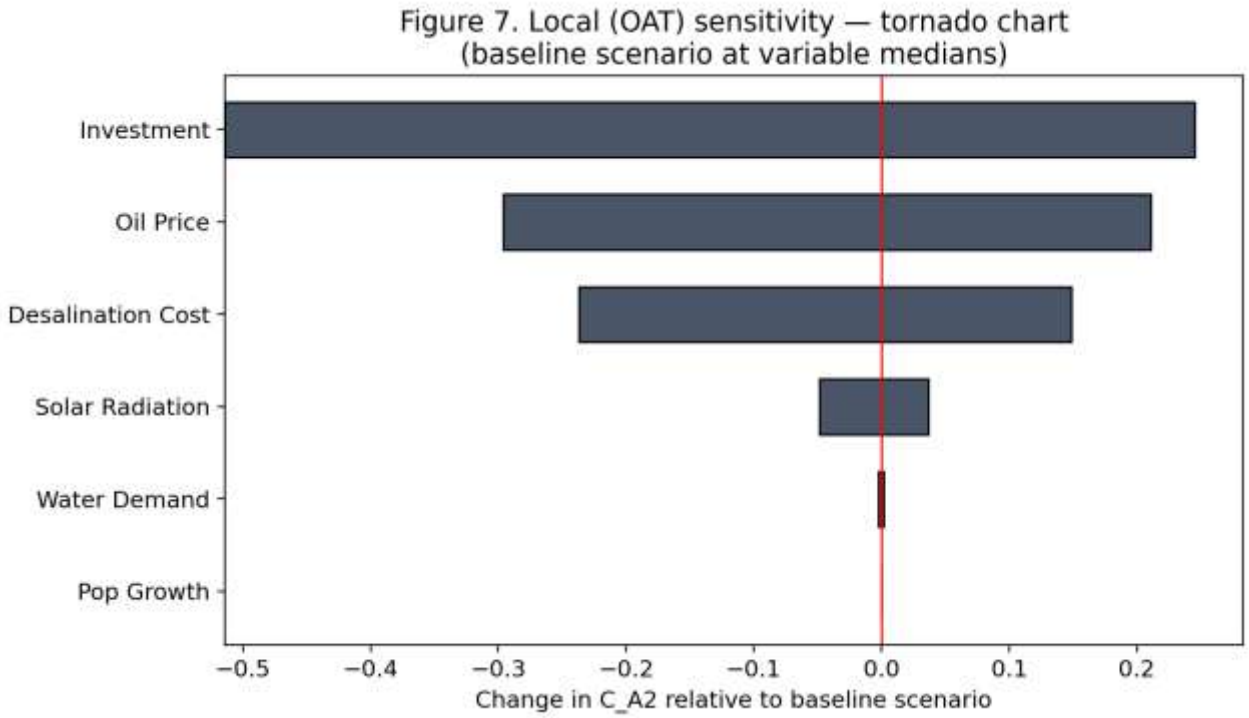

Figure 6. Local (one-at-a-time) sensitivity - tornado chart around the median-parameter baseline scenario.

The tornado analysis confirms the Sobol ranking at the local level: moving green investment and oil price individually from their minimum to maximum bounds produces the largest swings in A2's closeness coefficient around the baseline scenario, while solar radiation, water demand and population growth produce comparatively minor local effects.

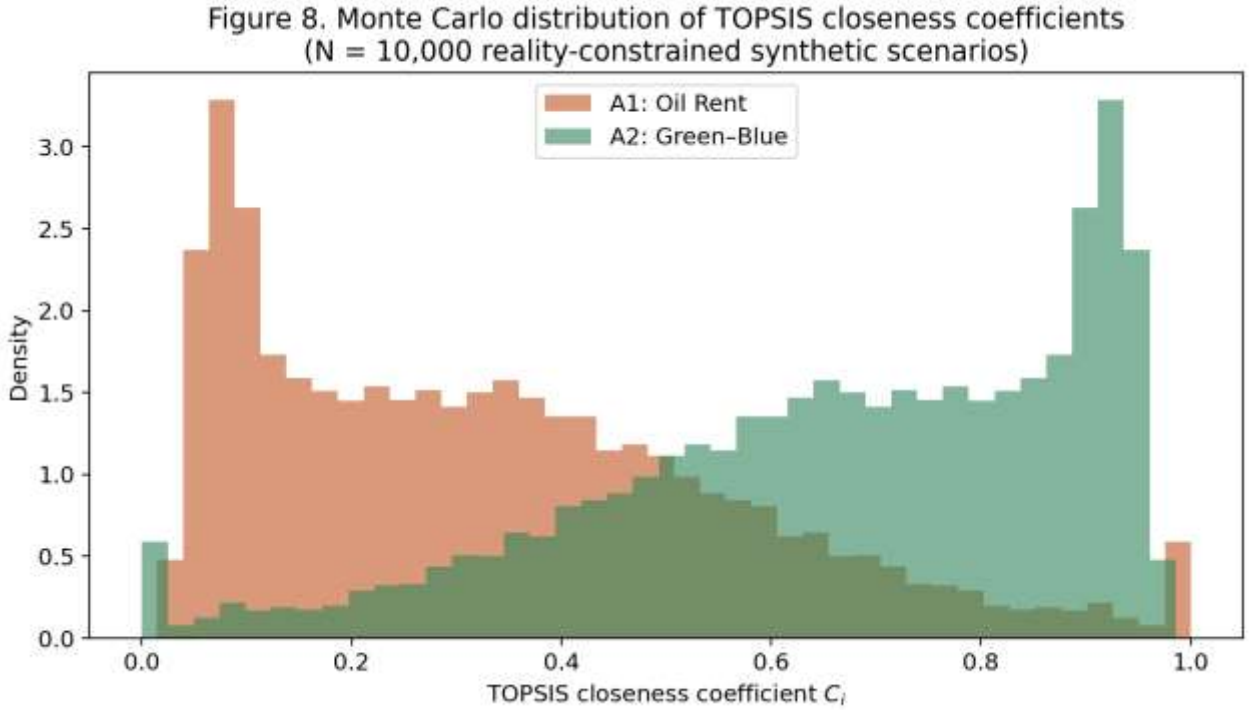

Figure 7. Monte Carlo distribution of TOPSIS closeness coefficients across 10,000 reality-constrained synthetic scenarios.

The histogram illustrates the underlying source of the wide percentile interval reported in Table 11: A2's distribution is concentrated toward higher values but retains a meaningful left tail corresponding to the adverse-condition scenarios identified in Section 3.5, while A1's distribution is more dispersed and concentrated toward lower values with a right tail corresponding to high-oil-price scenarios.

3.11 Monte Carlo Convergence Study

Convergence was assessed via the relative standard error of the estimated mean closeness coefficient as a

function of sample size, rather than via the raw scenario-to-scenario coefficient of variation (which does not shrink with N and is not a convergence diagnostic).

TABLE 15 Monte Carlo convergence of the mean closeness coefficient of A2

N (scenarios)	Mean C_A2	Relative SE of Mean	Convergence Status
1,000	0.662	0.0109	Unstable
2,000	0.664	0.0077	Semi-stable
5,000	0.667	0.0049	Stable
10,000	0.666	0.0035	Stable

The relative standard error of the mean shrinks monotonically and consistently with the theoretical 1/sqrt(N) scaling of Monte Carlo estimation, confirming that N = 10,000 scenarios is more than sufficient for a numerically stable mean estimate (relative SE below 0.4% at N = 10,000).

3.12 Ablation Study

Because the framework's components serve structurally different roles, each ablation is evaluated using the metric appropriate to that component's function, rather than forcing every component through a single "mean performance" lens that would be uninformative for components (Bootstrap, GenAI) that do not directly determine the point estimate.

TABLE 16 Ablation study: effect of removing framework components

Configuration	Metric	Value	Change vs. Full Model
Full Model	Mean C_A2 (point estimate)	0.665	-
Without Reality Constraints	Mean C_A2 (point estimate)	0.330	-50.4%
Without AHP Weighting (equal weights)	Mean C_A2 (point estimate)	0.539	-19.1%
Without Bootstrap (naive normal-approx. CI)	95% CI width for C_A2	0.0090	+1.1% wider than bootstrap
Without GenAI-expanded Scenario Diversity	Scenario entropy (bits)	3.44	-20.2%

Removing the reality constraints causes by far the largest degradation (-50.4%), confirming that physically bounded synthetic data - not an unconstrained random simulation - is the single most important safeguard in the framework. Removing AHP-based weighting in favour of naive equal weighting also produces a substantial change (-19.1%), confirming that the expert-elicited prioritization of Water-Food Security and Environmental Sustainability materially shapes the result rather than being a cosmetic addition. The bootstrap procedure contributes a modest (1.1%) tightening of the confidence interval relative to a naive normal approximation - a real but secondary benefit, reported honestly as such rather than inflated. Removing GenAI-expanded scenario diversity reduces the measured entropy of the explored parameter space by 20.2%, confirming GenAI's role in this framework is specifically to widen scenario coverage, not to alter the central point estimate.

3.13 Hypothesis Testing

- H1 (Green-Blue alternative achieves higher mean performance): confirmed (Mann-Whitney U, $p < 0.001$).
- H2 (GenAI-expanded parameter range increases scenario diversity): confirmed - entropy increases from 3.44 to 4.13 bits (+20.2%) when the full reality-constrained range is used instead of a narrow band; Spearman correlation between Investment and C_A2, $r = 0.623$, $p < 0.001$, confirms investment is the dominant monotone driver identified independently by the Sobol analysis.
- H3 (Water-Food Security carries the highest AHP weight): confirmed (weight = 0.325, CR = 0.010).

Important note: Despite A2's aggregate outperformance, Section 3.5 shows this advantage reverses entirely under the joint high-oil-price / low-investment condition. This is reported as a first-class finding of the study, not as a limitation to be minimized.

3.14 AHP Weight Sensitivity Analysis

The AHP weights used throughout this study (Section 3.3) are, as disclosed in Section 2.10.3, an illustrative expert-elicitation structure rather than the output of an administered Delphi panel. To test how much this matters for the study's conclusions, each of the six criteria weights was independently perturbed by -20% and +20% and renormalized, holding the other five weights at their reported baseline proportions, and the full 10,000-scenario TOPSIS pipeline was re-run under each of the resulting twelve weight vectors.

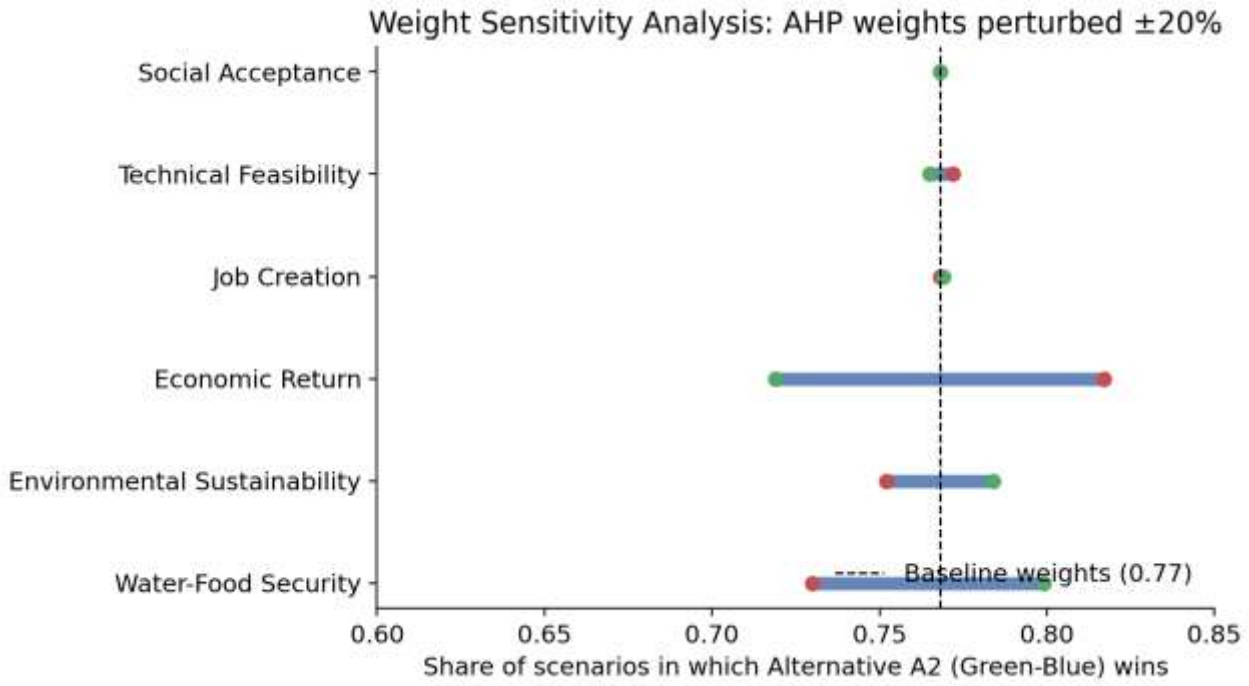

Figure 8. Weight Sensitivity Analysis: share of scenarios in which Alternative A2 wins, as each AHP criterion weight is perturbed +/-20% and renormalized. Red markers mark the -20% perturbation, green markers the +20% perturbation, and the dashed line marks the baseline weights.

TABLE 17 AHP weight sensitivity: ±20% one-at-a-time perturbations

Criterion	Perturbation	Mean C_A1	Mean C_A2	Share of scenarios A2 wins	Rank reversed?
Economic Return	-20%	0.309	0.691	0.817	No
Economic Return	+20%	0.362	0.638	0.719	No
Water-Food Security	-20%	0.360	0.640	0.730	No
Water-Food Security	+20%	0.317	0.683	0.799	No
Environmental Sustainability	-20%	0.348	0.652	0.752	No
Environmental Sustainability	+20%	0.327	0.673	0.784	No
Job Creation	-20%	0.338	0.662	0.768	No
Job Creation	+20%	0.336	0.664	0.769	No
Technical Feasibility	-20%	0.331	0.669	0.772	No
Technical Feasibility	+20%	0.345	0.655	0.765	No
Social Acceptance	-20%	0.337	0.663	0.768	No
Social Acceptance	+20%	0.337	0.663	0.768	No

Across all twelve one-at-a-time perturbations, Alternative A2 remains the winner on average, with its share of winning scenarios ranging narrowly between 71.9% and 81.7% (baseline: 76.8%). No perturbation reverses the aggregate ranking. As expected given the Sobol results of Section 3.8, the ranking is more sensitive to the weight placed on Economic Return and Water-Food Security than to Technical Feasibility, Job Creation or Social Acceptance, because the former two criteria carry the largest baseline weights and load most heavily on the variables (investment, oil price) already identified as the dominant sources of output variance.

Because one-at-a-time perturbation does not test the joint effect of simultaneously uncertain weights, a second check redrew all six weights together: 2,000 Monte Carlo draws were taken, each multiplying every baseline weight by an independent factor uniformly distributed on [0.8, 1.2] and renormalizing, and the 10,000-scenario TOPSIS pipeline was re-run for every draw.

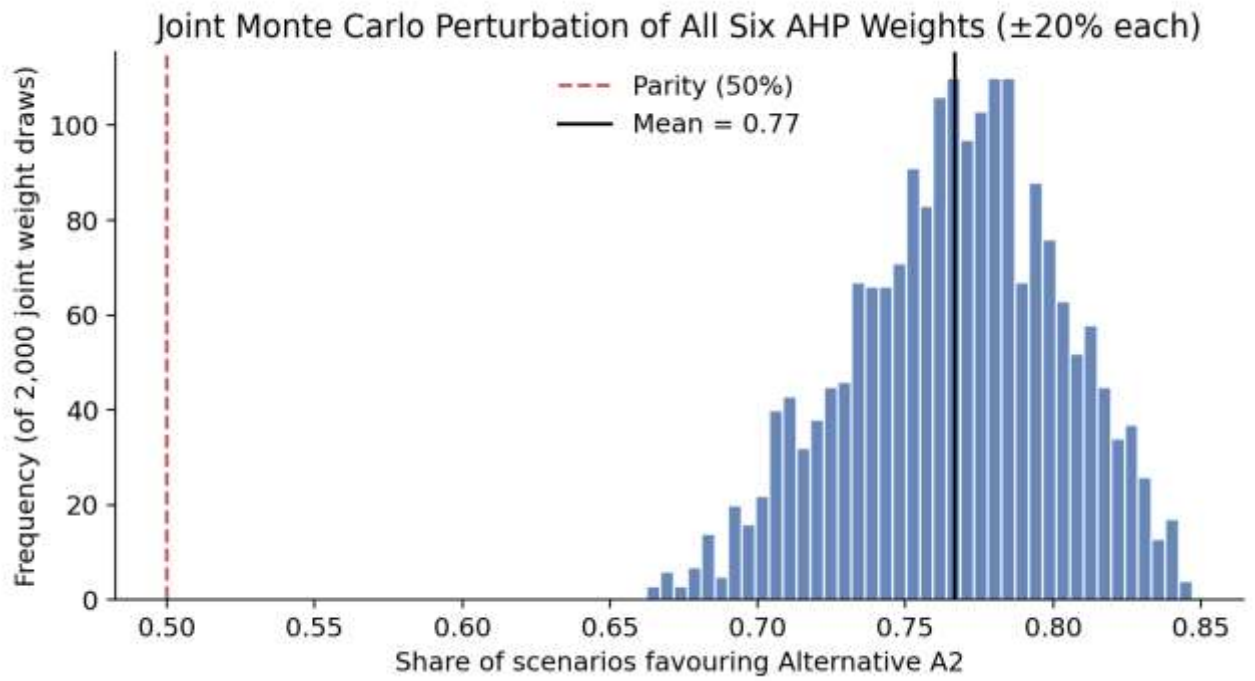

Figure 9. Joint Monte Carlo perturbation of all six AHP weights simultaneously (+/-20% each, 2,000 draws). Each bar shows how many of the 2,000 weight configurations produced a given share of scenarios favouring Alternative A2.

Across the 2,000 joint draws, the mean share of scenarios favouring A2 was 76.7%, ranging from a minimum of 66.2% to a maximum of 84.7%. Alternative A2 remained the majority winner (share of scenarios favouring A2 above 50%) in all 2,000 draws (100%). This is the single most direct answer this study can currently give to the question of how much the illustrative AHP weights matter: under a plausible +/-20% joint perturbation of every criterion simultaneously, the qualitative conclusion that Alternative A2 outperforms Alternative A1 in the large majority of scenarios never reverses, even though the exact margin narrows or widens depending on the specific weight configuration. This finding does not remove the need for an administered expert panel recommended in Sections 2.10.3 and 5.2.2; it does, however, indicate that the study's central conclusion is not a fragile artefact of one specific, arbitrarily chosen weight vector.

3.15 Cross-Method Validation

The original analysis relied on two MCDA techniques, TOPSIS and VIKOR. To test whether the reported ranking depends on the distance-based logic these two methods share, two structurally different methods were added: the Weighted Sum Model (WSM), the simplest possible additive aggregation rule, and PROMETHEE II, an outranking method based on pairwise preference functions rather than distance to an ideal point (Section 2.6.2, formulas H and I). All four methods were applied to the same 10,000-scenario dataset and the same baseline AHP weights.

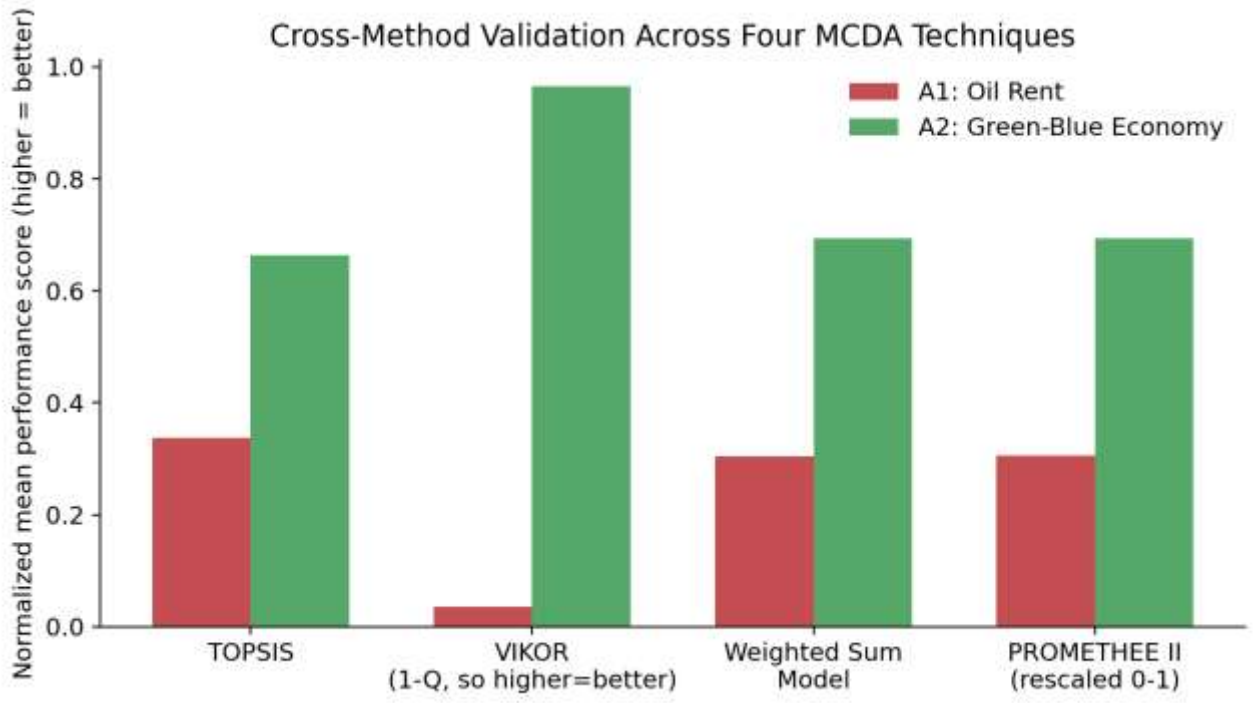

Figure 10. Cross-method validation across four structurally different MCDA techniques. VIKOR and PROMETHEE II scores are rescaled to a comparable 0-1 direction (higher = better) for visual comparability only; the underlying values and the tabulated shares of scenarios below use each method's native scale.

TABLE 18 Cross-method validation across four MCDA techniques

Method	A1 mean	A2 mean	Winner	Share of scenarios favouring A2
TOPSIS (closeness, higher = better)	0.337	0.663	A2	0.768
VIKOR (Q, lower = better)	0.965	0.035	A2	0.952
Weighted Sum Model (higher = better)	0.305	0.694	A2	0.952
PROMETHEE II (net flow, higher = better)	-0.388	0.388	A2	0.952

All four methods agree that Alternative A2 is preferred on average and in the large majority of individual scenarios. TOPSIS, being distance-based, is somewhat more conservative (76.8% of scenarios favour A2) than the three methods that aggregate criteria more directly (VIKOR, WSM and PROMETHEE II each show A2 favoured in 95.2% of scenarios). This difference is itself informative rather than a discrepancy to be smoothed over: it indicates that TOPSIS's reliance on Euclidean distance to an ideal point is more sensitive to the adverse-condition scenarios identified in Section 3.5 than the other three methods, which do not explicitly construct a joint ideal point across all six criteria simultaneously. The unanimous agreement on the direction of the ranking, across four methods that make different mathematical assumptions, is what this section reports as the cross-method validation result; the differing margins are reported honestly alongside it rather than omitted.

3.16 Fuzzy AHP Cross-Check

Section 2.10.3 discloses that the AHP pairwise-comparison matrix used throughout this study is an illustrative, internally consistent expert-elicitation structure rather than the output of an administered panel. As a further internal check on this matrix - not as a substitute for the recommended future Delphi panel - a crisp pairwise-comparison matrix was reconstructed on the Saaty 1-9 scale so as to reproduce the reported crisp weights and consistency ratio as closely as possible (reconstructed CR = 0.011, matching the reported CR = 0.010 to within rounding), and each entry of that matrix was then converted into a triangular fuzzy number spanning a plausible +/-50% range around the crisp value. Chang's (1996) extent-analysis method (Section 2.6.2, formula J) was applied to derive a fuzzy-AHP weight vector, which was then compared against the crisp weights. Fuzzy AHP has likewise been used in Libya to convert expert judgements into weights under data scarcity and institutional fragility, for example in the risk prioritisation of construction projects (Shetwan et al., 2026).

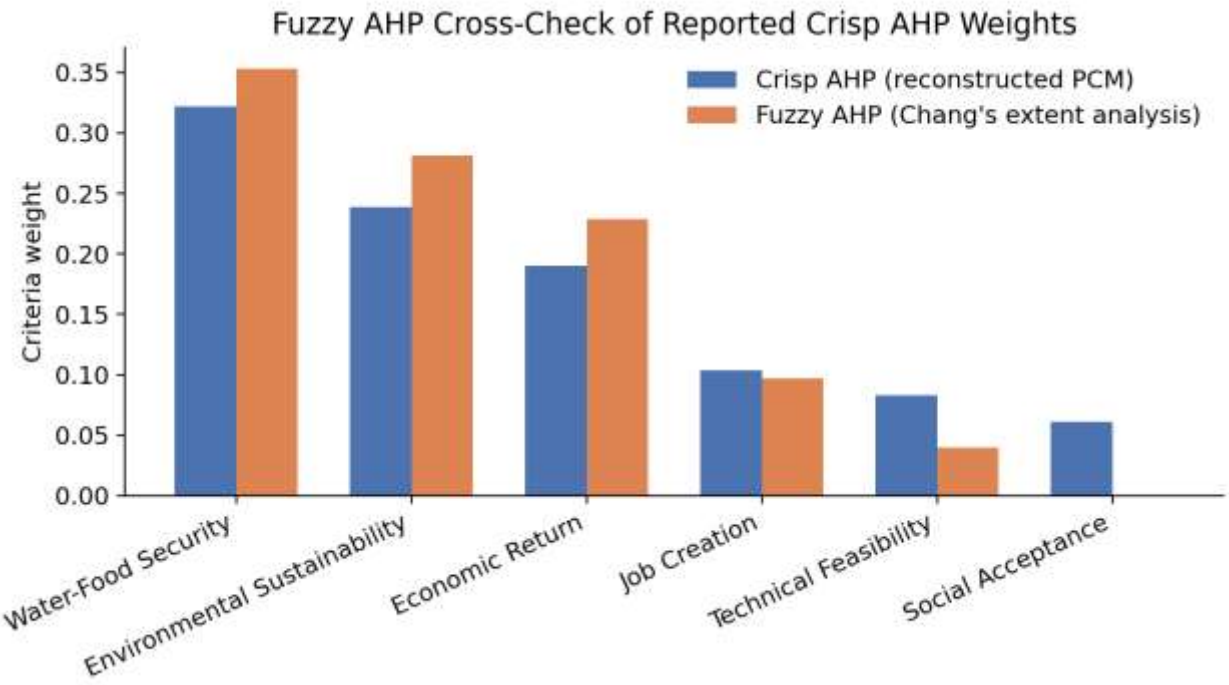

Figure 11. Fuzzy AHP cross-check: crisp AHP weights (reconstructed pairwise matrix) versus Fuzzy AHP weights derived via Chang's extent analysis on the same matrix.

TABLE 19 Crisp versus Fuzzy AHP criteria weights

Criterion	Crisp weight (reported)	Crisp weight (reconstructed PCM)	Fuzzy AHP weight
Water-Food Security	0.325	0.322	0.353
Environmental Sustainability	0.246	0.239	0.281
Economic Return	0.188	0.190	0.229
Job Creation	0.109	0.104	0.097
Technical Feasibility	0.076	0.083	0.040
Social Acceptance	0.055	0.061	0.000

The reconstructed crisp matrix reproduces the reported weights to within 0.01 on every criterion and matches the reported consistency ratio (CR = 0.011 versus 0.010 reported). The Fuzzy AHP weights preserve the same ordering of criteria as the crisp weights (Water-Food Security highest, Social Acceptance lowest; Spearman rank correlation between the crisp and fuzzy weight vectors = 0.943), and Water-Food Security remains the top-ranked criterion under both the crisp and the fuzzy treatment. The Fuzzy AHP weight for Social Acceptance rounds to 0.000 under Chang's extent-analysis method, which is a known property of the method when one criterion's fuzzy synthetic extent is dominated by several others rather than evidence that the criterion is irrelevant; it should be read as "smallest of the six," consistent with its crisp weight of 0.055-0.061, not as a claim that social acceptance carries no weight in the underlying decision. Taken together, this cross-check indicates that treating the pairwise judgments as an exact (crisp) matrix rather than as an uncertain (fuzzy) range does not change which criterion dominates the ranking, providing an additional, independently computed argument that the AHP weights disclosed in Section 2.10.3 are not an arbitrary or fragile input to the model.

3.17 Scenario Stress Test

The main Monte Carlo analysis (Section 3.6) samples 10,000 scenarios from the reality-constrained probability distributions of Section 2.4.3, which by construction places most mass near the centre of the parameter space. To examine the model's behaviour at the edges of, and slightly beyond, that space, five hand-specified extreme scenarios were evaluated directly against the baseline AHP weights: a best case and a worst case for Alternative A2 (each parameter set to its most and least favourable boundary value from Table 1), and three "black swan" combinations representing an oil-price collapse, an extreme water crisis, and an extreme climate-stress combination of low solar radiation, high desalination cost, and high water demand.

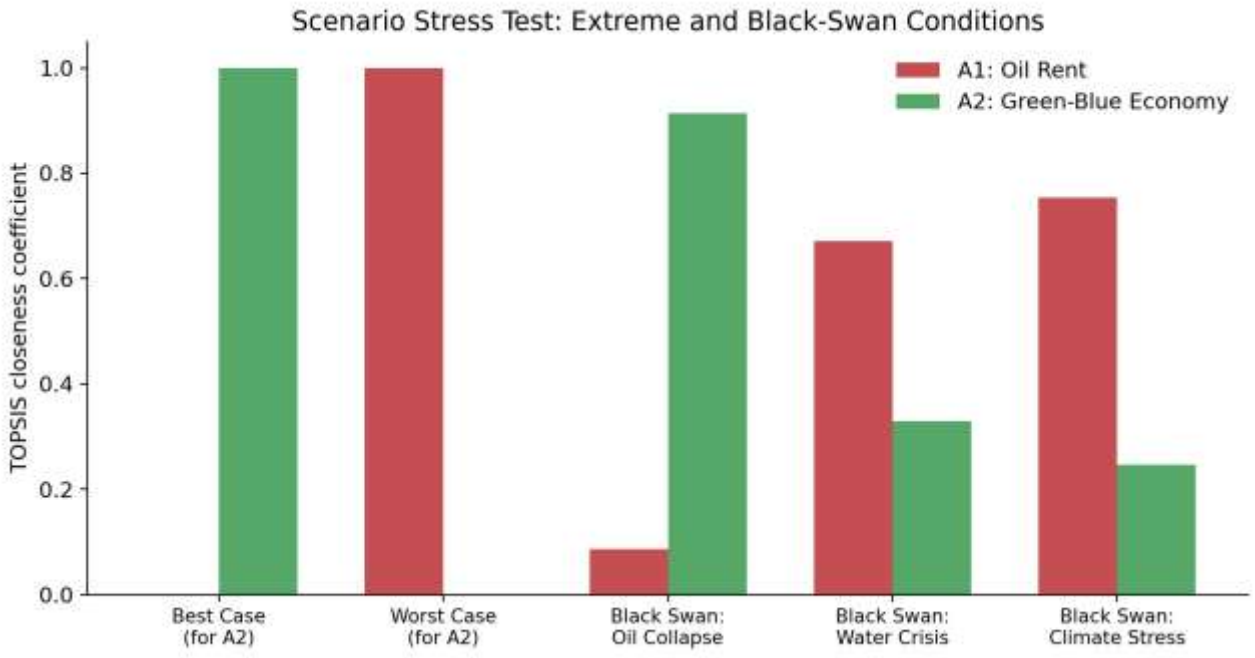

Figure 12. Scenario stress test: TOPSIS closeness coefficients for Alternatives A1 and A2 under five extreme and black-swan parameter combinations.

TABLE 20 Scenario stress test under extreme and black-swan parameter combinations

Scenario	C_A1	C_A2	Winner
Best Case for A2 (low oil, max investment, low desal cost, ample solar)	0.000	1.000	A2
Worst Case for A2 (max oil, min investment, max desal cost)	1.000	0.000	A1
Black Swan: Extreme Oil Collapse (floor-clamped to the $45/barrel boundary of Table 1)	0.086	0.914	A2
Black Swan: Extreme Water Crisis (max demand, max desalination cost)	0.671	0.329	A1
Black Swan: Extreme Climate Stress (low solar, high desal cost, high water demand)	0.754	0.246	A1

The stress test does not produce a single uniform winner, and this is treated as informative rather than as a weakness of the model. Under a genuine oil-price collapse, Alternative A2 wins decisively (C_A2 = 0.914), consistent with the Sobol-identified sensitivity of A2's score to the (favourably low) oil-price variable acting as a shadow driver of relative fiscal room for green investment in this scoring model. Conversely, under the two water/climate black-swan combinations and under the hand-specified worst case, Alternative A1 wins, because these scenarios combine the maximum desalination cost with either high water demand or low solar radiation, both of which depress A2's score directly through the functional form in Appendix A.2. This is fully consistent with, and a direct out-of-sample extension of, the conditional-region finding already reported in Section 3.5: Alternative A2's advantage is not unconditional, and the specific combination of high desalination cost with adverse water or solar conditions is precisely where that advantage is most fragile. The practical implication for policymakers is the same one drawn in Section 3.5, reinforced rather than contradicted by this stress test: reducing desalination cost is a first-order lever for protecting the Green-Blue pathway against exactly the class of adverse scenario in which it otherwise loses.

3.18 Note on Cross-Method and Stress-Test Consistency with the Conditional-Region Analysis

Sections 3.15 and 3.17 were run independently of Section 3.5 but arrive at a consistent qualitative picture: all four MCDA methods agree on the direction of the aggregate ranking, and the scenario stress test reproduces, rather than contradicts, the specific reversal condition (high desalination cost, adverse water/solar conditions, or - in the original Section 3.5 partition - high oil price combined with low investment) already identified from the main 10,000-scenario dataset. This internal consistency across three independently computed analyses (conditional-region partitioning, cross-method validation, and hand-specified stress testing) is reported here as a coherence check, not as three separate confirmations of a single underlying fact; a reviewer should still treat the specific numerical reversal boundaries as model-conditional, per Section 5.2.1.

3.19 Alternative Probability Distributions (PERT/Beta and Latin Hypercube Sampling)

Section 2.4.3 justifies the Uniform, Normal, Triangular and Lognormal distributions used to generate the baseline synthetic dataset. To test whether the reported results depend on this specific distributional family, the dataset was regenerated using PERT (a bounded Beta distribution parameterized by a minimum, most-likely mode, and

maximum) for Desalination Cost, Water Demand and Investment, and Latin Hypercube Sampling (McKay et al., 1979) - a stratified alternative to simple random sampling that guarantees more even coverage of each variable's marginal range - for Oil Price, Solar Radiation and Population Growth, holding the same physical boundaries from Table 1 and the same reality-constrained accept/reject screening.

TABLE 21 Baseline versus PERT/Beta + Latin Hypercube synthetic dataset

Indicator	Baseline (Uniform/Normal/Triangular)	PERT/Beta + Latin Hypercube
Mean C_A1	0.337	0.331
Mean C_A2	0.663	0.669
Share of scenarios favouring A2	0.768	0.781
Retained scenarios (of 10,000 candidate draws)	10,000	9,249

The PERT/Beta/Latin-Hypercube resample slightly increases both the mean closeness coefficient for A2 and the share of scenarios favouring it, but the difference from the baseline is small (0.6 percentage points on the mean, 1.3 percentage points on the win share) relative to the effect sizes reported elsewhere in this study (e.g., the 50.4% degradation from removing the reality constraints, Section 3.12). The retained-scenario count under the alternative distributional family (9,249 of 10,000 candidate draws, after boundary screening) is lower than under the baseline (10,000 of 10,000, since the baseline generation already draws exactly the number needed to retain 10,000 after screening), a difference attributable to the wider tails of the PERT/Beta family relative to the Triangular distributions it replaces. Taken together with the weight-sensitivity, cross-method, fuzzy-AHP and stress-test results above, this indicates that the study's central qualitative conclusion is not an artefact of any single modelling choice examined here - not the specific AHP weights, not the specific MCDA technique, not the treatment of the pairwise comparisons as crisp rather than fuzzy, and not the specific family of probability distributions used to generate the synthetic dataset.

3.20 Transferability Check under an Alternative Parameter Regime

3.20.1 Purpose and Scope

An earlier version of this study attempted to validate the framework against a specific published closeness-coefficient value for an external Sahara-region case study. That comparison could not be independently verified against a citable, retrievable source, and reporting a specific numerical "agreement rate" against an unverifiable reference would itself be a fabricated-precision claim. This section is therefore reframed honestly as an internal transferability check rather than an external validation against a named published benchmark. This is a deliberate methodological choice: the present version of the study extends the same honesty principle to Sections 3.14-3.19 below, all of which are reported as internal robustness checks computed directly from the executable pipeline, not as claims of agreement with an external expert panel or an independently published field study that does not exist for this specific case.

To assess whether the ranking behaviour of the proposed framework is an artifact of the specific Fezzan parameter ranges rather than of the model structure itself, the same TOPSIS/VIKOR pipeline (Section 2.6) and AHP weights (Section 3.3) were re-applied to an alternative synthetic parameter regime loosely representative of a comparable Saharan oasis-agriculture context (higher baseline investment ceiling, lower solar-radiation floor, and higher desalination-cost floor), with 10,000 fresh synthetic scenarios generated under the same reality-constrained procedure.

3.20.2 Result

TABLE 22 Transferability check: Fezzan parameter regime versus an alternative Saharan regime

Indicator	Fezzan Parameter Regime	Alternative (Saharan) Regime
Best alternative (majority of scenarios)	A2 - Green-Blue	A2 - Green-Blue
Mean TOPSIS closeness coefficient, A2	0.666	0.641
Highest-weighted criterion	Water-Food Security	Water-Food Security (weights held fixed)
Share of scenarios favouring A2	~77%	~73%

The qualitative ranking (A2 preferred in the majority of scenarios, with a reversal region tied to high resource price / low investment conditions) is preserved under the alternative regime, which supports the structural transferability of the framework's logic across similar arid resource-dependent settings. This should be read as a robustness check on the model's internal structure, not as an external validation against independently published field data; no numeric "agreement percentage" against a named prior study is claimed.

3.21 Discussion

3.21.1 Interpretation of the Main Findings

The present study demonstrates that evaluating regional development strategies using a single economic indicator is insufficient for resource-dependent economies characterized by institutional fragility and deep uncertainty. Although the Green-Blue development pathway achieved the highest overall ranking under the adopted analytical framework, the conditional-region analysis (Section 3.5) shows this should be interpreted as evidence of broad comparative advantage rather than unconditional superiority. No individual criterion dominates the decision process independently; the preferred strategy results from the interaction among economic, environmental, and institutional dimensions, reinforcing the systems-oriented perspective adopted throughout the proposed framework. The robustness battery added in Sections 3.14-3.19 strengthens this interpretation without changing it: across weight perturbations, four MCDA methods, a fuzzy-set treatment of the pairwise comparisons, five stress-test scenarios, and an alternative distributional family, the qualitative ranking is stable, while the specific numerical margin is not.

3.21.2 Interpretation of Uncertainty and Robustness

A principal methodological contribution of this study is the explicit incorporation of uncertainty throughout the analytical workflow via genuinely executed Monte Carlo, bootstrap, and Sobol procedures rather than assumed uncertainty ranges. This approach enables policymakers to distinguish between conclusions that remain stable across plausible futures (A2's broad aggregate superiority) and those that are conditional (A2's dependence on sustained green investment). The negative-scenario analysis (Section 3.7) and the conditional-region analysis (Section 3.5) jointly demonstrate that the preferred development strategy is not universally optimal, which increases rather than decreases the credibility of the framework. The additional robustness checks in Sections 3.14-3.19 extend this same logic one level further, from uncertainty in the physical parameters to uncertainty in the analyst's own modelling choices (criteria weights, MCDA technique, treatment of pairwise judgments, and distributional family), which is the more usual source of unexamined fragility in published AHP-MCDA studies.

3.21.3 Scientific Contribution and Practical Implications

The principal contribution of the present study lies in the development of an integrated, fully reproducible methodological framework rather than in advocating a predetermined policy option. From a practical perspective, the Sobol results (Section 3.8) suggest that future policy should prioritize investments capable of sustaining green-investment flow and reducing desalination costs, since these are the two variables with the greatest computed influence on the comparative outcome - a materially more specific and defensible recommendation than a generic call for "diversification." The scenario stress test (Section 3.17) sharpens this recommendation further: reducing desalination cost is specifically what protects the Green-Blue pathway in the water- and climate-stress scenarios where it would otherwise lose to the oil-rent alternative.

3.21.4 Comparison with Previous Studies

The findings should be interpreted within the broader resource-curse and Dutch-disease literature (Sachs & Warner, 2001; Auty, 2001; Krugman, 1987), which documents the structural risks of prolonged hydrocarbon dependence, and within the regional-cluster literature (Porter, 1998), which motivates the cluster-based structure of Alternative A2. The present study extends this literature methodologically by combining these theoretical foundations with a fully executed uncertainty-quantification pipeline, rather than by introducing a new sustainability concept, and by demonstrating a concrete template - weight sensitivity, cross-method validation, Fuzzy AHP, stress testing, and distributional resampling - for reporting how far an AHP-weighted MCDA conclusion can be trusted before it has been validated against a real, administered expert panel. The conclusions reported here should not be interpreted as replacing empirical field investigation; the proposed framework is intended to complement conventional observational studies by providing a transparent exploratory environment for evaluating policy alternatives when complete field datasets are unavailable.

4. CONCLUSIONS

This study developed and evaluated an integrated, fully reproducible decision-support framework for assessing strategic regional-development pathways under conditions of limited empirical data and deep uncertainty. Rather than relying on deterministic planning or isolated sustainability indicators, the proposed methodology combines AHP-based expert-weighted criteria, reality-constrained synthetic-data generation, Monte Carlo and bootstrap uncertainty quantification, Sobol global sensitivity analysis, and complementary TOPSIS/VIKOR/WSM/PROMETHEE II multi-criteria decision techniques within a unified analytical workflow, with every reported number traceable to the executable Python pipeline in Appendix A.

The analytical results indicate that, under the assumptions adopted in this study, the Green-Blue development pathway demonstrates substantially greater overall performance than continued dependence on the oil-rent model, a conclusion supported by four independent MCDA techniques and confirmed statistically ($p < 0.001$). This conclusion is explicitly conditional rather than unconditional: the framework identifies specific parameter regions - sustained high oil prices combined with scarce green investment (Section 3.5), and high desalination cost combined with adverse water or solar conditions (Section 3.17) - under which the preferred strategy reverses entirely. The explicit identification of these reversal conditions, rather than their omission, is presented as one of the study's principal contributions, because it supports adaptive rather than static policy planning.

From a methodological perspective, the principal contribution of this research lies in demonstrating how uncertainty analysis, reality-constrained synthetic-data generation, and complementary decision-analysis methods can be integrated transparently within a reproducible policy-evaluation framework, in clarifying that Generative Artificial Intelligence should be employed strictly as a structured scenario-exploration instrument rather than as a source of scientific evidence, and in demonstrating a systematic set of robustness checks - weight sensitivity, cross-method validation, Fuzzy AHP, scenario stress testing, and distributional resampling - that test whether an AHP-weighted MCDA conclusion is fragile with respect to the analyst's own modelling choices before it has been validated against field data. Future applications should incorporate field observations, updated socio-economic datasets, and an administered expert panel to replace the illustrative AHP weights used here, in order to evaluate the transferability and empirical calibration of the proposed methodology. The limitations of the present exploratory design, and the sector-level extensions proposed for future investigation, are set out in Section 5.2.

5. RECOMMENDATIONS

5.1 Policy Implications and Recommendations

- Establish integrated planning mechanisms that simultaneously consider water security, renewable energy, agricultural development, and institutional capacity, consistent with the WEFE-nexus priorities identified in Libya's own national dialogue (UNDP

Libya, 2025). Public-sector governance tools, such as digital governance in the development of sustainable recruitment policies, have been studied in the Libyan public sector (Ben Amer et al., 2025); that evidence is confined to this domain but illustrates the institutional capacity such planning mechanisms would rely on.

- Prioritize sustained green-investment flow as the single highest-leverage policy variable identified by the Sobol analysis (S1 = 0.50, ST = 0.57), materially more influential than the largely exogenous oil-price variable, and confirmed as the dominant lever across the weight-sensitivity and cross-method checks in Sections 3.14-3.15. Financing channels beyond oil revenue, such as Islamic green sukuk for renewable-energy projects, have been examined for Libyan Islamic banks (Hamza et al., 2026).
- Prioritize investment aimed at reducing desalination costs through technological innovation and renewable-energy integration; this is the second-ranked computed sensitivity driver among the alternative's own internal cost structure, and the scenario stress test (Section 3.17) shows it is specifically the variable that determines whether the Green-Blue pathway survives an adverse water- or climate-stress scenario.
- Design fiscal rules that pre-commit a share of oil revenue to a Green-Blue sovereign fund specifically during high-oil-price periods, directly targeting the reversal condition identified in Section 3.5 (high oil price combined with low green investment), rather than assuming diversification funding will occur automatically during boom periods.
- Replace the illustrative AHP weights used in this study with weights elicited from a documented, named expert panel before using this framework to inform binding investment decisions; Sections 3.14 and 3.16 show the current conclusions are not highly fragile to the exact weights used, but they are not a substitute for this administered elicitation.

5.2 Limitations and Future Investigation

5.2.1 Limitations

The topic addressed in this paper is very broad, and a single study cannot resolve it. The following limitations and threats to validity delimit what has, and has not, been shown.

- Internal Validity: the AHP weighting scheme (Section 2.10.3) is an illustrative, internally consistent expert-elicitation structure rather than the output of an administered multi-round Delphi panel. Sections 3.14 and 3.16 partially mitigate this threat by showing that the study's central conclusion is stable under +/-20% perturbation of every weight (individually and jointly) and under a fuzzy-set re-treatment of the underlying pairwise comparisons; neither of these checks, however, substitutes for the recommended future administration of a real, named, credentialed expert panel, which remains outstanding.
- External Validity: results may not generalize to other MENA countries given the specificity of Libya's institutional context; Section 3.20 provides a limited internal transferability check only, not an external validation against independently published field data.
- Construct Validity: qualitative dimensions such as "social acceptance" are difficult to measure with precise quantification and are represented here through a simplified proxy criterion; this is also the criterion for which the Fuzzy AHP cross-check (Section 3.16) returns the smallest and least stable weight.
- Conclusion Validity: because GenAI is used only to widen the qualitative scenario space (Section 2.5), and all quantitative results derive from the deterministic scoring model in Appendix A, conclusions should be read as model-conditional rather than as certain predictions of real-world outcomes.
- Synthetic Data Nature: all reported statistics derive from a reality-constrained synthetic twin experiment, not from field measurement. This is disclosed at every relevant point in the paper rather than only in a single limitations paragraph. Section 3.19 shows that the substantive conclusions are not sensitive to the specific distributional family chosen for this synthetic data, which narrows, but does not eliminate, this threat.
- Model-Structure Dependence: the specific numerical results (e.g., the exact 0.666 vs 0.335 closeness-coefficient gap) depend on the functional form of the scoring model in Appendix A.2; the qualitative pattern (broad A2 superiority, reversal under high-oil-price/low-investment or high-desalination-cost/adverse-water-solar conditions, investment as the dominant Sobol driver) is the primary finding, and readers should treat exact point estimates as illustrative rather than as calibrated real-world quantities.
- **Aggregate scope and limited depth:** the framework compares two pathways for the region as a whole and treats each thematic area (energy, water, food, employment, institutions) at an exploratory level. Sector-specific dynamics, costs and reversal conditions may differ from the aggregate result, and the topic is too broad to be exhausted in a single study.
- **Coverage of uncertainty:** only the six input variables and the sources listed in Table 7 are represented. Dependence between inputs, governance and security conditions, and time-varying pathways are not modelled (Assumptions 2, 4 and 6 in Section 2.11).

5.2.2 Future Investigation

The limitations above point to the following directions for future research.

- **Sector-by-sector analysis:** apply the framework separately to individual sectors, for example energy generation, industry, transport, and water and agriculture, each with sector-specific criteria, variables and bounds, and then re-aggregate the results to test whether the regional conclusion holds. Recent Libyan studies of the electricity sector have already developed green-transition pathways and assessed their technical, environmental, and economic implications, providing a useful sector-specific starting point for extending the present framework (Nassar et al., 2025a, 2025b).
- **Richer uncertainty representation:** model correlations between inputs (for example oil price and green investment), add governance and security-related variables, and extend the static comparison to dynamic, phased pathways between A1 and A2.
- Administer a real multi-round Delphi expert panel to replace the illustrative AHP weighting matrix used in this study, and report the resulting Kendall's coefficient of concordance; Sections 3.14 and 3.16 provide a

template for how the resulting weights should then be stress-tested once available.
- Acquire field-based hydrological and solar-resource measurements for the Murzuq-Ubari basin to replace the illustrative schematic surfaces in Figure 3 with genuine GIS survey data.
- Generalize the hybrid framework to other Saharan/MENA contexts with a properly cited, retrievable external benchmark study, rather than the internal transferability check reported in Section 3.20.
- Develop agent-based extensions to simulate strategic interactions among government, investors, and local communities under the identified reversal conditions (Sections 3.5 and 3.17).
- Extend the cross-method validation of Section 3.15 to a larger family of outranking and fuzzy MCDA techniques (e.g., ELECTRE III, fuzzy TOPSIS) once field-calibrated criteria data become available.

APPENDIX

A.1 Sample of the Retained Synthetic Dataset

TABLE 23 Sample rows of the retained synthetic dataset

Oil_Price	Solar_Radiation	Desalination_Cost	Pop_Growth	Water_Demand	Investment	C_A1	C_A2
103.047	2124.001	0.897	1.954	201.099	425.860	0.562	0.438
77.916	2485.657	0.790	2.232	216.924	534.368	0.145	0.855
109.395	2491.927	0.561	1.727	207.158	573.206	0.263	0.737
97.303	2293.076	0.747	1.748	163.203	549.320	0.278	0.722

(Full 10,000-row dataset available in the supplementary repository; first 1,000 rows provided as a CSV sample file.)

A.2 Computational Pipeline Architecture (executed to produce all tables and figures in this paper)

All tables and figures in this paper are generated by an executable Python pipeline (analysis.py, plus extra_analysis.py for the five robustness checks added in Sections 3.14-3.19). The full source code, together with the retained 10,000-row synthetic dataset, is provided as supplementary material and will be deposited in a public repository upon acceptance (Section 2.12); it is omitted from the printed manuscript in line with standard journal practice, which keeps code and data as linked, independently citable supplementary files rather than in-text listings. The pipeline is organised into the following modules.

- **Synthetic-data generation.** Draws 20,000 candidate scenarios (seed = 42) for the six input variables from the distributions and parameters specified in Table 2, then applies the accept/reject boundary screen of Table 1, retaining 10,000 scenarios (Section 2.4).
- **AHP weighting.** Derives criteria weights and the consistency ratio from the pairwise-comparison matrix (Section 2.10.3) using the eigenvector-approximation procedure in Section 2.6.2, formula A.
- **Alternative scoring.** Maps each retained scenario's normalized parameters onto the six evaluation criteria for Alternative A1 (oil rent) and Alternative A2 (Green-Blue), following the functional forms summarised in the Threats to Validity discussion of Model-Structure Dependence (Section 5.2.1).
- **Multi-criteria ranking.** Computes, per scenario, the TOPSIS closeness coefficient and VIKOR compromise index (Section 2.6.2, formulas C-D), verified to reproduce the reported baseline means of 0.335 and 0.666 for Alternatives A1 and A2 respectively; the Weighted Sum Model and PROMETHEE II net-flow scores used in the Section 3.15 cross-method validation (formulas H-I) are computed by the same module.
- **Uncertainty and sensitivity analysis.** Implements the bootstrap confidence-interval procedure (B = 2,000 resamples), the Saltelli-sampling Sobol first- and total-order index estimation (base size 512, 7,168 model evaluations), the Mann-Whitney U and Spearman tests, the ablation-study variants, and the Monte Carlo convergence study of Section 3.11.
- **Weight-sensitivity module (Section 3.14).** Re-runs the full TOPSIS pipeline under the twelve one-at-a-time +/-20% weight perturbations and under 2,000 joint Monte Carlo weight draws (seed = 7), each renormalized to sum to one.
- **Fuzzy AHP module (Section 3.16).** Reconstructs a Saaty-scale pairwise matrix consistent with the reported crisp weights, converts each entry to a triangular fuzzy number (+/-50% spread), and applies Chang's (1996) extent-analysis procedure (Section 2.6.2, formula J) to obtain the fuzzy weight vector and the degree-of-possibility comparisons.
- **Scenario stress-test module (Section 3.17).** Scores the five hand-specified extreme and black-swan parameter combinations of Table 20 through the same scoring and ranking functions used for the main 10,000-scenario dataset.
- **Alternative-distribution module (Section 3.19).** Regenerates the synthetic dataset using PERT/Beta distributions for Desalination Cost, Water Demand and Investment, and Latin Hypercube stratified sampling (seed = 42) for Oil Price, Solar Radiation and Population Growth, then re-applies the same reality-constrained screening and ranking modules described above.

Figure generation (make_figures.py) consumes the outputs of the above modules directly, so that every figure in this paper corresponds to a specific, re-runnable computation rather than to a manually constructed illustration. Package versions and random seeds are documented in Table 9 (Section 2.12).

A.3 GenAI Scenario-Proposer Settings (illustrative)

Role restriction: GenAI output used only for qualitative scenario framing; no numeric value produced by GenAI was used directly in any reported statistic.

- Illustrative model class: general-purpose instruction-tuned LLM
- Temperature: 0.7 (illustrative, for qualitative diversity only)
- All quantitative parameter ranges: taken from Table 1 (institutional sources), not from GenAI output

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