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A Machine Learning-Based Multi-Criteria Decision-Making Approach Utilizing D-Numbers for Water-Energy-Food Nexus Assessment

Kanchana Anbazhagan[1], Nagarajan Deivanayagampillai[2,3]† and Nithya Thanagodi[4]

[1]Department of Mathematics, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India
[2]Department of Mathematics, Chettinad Institute of Technology, Chettinad Academy of Research and Education, Tamilnadu, 603103, India
[3]Faculty of Engineering and Technology, Multimedia University, Jalan Ayer Keroh Lama, 75450 Melaka. Malaysia
[4]Department of CSBS, Rajalakshmi Institute of Technology, Chennai, India
†Corresponding author: Nagarajan Deivanayagampillai; dnrmsu2002@yahoo.com

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ABSTRACT

The interdependency between the water and energy infrastructure represents the core challenge of resource management. Effective decision-making for water-energy-food (WEN) scenarios requires robust tools. Traditional Multi-Criteria Decision-Making (MCDM) approaches are undermined by uncertainty because they assume perfect and complete information, which rarely occurs in Water-Energy Nexus (WEN) issues. Classical models oversimplify the complex interconnections between water and energy systems and therefore result in suboptimal decision-making approaches. Although fuzzy and intuitionistic models are efforts towards uncertainty modelling, they also fall short of fully capturing the dynamics of real-world scenarios. They are inefficient in addressing conflicting and uncertain information, which hinders the practical implementation of these techniques. In addition, the lack of a platform that unites MCDM with integrated uncertainty management increases decision-making complications. To bridge these gaps, the current study proposes a new framework that integrates D-number-based multi-criteria analysis with Dempster-Shafer theory (DST) for WEN decision-making. The integration of DST rigorously enhances the ability of DST to process complete, uncertain, and conflicting information for WEN decision-making. The study also compared the performance of the Random Forest and Optimized Artificial Neural Network models.

INTRODUCTION

The Water-Energy Nexus (WEN) highlights the intimate interdependence and mutual interrelation of water and energy infrastructures. Water is vital for energy generation, from power to fuel extraction, whereas energy is required for water sourcing, treatment, distribution, and wastewater handling. This interrelationship places water and energy as essential pillars of economic development, environmental resilience, and human health. Mitigating the uncertainties in this nexus, much like in supply chain management or sustainable production models, calls for sophisticated decision-making paradigms that transcend conventional practices, fusing fuzzy logic, neutrosophic techniques, and multi-attribute decision-making to improve resource optimization. As the global population increases, industrialization and urbanization fuel the demand for water and energy, and the challenge of resource scarcity grows more intense. Climate change exacerbates the situation by causing shifts in precipitation patterns, lowering the supply of freshwater resources, and raising the demand for cooling and desalination of energy. Historically, separate infrastructures for water and energy have been integrated for efficient and sustainable resource consumption. Policymakers, researchers, and engineers need to understand the Water-Energy Nexus to develop plans that achieve maximum utilization of resources, minimum environmental footprint, and resilience in water and energy systems. Some sustainable solutions include desalination powered by renewable energy, smart water grids, and energy-efficient wastewater treatment plants. Societies can become water- and energy-secure and minimize climate and environmental risks through an integrated approach (Ding et al. 2020). Water and energy are critical inputs for modern economies. Over the past several years, both sectors have experienced profound reforms, prompted by the imperatives of supply security, sustainability, and economic efficiency. However, their interdependence creates challenges for policymakers (Hussey & Pittock 2012). Over the past decade, the Water-Energy Nexus analysis has drawn increasing attention from the scientific community and policymakers. In a review of the recent scientific literature, 70 relevant studies were identified, and 35 were selected for a detailed case study analysis (Dai et al. 2018). A review of more than 120 studies analyzed their objectives, scope, methodology, and limitations. Additionally, 23 case studies were summarized based on their titles, objectives, and key findings, and 21 case studies were critically analyzed within the context of water-energy nexus research in urban systems (Fayiah et al. 2020). The nexus framework has become increasingly important for analyzing the challenges associated with these vital resources and comprehending the relationships between them (Al-Sumaiti et al. 2020). The most significant contribution of this research is that it offers a valuable knowledge base for successfully managing this nexus. The use of a nexus approach in tourism resource conservation is a necessary step to achieve relative and absolute reductions in resource use (Becken & McLennan 2017). The findings underscore that Ghana's exposure to electricity significantly boosts the share of renewable energy and lowers carbon emissions (Bieber et al., 2018). The results further indicate gaps in the realization of the Sustainable Development Goals. The food-energy-water nexus must be prioritized for sustainable development (Apeh & Nwulu 2024). This study provides a conceptual model for emerging technologies in the WEF sector of new cities. Its primary focal points are internal relations, external drivers, and linkage system evaluation in the WEF nexus (Abdelzaher et al. 2023). This study emphasizes the dual role of water in treatment and processing and its interdependence. The use of integrated and strategic solutions can direct research and development toward addressing local water and energy issues. Enhancing models and data engagement will better serve researchers, policymakers, and the community (Maftouh et al. 2022). This review contrasts the various policy initiatives African nations have embarked on regarding the management of the WEN, their efficiency, and areas. It further locates innovative practices and effective interventions in the African context, with insightful recommendations and local initiatives devoted to simplifying the interface between water and energy resources (Nwokediegwu et al. 2024). Approximate technical outcomes show that hybrid renewable energy plants in North African countries are the most appropriate choice for a regional transmission grid to meet future electricity demand, given the high intermittency of renewable energy sources. Lastly, achieving the aspirations of renewable energy in the region demands meticulous consideration and implementation of diverse policy strategies, particularly in light of North Africa's strong dependence on fossil fuels for national revenue (Adun et al. 2022). Carbon emissions from different energy sources and main scenarios (van Huyssteen et al. 2023). Simultaneously applying the WEF nexus perspective to WEF resource security at the same time has tremendous potential to enhance overall sustainability (Simpson et al. 2023). This article compiles an "ensemble" of water-use indicators across electricity-generation technologies from existing published research to demonstrate the level of detail or lack thereof in the extant large-scale energy-sector water-use data. Using these indicators, this study evaluated the adequacy of such estimates for modeling electricity-production water use at broader scales (Larsen & Drews 2019). Coupled with the coal-led electricity sector in the region, high water demand will remain a long-term constraint (Sun et al. 2018). This study synthesizes the interrelation between energy and water based on two primary considerations: the level of dependence of energy on water and the drivers of this dependence. This study first synthesizes the literature on the water dependence of the energy-by-energy type. It then elaborates on the primary drivers of this relationship. It further summarizes the primary methodologies in the existing literature. Finally, this paper outlines the primary advancements and gaps in the literature (Tan & Zhi 2016). It is essential to synthesize this dependence through analysis and review to design more efficient and sustainable infrastructure systems that optimize resource conservation (Simpson 2023). The study demonstrates that past policy designs have largely been cast in sector-specific mandates (Venghaus & Hake 2018). In the new model, the team members' ratings are presented in the form of D numbers (Bian et al. 2018). In this study, we present a hybrid decision-making support model in the form of D numbers and D, which are employed to acquire input parameters for computing the weight coefficients of the criteria (Božanić et al. 2021). This study expands the ANP methodology within the D-numbers framework to address three types of imprecise information (Chatterjee et al. 2018).

This article introduces a conceptual framework, the "Informational Paradigm," for addressing this issue. This study systematically explored several approaches to these uncertainties, beginning with easier cases that addressed one source and proceeding to more complex cases in which multiple sources interacted (Coppi 2008). This research can be coupled with the D-AHP (D numbers extended AHP) model developed earlier, and it is an integrated solution for MCDM (Deng et al. 2015). Consequently, fuzzy risk assessment has been an active research trend, with increasing interest in its potential to circumvent these drawbacks (Deng & Jiang 2017, 2019). An extension principle is then defined to allow the use of aggregation operators (Li & Chen 2018). To further advance knowledge integration, we developed D-number fuzzy cognitive maps (DFCMs) by integrating D-number theory with fuzzy cognitive maps (Li & Shao 2022). It integrates the strengths of D numbers in handling the weights of criteria (Mousavi-Nasab & Sotoudeh-Anvari 2020). They develop the rough D-TOPSIS approach by integrating D numbers, rough weights, and rough entropy weights, enabling the analysis of uncertain and vague information without additional assumptions (Sarwar 2020). The growing threat of chemical weapons poses a significant global risk. This study proposes a hybrid model of fuzzy VIKOR and an optimal search model to address the urgent need for the identification of illegal chemical warehouses. As such activities are highly clandestine, the issue is beset by multiple layers of uncertainty and ambiguity. Fuzzy VIKOR is applied to rank suspect warehouses according to search time and cost in a fuzzy decision environment (Sotoudeh-Anvari and Sadi-Nezhad 2022). To further test their effectiveness, a case study was conducted by applying the developed D-number method to bridge condition assessment (Xia et al. 2019). This study illustrates that ecosystems are core elements of the WEF nexus. Existing tools are resource interaction-based and largely do not account for dynamic ecosystem functions and services. Aquatic ecosystem models (AEMs) provide a useful framework for quantifying such services, including water purification, carbon sequestration, and biodiversity support. By integrating AEMs into nexus assessments, decision-making can be enhanced with a greater appreciation of how ecosystems enhance resource sustainability. Such integration would provide a more comprehensive management framework for water, energy, and food systems while maintaining ecological integrity (Hülsmann et al. 2019). This study reviews a range of methods. Interdisciplinary methods are used to integrate interrelated variables, graphically represent complex problems, evaluate significant issues and simulate system behavior. Qualitative methods, in particular, can be utilized to delineate the nexus in a specific region, employing direct research methods such as questionnaire surveys and indirect methods such as ontology engineering and integrated maps. With such methods, researchers can better comprehend WEF interdependencies and facilitate more effective decision-making and policy-making (Endo et al. 2015). These categories provide valuable hydrological insights, showing various ways in which water is linked to energy and food systems under varying environmental and socio-economic conditions. Understanding these connections is important for integrated and sustainable resource management (Endo et al. 2017). The application of systematic assessments of water, energy, and food interlinkages or the shaping of socially and politically relevant resource policies is still in its infancy (Albrecht et al. 2018). This study then examines the prospects for integrating nexus thinking more effectively within IWRM frameworks (Benson et al. 2015). This study looks through the lens of water quality to shed light on the potential for agriculture to maximize the system (Bell et al. 2016). Our most important resources are land, energy, and water; however, their utilization is a major driver of climate change. Resource systems are extremely vulnerable to climate change. Therefore, efficient management is crucial for both mitigation and adaptation. Howells et al. (2013). The models should be geographically flexible to enable resource management at the project, watershed, regional, and national levels. The integration of spatial–temporal drivers would create more integrated models, resulting in more effective policies for sustainable development, greater institutional synergies, and greater social welfare (Mabrey & Vittorio 2018). Current nexus thinking is focused primarily on the social-ecological systems paradigm, which complements adaptive responses to global change (De Grenade et al. 2016). This is counterintuitive, considering that livelihood is a foundational pillar for attaining sustainable development (Biggs et al.2015). This paper provides a conceptual overview of significant interlinkages, primarily from a developing country perspective, and analyzes case studies to define promising strategies for Nexus management. It also provides the features of a modeling framework for the nexus and information to guide more effective regulations and policies at the national level (Bazilian et al. 2011). With the world increasingly populated and urbanizing, and with material consumption-based lifestyles, greater focus is being placed on the interlinked system supplying energy, water, and food—the Nexus. Simultaneously, there is growing concern regarding climate and environmental degradation of this system, which is crucial for maintaining critical ecosystem services (Keairns et al. 2016). The research revealed twenty-four ideas on governance that underpin this literature and fall within these categories (Urbinatti et al. 2020).

LITERATURE REVIEW

A review was conducted to assess the situation in the water–energy–food nexus in terms of methodology and how the nexus approach has expanded geographically and academically. This research examines how this approach brings together several discourses, disciplines, and fields using integrated and interdisciplinary methodologies (Endo et al. 2020). This paper provides an overview of 20 case studies featured in this special issue, with an emphasis on the practice and scientific foundations of the Nexus (Taniguchi et al. 2017). The reviewed studies were categorized and evaluated based on their geographic scale and nexus scope (Dai et al. 2018). This study sets out a balanced Nexus framework and applies it to the Mekong Basin. The analysis highlights the strengths of a sectorally balanced, dynamic Nexus approach, particularly its ability to uncover new cross-sectoral relationships or shifts in such relationships as a result of single-sector interventions (Smajgl et al. 2016). Recent literature increasingly demands a shift from "nexus thinking" to "nexus action," with an emphasis on actual implementation. Nexus policies should be implemented across various geographic levels, supported by effective measures and a range of tools developed through research programs and on-the-ground projects. Far from being a one-size-fits-all solution, however, the nexus approach should be seen as a flexible framework that must be adapted to each situation in order to be effective in managing complex resource interdependencies (Simpson & Jewitt 2019). The nexus strategy is likewise concerned with addressing the needs of the most vulnerable people in the world (Leese & Meisch 2015). is increasing awareness of the need to break away from a sector-based framework in science, policy, and practice to an integrated framework that considers the interlinkages between water, food, and energy resources. This realization identifies synergies and trade-offs in managing all three resources (Reinhard et al. 2017). This research examines how nexus discourse is unfolding and being mobilized by various stakeholders in the UK natural resource discourse (Cairns & Krzywoszynska 2016). This study seeks to establish a method for comparing the perceived complexity of nexus tools identified by international organizations and primary literature sources (Dargin et al. 2019). This study investigated the problems and prospects for enhancing water efficiency in thermoelectric power plant cooling systems (Pan et al. 2018). The systems for all three resources are interdependent, and there is a need to create assessment tools that reflect their interdependencies, particularly in assessing the environmental performance of food production systems (Al-Ansari et al. 2015). As a pilot project for the multiple interlinkages among the three elements, this study explored biogas production from energy crops through anaerobic digestion. Similar to all bioenergies, greater production from energy crops raises concerns about potential negative environmental impacts, competition in food markets, and progressive land-use changes (Pacetti et al. 2015). System dynamics models provide a framework for simulating and assessing the system-wide impacts of interventions in a given area (Purwanto et al. 2021). These studies include water resources required to generate various foods and energy, energy per unit of water or agricultural product delivered, and CO_2-equivalent emissions for water and energy delivery (Sadegh et al. 2020). The integrated framework thus developed was then utilized in four case studies in irrigation: food production and energy consumption using water allocation in a Spanish irrigation project; food and bioenergy production and delivery using treated water in Germany; water allocation for food production and urban use in Kenya; and energy production and delivery for food production in Hyderabad, India (Villamayor-Tomas et al. 2015). The interdependence between developments on a global and Brazilian scale is investigated, focusing on how changes in the world and Brazil influence each other and how Brazil influences other countries and the world. Reform in the scientific approach to such issues is needed as a facilitator for strengthening science-policy bridging in sustainability policies (Mercure et al. 2019). This article sets out a generic scenario-based methodology employing the Q-Nexus Model to assess nexus effects to be addressed in WEF planning and policymaking (Karnib 2018). integrating both the production (supply) and demand aspects of WEF systems into one system-of-systems framework (Wu et al. 2021). This study examines the San Antonio Region in Texas, a high-growth resource-intensive region with expanding energy production in the Eagle Ford Shale Play and rising agricultural activity. It summarizes the findings of a survey conducted with 370 researchers and regional stakeholders from the government, non-governmental/non-profit, and business sectors in the region's water, energy, and food industries (Daher et al., 2020). This study applies a participatory modeling process to outline significant interlinkages in the Water-Energy-Food (WEF) nexus of Andalusia as a basis for constructing a system dynamics model. Using fuzzy cognitive mapping, 14 decision-makers were asked to contribute insights to enhance knowledge regarding the WEF nexus and enhance stakeholder awareness and consensus (Martinez et al. 2018). This study explored nascent vulnerabilities in Bwaise and Kanyogoga's informal settlements (Mguni et al. 2020). This technique enables quantifiable measures of stakeholder satisfaction and resource integration in economic and environmental terms. A case study was conducted in a region in Mexico due to industrial activity and challenges in meeting resource demands with low water levels (Cansino-Loeza & Ponce-Ortega 2021). The principal scientific challenges arise from gaps in data, information, and knowledge in understanding the interlinkages in the WEF nexus. Additionally, it is constrained by a deficiency in systematic tools that can manage all interlinked trade-offs. Increasing the pool of information is a priority for future research (Liu et al. 2017). Classical MCDM approaches are confronted with the issue of uncertainty because they presume complete and perfect information, which is scarcely present in WEN contexts. Furthermore, the absence of a general platform for coupling MCDM with holistic uncertainty management contributes to decision-making complexity. To fill these research gaps, this study develops a novel framework that combines D-number-based Multi-Criteria Analysis and Dempster-Shafer Theory to enhance WEN decision-making.

The major drawback of conventional Multi-Criteria Decision-Making (MCDM) models in Water-Energy Nexus (WEN) decision-making is their presumption of complete and perfect information, which is not a reality in most real-world WEN situations. The Models cannot deal effectively with uncertainty, ambiguity, and conflicting information, and tend to provide oversimplified descriptions of the intricate interdependence among water and energy systems. Consequently, conventional MCDM techniques tend to yield suboptimal or unreliable decisions in the context of WEN. The Dempster-Shafer theory (DST) plays an important role in promoting uncertainty management using a flexible mathematical representation for reasoning in the presence of incomplete, imprecise, and contradictory information. In contrast to the conventional theory of probability, which only permits the assignment of belief to individual events and not to sets of possibilities, DST models uncertainty more effectively. In the Water-Energy Nexus (WEN) decision-making, the use of DST improves the resilience of Multi-Criteria Decision-Making (MCDM) through evidence-based information synthesis using information that may come from various uncertain sources and results in more informed and credible decisions. The integration of a strong uncertainty-handling mechanism in Multi-Criteria Decision-Making (MCDM) for Water-Energy Nexus (WEN) problems is important because WEN systems are dynamic, complex, and data-sparse in nature, usually entailing conflicting goals, incomplete data, and ambivalence among stakeholders. In these settings, traditional MCDM techniques that presume inputs to be deterministic are insufficient. A strong mechanism, such as that founded on Dempster-Shafer Theory or D-numbers, allows decision-makers to capture, represent, or analyze uncertainties in a better way, resulting in more credible, transparent, and adaptive decisions that are a true representation of the real-world complexities involved in the management of interrelated water and energy resources. The performances of the random forest and optimized ANN models were compared. It measures the degree to which the model accounts for the variation in the target variable. Higher R^2 values represent good model performance and predictability. These measures determine the accuracy, precision, and interpretability of the forecasts made by the models in the context of the Water-Energy Nexus (WEN).

Current systems simplify the complex relationships among water and energy systems to a level that leads to suboptimal decision-making approaches. In spite of the fact that fuzzy and intuitionistic models are an improvement of uncertainty representation, they also fall short in fully capturing the dynamic nature of real-life situations. They are deficient in the management of conflicting and uncertain information, which forms a barrier to the application of these approaches in practice. Furthermore, the absence of an existing platform that integrates MCDM and the management of all uncertainties escalates the complexity of decision-making.

Existing MCDM approaches within the WEF environment tend to ignore or inadequately address the uncertainty and complexity of such systems. Our research brings Dempster-Shafer Theory (DST) and MCDM to provide a strengthened approach to dealing with uncertainty and conflicting data, which has been relatively under-addressed in previous studies. While MCDM methods have been traditionally employed in WEF problems, there has been limited research on the integration of machine learning approaches for predictive decision-making. Our research fills this gap by integrating Optimized ANN and Random Forest techniques with MCDM, using a data-driven methodology to improve the accuracy of decisions. Existing studies usually address single elements of WEF systems (e.g., energy policy, water management, and food security) independently. We combine all these dimensions in one integrated decision-making context to enable a more in-depth consideration of the interdependencies in WEF systems.

MATERIALS AND METHODS

Consider a set of m WEN $S = \{S_1, S_2, \ldots, S_m\}$ scenarios and n evaluation criteria $C = \{C_1, C_2, \ldots, C_n\}$. Each scenario was assessed based on these criteria, and uncertain expert judgement was represented using D-number theory.

In D-number theory, a D-number is a generalization of the Dempster-Shafer Theory (DST), which captures incomplete, imprecise, or uncertain data.

Each expert k provided a judgment on the scenario. S_i under criterion C_j as

$$D_k(S_i, C_j) = \{(H, d_k(H), (\Omega, 1 - d_k(H))\} \quad \dots(1)$$

Where H is the hypothesis

d_k (H) is the belief degree assigned by expert k $0 \leq d_k$ $(H) \leq 1$

 represents uncertainty.

$1 - d_k$ (H) represents the remaining uncertainty.

For multiple experts, the aggregated D-number for the scenario S_i under criterion C_j is

$$D(S_i, C_j) = \{(H, d(H), (\Omega, 1 - d(H))\} \quad \dots(2)$$

Where $d(H)$ is computed as: $d(H) = \frac{1}{K}\sum_{k=1}^{K} d_k(H)$

To ensure consistency, the D-number values were normalized across all scenarios.

$$D_{norm}(S_i, C_j) = \frac{D(S_i, C_j)}{\sum_{i=1}^{m} D(S_i, C_j)} \quad \dots(3)$$

This step removes the scale inconsistencies across the criteria.

Weighted D-Number Aggregation

Each criterion C_j has an assigned importance weight w_j, obtained via an entropy-based or expert-based weighting method:

$$W_j = \frac{-\sum_{i=1}^{m} D_{norm}(S_i, C_j) log D_{norm}(S_i, C_j)}{\sum_{j=1}^{m}(-\sum_{i=1}^{m} D_{norm}(S_i, C_j) log D_{norm}(S_i, C_j))} \quad \dots(4)$$

Then, the D-number-based performance score is computed for each scenario. S_i

$$D_{score}(S_i) = \sum_{j=1}^{n} W_j . D_{norm}(S_i, C_j) \quad \dots(5)$$

The scenario with the highest $D_{score}(S_i)$ is the optimal choice.

Scenario Ranking Using D-TOPSIS

To prioritize the scenarios, we integrated D-number theory with TOPSIS as follows:

Compute Positive & Negative Ideal Solution

$$D_j^+ = max_i D_{norm}(S_i, C_j) \quad D_j^- = min_i D_{norm}(S_i, C_j)$$

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(D_{norm}(S_i, C_j) - D_j^+)^2} \quad \dots(6)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(D_{norm}(S_i, C_j) - D_j^-)^2} \quad \dots(7)$$

Compute Relative Closeness Score

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad \dots(8)$$

Rank Scenarios

The scenario with the highest C_i is ranked as the most optimal.

Algorithm

Finds the ideal best and worst solutions.

The Euclidean distance to these solutions is computed.

Calculates the closeness score to rank the scenarios.

Ranking Output: A Higher closeness score indicates a better scenario.

Mathematical Model for D-Number-Based VIKOR

$A = \{A_1, A_2, \dots, A_m\}$ be the set of alternatives

$C = \{C_1, C_2, \dots, C_n\}$ be the set of criteria

xi_j be the performance value of the alternative A_i on criterion C_j

w_j be the weight of the criterion C_j, determined using D-number

D-Number representation for uncertain weight

Each criterion weight is expressed as a D Number

$$D(C_j) = (m(C_j), u(C_j)) \quad \dots(9)$$

Where $m(C_j)$ is the belief mass assigned to the criterion C_j

$u(C_j)$ represent the uncertainty in the weight assignment

The total belief mass satisfies $\sum_{j=1}^{n} m(C_j) + u(C_j) = 1$ …(10)

The final weight of the criterion (C_j) is computed as:

Where uncertainty is evenly distributed across all criteria.

For benefit criteria:

For cost criteria $r_{ij} = \frac{x_{ij} - min_i x_{ij}}{max_i x_{ij} - min_i x_{ij}}$, $\quad r_{ij} = \frac{max_i x_{ij} - x_{ij}}{max_i x_{ij} - min_i x_{ij}}$ …(11)

Where r_{ij} is the normalised value of the alternative A_i for Criterion C_j

Compute Utility and Regret Measures

Utility Measure (S_i)

$$S_i = \sum_{j=1}^{n} \omega_j . (f_j^* - r_{ij})/(f_j^* - f_j^-) \quad \dots(12)$$

Regret Measure (R_i):

$$R_i = max_j S_i = \sum_{j=1}^{n} \omega_j . (f_j^* - r_{ij})/(f_j^* - f_j^-) \quad \dots(13)$$

Where

$f_j^* = max_i r_{ij}$ (best value for criterion C_j, $f_j^- = max_i r_{ij}$ (Worst value for the criterion C_j)

The D VIKOR index is computed.

$$Q_i = v\frac{S_i - S^-}{S^* - S^-} + (1 - v)\frac{R_I - R^-}{R^* - R^-} \quad \dots(14)$$

Where $S^* = maxS_{i,}$ $S^- = minS_{i,}$
$R^* = maxR_{i,}$ $R^- = minR_{i,}$

v is the weight of the strategy (usually set to 0.5 for equal compromise between utility and regret).

Rank the alternatives

Rank alternatives based on Q_i

The best alternative A^* satisfies

Acceptable advantages $Q(A_2) - Q(A_1) \geq 1/(m-1)$

Acceptable stability: The best-ranked alternative should also be top-ranked in either S or R.

Given a D-number set:

$D = \{(A_i, d_i) | i = 1, 2, \ldots . n\}$

Where A_i is a focal d_i element and is the corresponding D-number satisfying $0 \leq d_i \leq 1, \sum_{i=1}^{n} d_i \leq 1$

(The sum can be less than 1, allowing for incomplete information.) The D-number entropy quantifies uncertainty by considering both the distribution and incompleteness. A commonly used entropy measure for D-numbers is

$$H(D) = -\sum_{i=1}^{n} d_i log d_i - (1 - \sum_{i=1}^{n} d_i) \log (1 - \sum_{i=1}^{n} d_i \quad \ldots(15)$$

The first term accounts for the uncertainty in the assigned D-values.

The second term measures the uncertainty due to incomplete information

The transition to data analysis takes place as we transform quantitative data into D-numbers and utilize the same to determine optimal decisions in light of uncertainty. Mathematical expressions form the basis of data analysis as a process, where the Euclidean distance of alternatives from the ideal solution is calculated using real data.

The theoretical model governs the calculation of compromise solutions, whereas data analysis deploys data from the decision matrix to calculate S and R values to determine ranking. The entropy calculation theory provides a formula for calculating consistency. Data analysis implements this formula to calculate the process of making decisions that coincide with the theoretical expectations derived from the input data.

Database

The dataset, sourced from open-access materials (Simpson 2023), is provided in an Excel file comprising four sheets labelled '2019,' '2020,' '2021,' and '2022.' It offers a comprehensive assessment of countries across multiple factors related to water, energy, and food security (WEF). It covers essential indices, such as the WEF Nexus Index Rank and Score, which reflect the overall rating of resource sustainability in a country. The dataset further analyzes water-related factors such as Water Pillar, Water Access, and Water Availability that reflect a nation's ability to supply sufficient and equal water resources. Similarly, energy-related factors measure factors such as the Energy Pillar, Energy Access, Electric Power Consumption (kWh/capita), and Energy Imports to reflect energy sustainability and dependency. Food-related factors integrate essential factors such as the Prevalence of Undernourishment, Malnutrition in children (wasting, stunting, obesity), Yield in cereals, and Value in Food Production to reflect a country's standing in food security. Through integrating these diverse measurements, the dataset provides an overall rating of interlinks between water, energy, and food security. The dataset utilizes various methods of decision-making to rank each alternative in terms of performance. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) ranks alternatives in accordance with closeness to the ideal optimum solution, where a greater DTOPSIS value indicates better performance. VIKOR (VIšekriterijumska Optimizacija i Kompromisno Rešenje) takes both optimum and worst-case options into consideration by ranking alternatives in favor of the closest compromise towards an ideal solution, where better performance is indicated by a lower value in DVIKOR. Additionally, the Entropy method ranks each alternative in importance by taking uncertainty into consideration, where greater importance is indicated by a greater value in D Entropy. Utilizing these methods in an integrated manner, the dataset provides an efficient system to perform multi-criteria decision making by ranking alternatives in comparative performance.

RESULTS AND DISCUSSION

The Total WEF Nexus Index holds a mean of 57.45 with a moderate balance between the management of resources within the examined areas. The most negative recorded index is 35.00, pointing toward serious difficulties within particular areas, while the best recorded index of 80.77 identifies areas with more efficient and more sustainable linking of resources together. The index displays moderate diversity with a standard deviation of 9.20, pointing toward serious inequalities between the performance of the WEF nexus within different areas.

Table 1 shows disaggregated WEF Nexus Index figures by its three pillars, water, energy, and food, that reflect big

Table 1: Descriptive Statistics of the Pillar Scores.

	Water Pillar	Energy Pillar	Food Pillar
Mean	58.87	57.27	56.96
Min	28.23	35.07	56.96
Max	81.87	94.34	78.24

differences in resource management and access at the various regions. A mean value of 58.87 and a wide spread from 28.23 to 81.87 under the Water pillar reflect big differences in the governance of water and the availability of resources in different regions. The widespread signifies unevenness in the distribution and efficiency of water use, as it is likely to reflect some of the regions experiencing serious constraints in water security, while some have relatively efficient systems. The Energy pillar is characterized by its mean score at 57.27, with the greatest disparity, varying from 35.07 to 94.34, indicating extreme differences in access to energy, sustainability, and technology integration. This is indicative of the fact that some regions have access to superior, dependable energy infrastructures while others are far behind, potentially because of limitations in infrastructure or inefficient policymaking. In the same manner, the Food pillar, with a mean of 56.96 and ranging from 27.55 to 78.24, evidences big differences in food security, agricultural output, and resource efficiency. This is indicative of mixed adherence to sustainable food systems and supply chain resilience within regions.

Table 2 provides a nuanced assessment of critical indicators under the Water-Energy-Food (WEF) Nexus, which captures significant disparity in the availability and access to critical resources by regions. The indicator for Water Availability (Ind.07), at an average of 1,149 cubic meters, varies widely from 18.1 to 3,240 cubic meters, signaling wide geographic disparity in freshwater availability. The indicator for Energy Access (Ind.08) is at 84.09% average but has a wide range of 7.24% to 100% coverage, evidencing both advances and ongoing disparities in electrification. With the high median, many countries have made great advances toward universal access to energy. For Food Security (Ind.18), the average of 81.72, ranging from 25.70 to 144.00, captures the dispersed nature of food availability and nutritional security.

Fig. 1 shows that the WEF Nexus Index of the Top 10 countries identifies countries that perform best in the integrated management of Food, Water, and Energy resources. The best performers are Iceland, closely followed by Canada and Norway, owing to the robustness of their resources and sustainability practices. The United States, New Zealand, Sweden, and Denmark are the other leading countries that perform well in terms of efficient utilization of resources and safety. Kuwait, Australia, and Brazil are the interesting additions that find place within the top 10, with the diversity of geographical and economic resources for WEF management. The index emphasizes the need for good policies, infrastructure, and governance for the efficient use of resources in different geographical areas.

Table 2: Descriptive Statistics Of The Selected Indicators.

	Water Availability	Energy Access	Food Security
Average	1149 cubic meters per capita	84.09% population with access	81.72
Max	3240 (High water abundance)	100% (Full access)	144.00
Min	18.1 (Severe water stress)	7.24% (Severe energy deficiency)	25.70

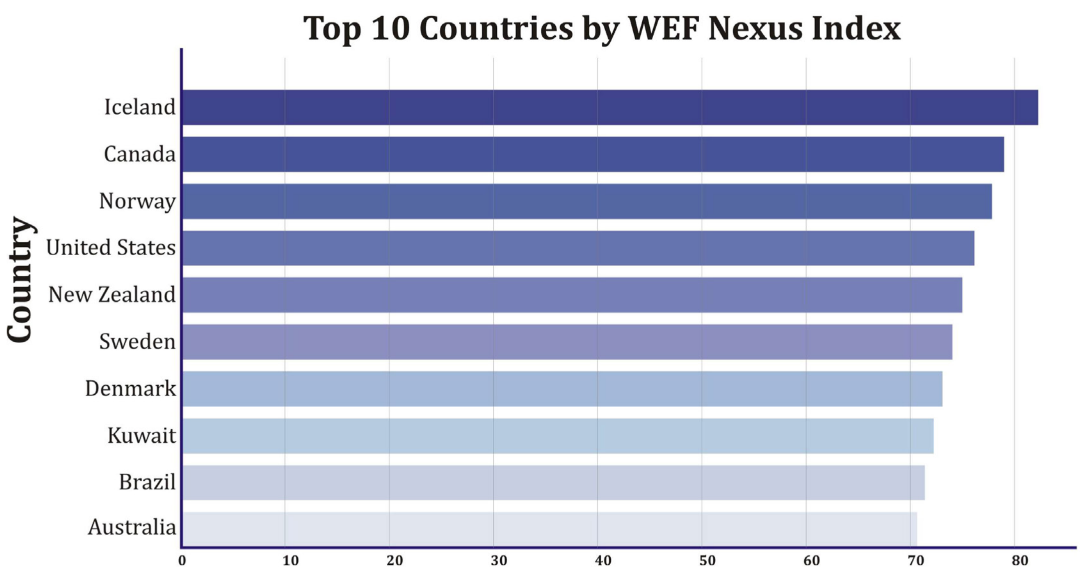

Fig. 1: WEF Nexus index.

Fig. 2 reveals that the WEF Nexus Index identifies the 10 countries with the most serious challenges with Water, Energy, and Food security. The lowest-ranked countries are the Central African Republic, South Sudan, and Chad, with the most serious scarcity of resources and infrastructural shortfalls. Haiti, Yemen, and Niger are the other countries with the poorest access to vital resources, with the added burden of political conflicts and climate vulnerability. Madagascar, Guinea-Bissau, Lebanon, and Mauritania are the countries with the most such bottlenecks that restrict the ability of these countries to manage their resources sustainably. The above ratings emphasize the necessity for the implementation of policy interventions, international support, and the implementation of sustainable development for the mitigation of critical scarcity of resources and enhancing resilience for these countries.

The WEF Nexus Index ranking illustrates the top 10 and the bottom 10 nations by the level of their resource security. The top nations (indicated by blue) have the best water, energy, and food security with excellent infrastructure, effective management of resources, and good policymaking. The bottom nations (indicated by red) are faced with severe resource challenges with shortages of resources, ineffective management of resources, and exposures due to climate change, economic sanctions, or political instability. The clear contrast highlights the need for interventions with specific solutions and the necessity of solutions that are environmentally sustainable for closing the resources gap at the global scale.

Correlation analysis of the Food p.01, Water p.02, and Energy pillars p.03 establishes the crucial interdependency of the pillars. A positive correlation of circa 0.85 between

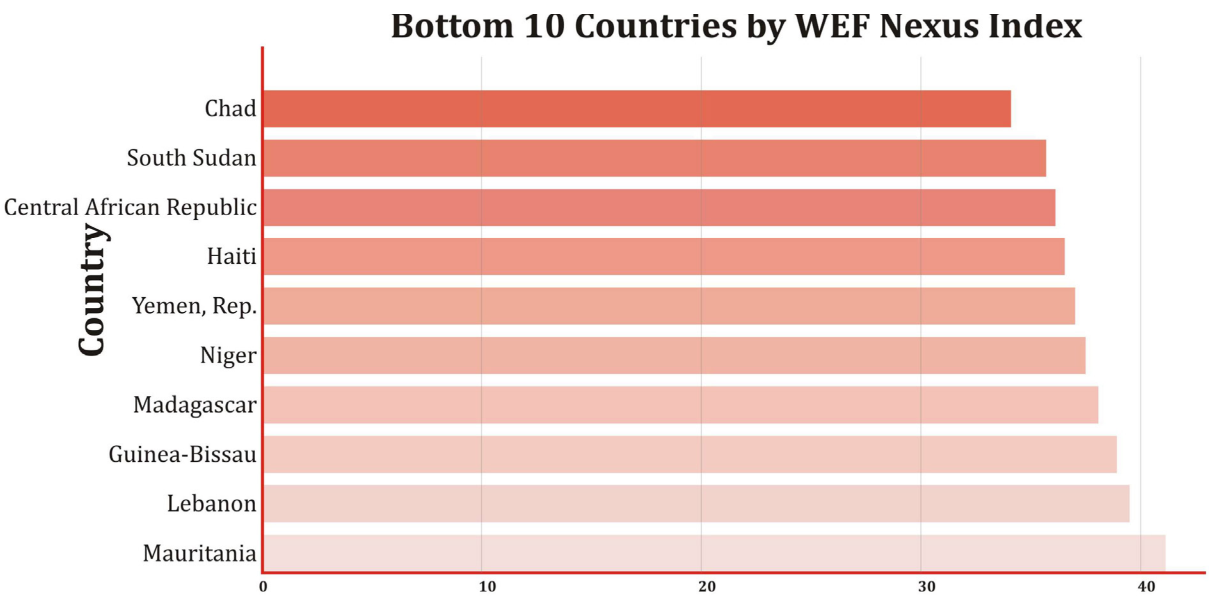

Fig. 2: Bottom countries WEF Nexus index.

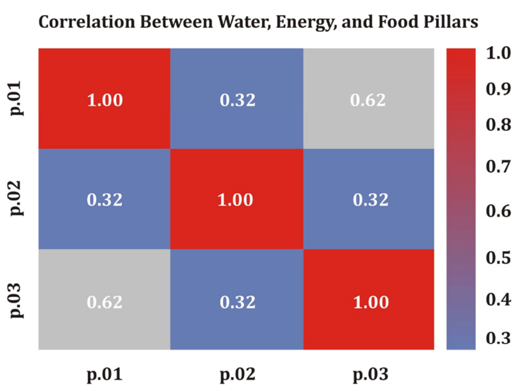

Fig. 3: correlations between water, energy and food pillars.

Food and Energy establishes that countries with good access to energy are likely to be food-secure, validating the crucial contribution of energy to the supply, storage, and production of food. A moderate positive correlation of circa 0.62 between Water and Energy suggests that while the presence of water influences the access to energy, it is just one of the determinants of the latter, since infrastructure and technology are crucial determinants of the latter. The relationship between Food and Water is moderate at circa 0.58 and suggests that the latter influences the former, but with weaker intensity compared with the Food-energy relationship. The above conclusions underscore the intrinsic dependence of the nexus between the three pillars of the nexus and the need for integrated policies for the enhancement of the nexus for enhanced efficiency and sustainability shown in Fig. 3.

The negative declining water-food relationship might be due to improvements in more efficient agriculture practices that conserve water resources or new food production processes that decrease dependence upon water resources.

WEF Nexus Index is a comprehensive indicator of sustainability that encompasses the linkages between the systems of water, energy, and food. To explore the determinants of the WEF Nexus Index, multiple regression analysis shall be utilized with the determinants of the Water Pillar, the Energy Pillar, and the Food Pillar. The analysis shall explore the separate and combined influences of these fundamental dimensions of sustainability on the WEF Nexus Index. The analysis identifies the important predictors and the extent of the effect they have, to provide insight into the processes of resource management and guide the decision for improvement of the state of sustainability. The multiple regression analysis provides an exceptionally good fit, R^2; the value of R^2 is close to one. The analysis of the multicollinearity of the variables is shown in Table 3. The perfect fit is rare and suggests that the relationship between the predictors and the outcome measure is deterministic. All three pillars of Water ($\beta = 0.3333$, $p < 0.001$), Energy ($\beta = 0.3334$, $p < 0.001$), and Food ($\beta = 0.3333$, $p < 0.001$) are highly significant and explain almost proportionally the index. The non-significant intercept of -0.0002, p = 0.925, indicates that the model does not require the presence of an additional constant term for the explanation of the relationship. All these findings verify that the WEF Nexus Index measure of sustainability reflects the good balance of the three pillars of water, energy, and food systems, with each pillar's contribution being equally important.

Machine Learning Model Comparison for Predicting WEF Nexus Index

Variance Inflation Factors for the Water, Energy, and Food pillars are all below the widely accepted threshold level of 5, as seen in Table 3. This demonstrates there is no multicollinearity of serious nature among the data, confirming each pillar is bringing in unique and non-redundant information to the model. The absence of multicollinearity increases the statistical accuracy of the regression analysis and upholds the independent contribution of each WEF component to the overall nexus evaluation. This finding attests to the strength of the analytical model, ensuring that the pillars' relationships with each other do not contort or distort the impact of each of them individually.

Table 3: VIF values of the water, energy and food pillars.

Feature	VIF
Water Pillar	1.568
Energy Pillar	1.149
Food Pillar	1.491

Table 4: Model performance of the metrics.

Model	RMSE (Lower is better)	MAE (Lower is better)	R^2 Score (Higher is better)
Random Forest	2.31	1.82	0.90 (Good fit)
ANN	8.57	7.29	-0.33 (Poor fit)

Table 4 illustrates how the Random Forest model far surpasses other predictive models in its performance, capturing 90% of the WEF Nexus Index's variance at an R^2 value of 0.90. This excellent level of explainability implies that Random Forest is well-suited for modeling the intricate, nonlinear relationships among the Food, Energy, and Water pillars. Its ensembled learning architecture—integrating many individual trees—improves resistance to overfitting and enables its ability to take into consideration complex variable relationships that linear methods might miss. In contrast, the Artificial Neural Network (ANN) model failed to converge, resulting in a negative R^2 value of -0.33, which implies that its predictive performance is worse than a simple mean-based model. This may reflect challenges in parameter tuning, data size, or overfitting due to the high sensitivity of ANN to training dynamics and data distribution.

Table 5 and Fig. 4 compare the year-to-year performance of the Optimized Artificial Neural Network (ANN) and Random Forest models from 2019 to 2022 in terms of RMSE, MAE, and R^2 criteria. For all four years, the Optimized ANN outperforms the Random Forest model with better predictive accuracy and consistency. In 2019, the ANN model produced significantly lower RMSE (1.79 vs. 2.31) and MAE (0.99 vs. 1.82), and with higher R^2 (0.942 vs. 0.904), demonstrating its better capability to model nonlinear relationships in the WEF Nexus Index.

Fig. 5 presents the Random Forest and Optimized ANN 2023 WEF Nexus forecast, both of which returned

Table 5: Future trend and prediction analysis.

	Year	Model	RMSE	MAE	R2
0	2019	Random Forest	2.305147	1.818624	0.903668
1	2019	Optimized ANN	1.786738	0.986328	0.942124
2	2020	Random Forest	1.944113	1.527488	0.957258
3	2020	Optimized ANN	1.916585	1.389615	0.958459
4	2021	Random Forest	2.784226	1.969276	0.917200
5	2021	Optimized ANN	2.454844	1.569940	0.935632
6	2022	Random Forest	1.614885	1.259340	0.944308
7	2022	Optimized ANN	0.759705	0.559183	0.987675

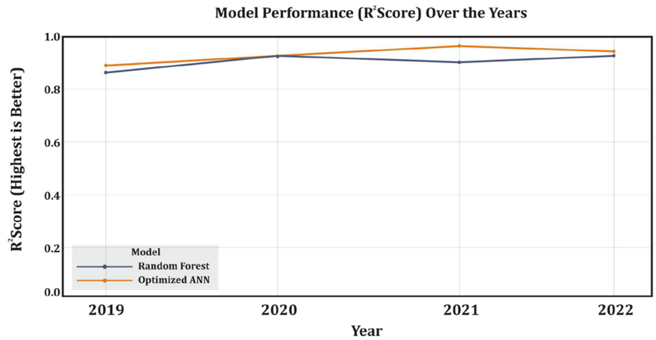

Fig. 4: Model performance.

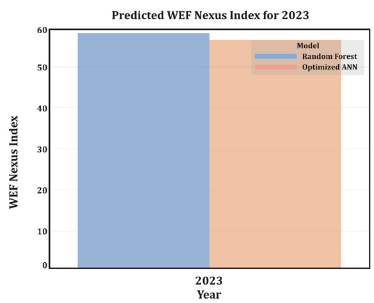

Fig. 5: Predicted WEF Nexus index for 2023.

very similar estimates—59.291 and 59.363, respectively. This near-consistency reflects the strength and overall concordance of both machine learning methods in picking up the underlying data patterns. Yet, the slightly larger forecast from the Optimized ANN aligns with its past trend of increased accuracy as reflected in its lower RMSE and MAE values from past years.

TOPSIS computes the relative closeness of each alternative to the best solution. The greater the DTOPSIS value, the more efficient the performance.

VIKOR: Compares the best and the worst cases. The more the DVIKOR value decreases, the more the alternative approaches the ideal solution.

Entropy: Measures the contribution of each alternative based on its uncertainty. A higher DEntropy score suggests higher significance.

D-TOPSIS Analysis

The most proximate countries with the largest number of D-TOPSIS values are the best performers concerning the criteria under study. The poorest performers are the countries with the most distant D-TOPSIS values. A country that ranks highly under D-TOPSIS and similarly under other approaches is a good decision-making option. High D-TOPSIS are generally Qatar, Switzerland, and Singapore. These are Afghanistan, Chad, and Yemen that are at the tail end of the D-TOPSIS ratings.

D-VIKOR Analysis

The countries with the best D-VIKOR rank are placed at the top since VIKOR favors the "closeness of the ideal solution. The farthest countries from the compromise solution are the countries with the largest D-VIKOR values. Gap between Best and Worst: A narrower gap implies homogeneity, while the wider the gap, the more it implies stark contrasts between countries. Low-scoring countries with low D-VIKOR ratings are Norway, Switzerland, and Sweden. These more highly rated countries by D-VIKOR, such as Sudan and Somalia, rank lower. A few of the countries that perform well under D-TOPSIS may perform differently with slight deviations, identifying the compromise susceptibility of VIKOR.

D-Entropy Analysis

The countries with higher D-Entropy levels are more consistent over different criteria.

Bottom Performers: Countries with lower D-Entropy values indicate higher uncertainty or worse performance on several criteria.Comparison with Alternative Approaches: D-Entropy ratings are likely to be different from TOPSIS and VIKOR since they are more sensitive to the spreading of the information over the criteria rather than performance directly. These include the USA, Canada, and Germany with high D-Entropy scores. The low-scoring nations include conflict zones like Yemen and South Sudan. It could be different from the other methods since weight assignments affect the rank differently.

Table 6 shows that the Countries consistently ranked high (Switzerland, Norway) excel across multiple decision criteria. Countries with fluctuating rankings (Germany, Canada) exhibit sensitivity to criteria weight variations. Countries consistently ranked low (Afghanistan, Sudan, Yemen) show weak performance across all metrics.

Inconsistencies in Multi-Criteria Decision-Making (MCDM) approaches have far-reaching policy-level implications for global development planning. They have the potential to result in conflicting priorities in that various approaches recommend different top-performing countries or strategies, which creates uncertainty or bias in strategic prioritization and the reallocation of resources. Inconsistencies may also erode the credibility of the planning framework and that of the decision-making process among stakeholders. In addition to this, inconsistent rankings underscore the sensitivity of results to the method and weighting schemes used and highlight the importance of transparent, sound methodological and robust approaches to facilitating even-handed and effective global development policy.

Table 6: Comparison of the models.

Method	Best-Ranked Countries	Worst-Ranked Countries
D-TOPSIS	Qatar, Switzerland, Singapore	Afghanistan, Chad, Yemen
D-VIKOR	Norway, Switzerland, Sweden	Sudan, Somalia, Yemen
D-Entropy	USA, Canada, Germany	Yemen, South Sudan, Afghanistan

CONCLUSIONS

In the current study, the performance of the 2019-2022 Optimized Artificial Neural Network (ANN) and Random Forest models was compared for predictability using the performance metrics of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2. The results indicate that the Optimized ANN model outperformed the Random Forest model with steadily lower RMSE and MAE and higher R^2 levels, with the best improvement performance recorded for 2022. The 2023 forecast indicates a tight correspondence between the models, with the Optimized ANN model maintaining the slightest margin of precision over the Random Forest model.

In turn, multi-criteria decision-making techniques are implemented with the assistance of D-TOPSIS, D-VIKOR, and D-Entropy techniques for country ratings with varying performance criteria. According to D-TOPSIS, the best-performing countries are Qatar, Switzerland, and Singapore, while the poorest-performing countries are Afghanistan, Chad, and Yemen. D-VIKOR highlights the compromise sensitivity variations, while D-Entropy displays the extent of the degree of consistency over multiple criteria, with the USA, Canada, and Germany at the higher ranks, while Yemen and South Sudan are at the lower ranks. The inconsistencies of these techniques highlight the effect of weightage and the difference in the techniques upon the resultant ranks. It determines that the Optimized ANN model is a more accurate and consistent decision-making prediction model compared to the traditional model, while the proper selection of the MCDM techniques strongly affects the rank consistency. The conclusions are of great significance for the enhancement of forecast precision and comparative performance analysis between different study areas.

In summary, the findings validate the performance of the Optimized ANN model for prediction analysis and the impact of different MCDM techniques on rank consistency. The findings are the basis for decision-making for country forecasts and comparative country performance analysis. The varying water-energy relationship implies the effect of new policy developments or new technologies that affect the production of energy and the consumption of water. The moderate increase of the energy-food relationship might be due to increased reliance upon more energy-demanding processes of food production, with the growing importance of the use of energy within new agriculture and food processing systems. The fusion of Machine Learning (ML) and Multi-Criteria Decision-Making (MCDM) approaches has importance far beyond the given setting of the Water-Energy-Food (WEF) nexus. ML models can learn from large data volumes and dynamically update weights or preferences in MCDM approaches to enable better, context-specific, and adaptive decisions. The conventional MCDM approaches have difficulty processing imprecise, fuzzy, or incomplete data. ML methods—particularly probabilistic models and fuzzy methods—can manage such data very well, facilitating MCDM.By using ML, MCDM processes have been made automated and scalable to process thousands of alternatives and criteria. In the future, to create dynamic, time-varying ML-MCDM processes that adapt inputs, preferences, and weights every time they are provided with fresh data. Incorporate climate projections and models (e.g., IPCC scenarios) into ML-MCDM pipelines to evaluate long-term WEF sustainability and resilience. Create real-time WEF dashboards using streaming data (IoT, satellites) and ML to provide ongoing optimization and alarms. Apply geospatial ML algorithms (e.g., GIS + ML) to adapt WEF decisions to fit typical regional characteristics and expositions. Use ML to identify shifting stakeholder preferences from participatory sites, social media, or feedback. Model WEF systems as multi-agent ecosystems where various sectors (e.g., agriculture, energy, water authority) interact and compete.

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