

Article

A Thorough Analysis of Potential Geothermal Project Locations in Afghanistan

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Abstract: In recent decades, many countries have shown a growing interest in the use of renewable energies for power generation. Geothermal energy is a clean and environmentally friendly source of renewable energy that can be used to produce electricity and heat for industrial and domestic applications. While Afghanistan has undeniably good geothermal potential that can be utilised to alleviate the country's current energy limitations, so far this potential has remained completely untapped. In this study, the suitability of 21 provinces for geothermal project implementation in Afghanistan was evaluated using multiple multi-criteria decision-making (MCDM) methods. The stepwise weight assessment ratio analysis (SWARA) method was used to weigh each criterion while the additive ratio assessment (ARAS) method was used to rank potential geothermal sites. The technique for order of preference by similarity to ideal solution (TOPSIS), the vlse kriterijumsk optimizacija kompromisno resenje (VIKOR), and the weighted aggregated sum product assessment (WASPAS) methods were also used in this study. These rankings were then examined via sensitivity analysis which indicated that a 5% change in criteria weights altered the rankings in all methods except the VIKOR method. Volcanic dome density was ranked the most important criteria. All the methods identified Ghazni province as the most suitable location for geothermal project implementation in Afghanistan.

Keywords: geothermal energy; location planning; MCDM method; sensitivity analysis; Afghanistan

1. Introduction

At present, the world heavily relies on fossil fuels as a source of energy. However, overreliance on these fuels has resulted in environmental pollution, climate change, rising sea levels, etc. [1]. Therefore, the development, acceleration, and dissemination of newer, more sustainable technologies that do not exacerbate the effects of climate change are of utmost importance [2]. In order to meet the ever-increasing global demand for energy without compromising on environmental protections and sustainable development goals, it is essential that fossil fuel-burning power plants are gradually replaced

by renewable energy systems [3]. A crucial component of sustainable development, the development and expansion of renewable energy systems should greatly increase national endeavours to satisfy the economic, environmental, and social goals of the 21st century [4]. Geothermal energy is not only one of the most reliable, stable, and clean energy sources available, but it can be harvested regardless of the weather and climate conditions [5]. The limited environmental impact, low greenhouse gas emission, and low technology requirements of geothermal energy give it immense potential as a renewable energy source [6,7]. Geothermal energy is harvested from the heat produced in the earth's core [8] and its internal structures [9] which lie stored in rocks lying deep below the surface [10,11]. This source of energy is not only used in electricity and heat generation but also in oil extraction, paper production, gold mining and processing as well as silica dust production [12]. However, it is mainly utilised in electricity generation, direct heating, and heat pumps [13]. Depending on the economic, social, and environmental conditions of a region, geothermal energy can be harvested for industrial, agricultural, or domestic use [14]. In recent decades, geothermal energy has seen significant growth in the rate of utilisation worldwide.

In underdeveloped countries such as Afghanistan, the absence of extensive electrical infrastructure as well as the sad state of the electricity industry are obstacles in the road to development [15]. However, increased public awareness on the importance of sustainable power sources has led to a growing demand for the development and utilisation of renewable energy sources [16]. As Afghanistan has numerous volcanic sites and hot springs, it is more than likely that the country not only has significant power generation potential, but a vast quantity of untapped geothermal power [17]. Therefore, geothermal power plants may be able to meet a significant part of Afghanistan's current and future electricity demands [15]. This calls for special consideration of potential renewable energy sources, especially geothermal power, in Afghanistan and the role that these sources can play in meeting the country's increasing energy demands.

The present study aims to identify potential geothermal project locations in Afghanistan and assess their suitability. As the shortlisted locations needed to be appraised across multiple criteria, multiple multi-criteria decision-making (MCDM) methods; specifically (1) stepwise weight assessment ratio analysis (SWARA), (2) additive ratio assessment (ARAS), (3) technique for order of preference by similarity to ideal solution (TOPSIS), (4) vlse kriterijumsk optimizacija kompromisno resenje (VIKOR), and (5) weighted aggregated sum product assessment (WASPAS); were utilised in this study. SWARA was used to assign a weight to each criterion while ARAS was used to rank regions and provinces in Afghanistan by order of potential suitability for geothermal project implementation. TOPSIS, VIKOR, and WASPAS were used to validate the findings of the SWARA and ARAS methods. The ranking results were then compared with each other before sensitivity analysis was performed to determine the impact of each criterion as well as the method of results evaluation.

2. Literature Review

As MCDM methods have extensive applications in energy planning, decision-making, and many other related areas, this section first reviews existing studies on the application of MCDM methods in renewable energy utilisation, then focuses on their use in geothermal project site location.

2.1. MCDM Methods in the Assessment of Renewable Energy Sources

MCDM methods can be very effective in providing solutions for energy-related decision-making problems that have multiple conflicting criteria and objectives [18]. Over the years, MCDM methods have been used in a wide variety of energy-related areas such as planning, resource allocation, policymaking, and management [19]. This section briefly examines prior studies that have used MCDM methods to rank renewable energy sources. Yazdani-Chamzini et al. [20] integrated the complex proportional assessment (COPRAS) and analytic hierarchy process (AHP) methods to identify the best renewable energy project and proved its validity by comparing their results with the findings of five other MCDM methods. Stein [21] used the AHP method to assess and rank several renewable

and non-renewable energy generation technologies. It concluded that the most important renewable energies were solar, wind, hydroelectric, and geothermal. Kabak & Dagdeviren [22] examined the opportunities, risks, benefits, and cost of renewable energies in Turkey and used the analytic network process (ANP) method to rank them. Their results suggest that hydropower is the most suitable source of renewable energy for the country. Tasri et al. [23] investigated the best source of renewable energy for electricity generation in Indonesia and found that hydropower was most appropriate followed by geothermal, solar, wind, and biomass energies. Ahmad & Tahar [24] used the AHP method to rank renewable energy technologies for Malaysia and concluded that photovoltaic (PV) systems were most suited. In a study by Sengul et al. [25], the fuzzy TOPSIS method was used to rank renewable energy systems in Turkey while the Shannon entropy method was used for criterion weighting. Their findings indicate that hydropower was the best renewable energy system for Turkey. Streimikiene et al. [26] combined the ARAS and AHP methods to rank power generation technologies for Lithuania and found that biomass technologies should be given the highest priority. Buyukozkan & Guleryuz [27] developed an integrated MCDM model in which the decision-making trial and evaluation laboratory (DEMATEL) method was used for weighting and the ANP method to rank them. Al Garni et al. [28] presented an AHP-based MCDM method for assessing renewable energy sources in Saudi Arabia which concluded that solar photovoltaic was best suited followed by concentrated solar power. Celikbilek & Tuysuz [29] developed a DEMATEL, ANP, and VIKOR-integrated model to evaluate renewable energy sources and demonstrated its effectiveness via a case study. They also examined two review studies on the application of decision-making tools in renewable energy utilisation. A comprehensive study by Kumar et al. [30] reviewed the criteria used in decision-making models for renewable energy source assessments and provided valuable insight into various MCDM techniques, their contribution to the use of renewable energies, and future prospects in this field. It also included extensive research on the potential use of MCDM techniques in the area of sustainable energy. Kaya et al. [31] reviewed existing literature on energy-related policymaking and decision-making using MCDM methods. It showed that the fuzzy AHP method was the most commonly used, either individually or in combination with other MCDM methods, in this field of study. Xu et al. [32] used two MCDM methods to study potential renewable energy sources for hydrogen production in Pakistan. The fuzzy AHP method was used to weight each criterion before the data envelopment analysis (DEA) method was used to rank the renewable energy sources. They found that wind and solar energy were the best renewable energy sources for hydrogen production in Pakistan. Ghost et al. [33] created a fuzzy-COPRAS framework to analyse six renewable energy sources in West Bengal, India based on eight criteria and discovered that solar energy was the most suitable option. Anwar et al. [34] ranked renewable energy sources in Pakistan by utilising the AHP method to weight the criteria and the TOPSIS method to rank the energy sources. Their analysis showed that solar energy was the best renewable energy source for Pakistan. Campos-Guzmán et al. [35] carried out a comprehensive literature review of the methods used to assess the sustainability of renewable energy systems and concluded that a combination of life cycle analysis (LCA) and MCDM methods could be an effective tool in the sustainability assessment of renewable energy systems and in obtaining a set of sustainability criteria. A study by Siksnyte-Butkiene et al. [36] examined scientific articles that have used MCDM methods to evaluate renewable energy technologies in households. Their paper provides an in-depth overview of MCDM methods and outlines their advantages and disadvantages when used in technology assessment.

The literature review above clearly shows that many studies have used MCDM methods to assess and rank renewable energy sources in different countries. However, any change in the method or evaluation criteria significantly changed the rankings in these studies. Since it is irrational to assess multiple renewable sources based on a single set of general criteria, a comprehensive set of criteria for each renewable energy source and its measurements needs to be identified. It is also imperative to apply several different MCDM methods to each problem and compare the results in order to ensure that the results are accurate and valid.

2.2. MCDM Methods in the Assessment of Geothermal Projects

Many researchers have used MCDM methods to determine geothermal project site location and, more precisely, for the weighting of selection criteria as well as the ranking of potential locations [37]. They have also been used to assess and rank potential geothermal power plant sites in different countries [38]. This section briefly reviews existing studies that have used MCDM methods to assess potentially suitable locations for geothermal projects: Ramazankhani et al. [1] used the DEA method to rank 14 Iranian provinces according to adaptability to geothermal-powered hydrogen production. The results were then compared with the results of the TOPSIS and VIKOR methods which showed that the provinces of East Azerbaijan, Bushehr, and Hormozgan were the most adaptable. A similar study by Mostafaeipour et al. [14] integrated the Shannon entropy method and the fuzzy multi-objective optimization on the basis of ratio analysis (Fuzzy-MOORA) method to rank the feasibility of geothermal-energy hydrogen production among 14 Iranian provinces. The Shannon entropy technique was applied to weight the criteria and the fuzzy-MOORA method was used to rank the provinces. The study found that the provinces of Bushehr, Hormozgan, and Isfahan were the most suitable for geothermal-powered hydrogen production. Yalcin et al. [39] used a combination of multiple-criteria decision analysis (MCDA) and a geographic information system (GIS) framework to assess geothermal sources in the Akarcay basin in Turkey. In the MCDA phase, the relative weights of each selection criterion were determined with the help of the AHP method and pairwise comparisons. Their findings indicate that all the examined hot springs had great geothermal energy potential. In a paper by Kiavarz et al. [40], a GIS-based framework, working on the basis of ordered weighted averaging (OWA), was used to generate geothermal maps of the prefectures of Akita and Iwate in Japan. The researchers stated that the use of the OWA method provided a model for generating prospective geothermal maps with different optimistic and pessimistic strategies. Tinti et al. [41] used a GIS framework and the AHP method to assess the suitability of shallow geothermal technologies. This study, which involved comparing a large number of shallow geothermal source-related criteria and factors, reported that it was possible that one can draw a suitability map of technologies for Europe using the AHP method. Puppala et al. [42] assessed potential geothermal fields in India using the fuzzy AHP method to weight criteria. The paper identified the Puga field as the most important geothermal field in the studied region. Cambazoğlu et al. [38] used a GIS framework and the TOPSIS method to examine the potential of geothermal sources in Gediz Graben, Turkey and showed that 76% of the examined geothermal wells were of the two most favourable classes in terms of suitability. An article by Raos et al. [43] examined the main features of MCDM tools for the economic and environmental assessment of geothermal projects. They used decision support and MCDM methods with a weighted decision matrix (WDM) to study the various options of a geothermal system based on a set of criteria. Their findings were validated for use in several scenarios based on the results of a sensitivity analysis. The method proposed in this study can be used by investors and decision-makers to mitigate investment risks. Bilić et al. [44] analysed five potential geothermal sites in north-eastern Croatia, a part of the Pannonian basin, using the weighted decision matrix (WDM) and discovered a high degree of consistency between the results and the actual use of five geothermal fields.

Since neither MCDM method is superior to the other, the best way to obtain reliable and robust results is to use two or more of them and compare the results [45]. Our literature review, however, shows that most of the existing studies in this field have used either one or only a limited number of MCDM methods; a choice which makes their result highly dependent upon the chosen method and the selection criteria. In order to mitigate against this as well as to address the gap in the current literature, this study used five MCDM methods, namely SWARA, ARAS, TOPSIS, VIKOR, and WASPAS, to rank the regions of interest in terms of suitability for geothermal projects. These rankings were then compared and subjected to sensitivity analysis to determine how the choice of method and selection criteria affect them. It should be noted that the SWARA, ARAS, and WASPAS methods were chosen due to their relative novelty, simplicity, and reputation of producing robust results. Another innovation of this research was to focus on regions in Afghanistan that, despite having a wealth of geothermal

potentials such as hot springs, volcanoes, magma springs, and hot surface waters, have not received much attention in terms of geothermal potential analysis. Nevertheless, recent geological studies have revealed enormous geothermal potential in Afghanistan which, if harvested properly, could significantly influence the electricity and energy supply of the country. Therefore, this study used multiple MCDM methods to rank Afghan provinces in terms of suitability for geothermal projects and conducted a comparative analysis of the results.

3. Geography of Afghanistan

Afghanistan is a Central Asian country with a population of 32 million people and a land area of 647,800 km² making it the 42nd most populous and 40th largest country in the world [46]. The studied area as well as a map of the Afghan provinces is displayed in Figure 1. At present, the country's electricity sector is in dire straits and it suffers from a complex set of stability and security problems which make it difficult for it import power from its neighbours: Turkmenistan, Tajikistan, Iran, Uzbekistan, and Kyrgyzstan [47]. Only 10 to 15% of the population have stable access to power which is very low in comparison to other countries in the world [46]. According to the Afghanistan Power Sector Master Plan (APSMP), the electricity demand of the country is expected to reach about 3500 MW by 2032 [47]. Therefore, the Afghan government has made the acquisition of off-grid technologies, including renewable energies, the highest priority as it provides the best long-term solution to Afghanistan's electricity problems [48]. Renewable energies offer great opportunities for bringing electricity to Afghans, especially those living in rural and remote areas [49]. Although geothermal energy can satisfy part of the country's electricity demand, generating electricity from geothermal sources has two major requirements: adequate equipment and large resources of water or steam [50]. The presence of many magma springs, volcanoes, and surface hot water in Afghanistan is a testament to the enormous geothermal potential of this country; a potential that has also been reaffirmed by recent geological studies [17]. Afghanistan also has access to the technologies needed to effectively harness geothermal energy potentials [51]. The terrain in Afghanistan suggests that there are vast systems of groundwater circulating beneath the country [48]. However, despite the excellent geothermal potential present here, Afghanistan still does not have a single geothermal power plant [17].



Figure 1. The studied area and map of provinces in Afghanistan.

4. Methodology

Multiple MCDM techniques were used in this study to rank a number of Afghan provinces according to their suitability for future geothermal projects. First, the ranking criteria were weighted using SWARA then the sites were ranked using ARAS, TOPSIS, VIKOR, and WASPAS before the results were compared.

4.1. SWARA

In MCDM methods, decision makers play a central role in determining which criteria to use and how they should be weighted. Indeed, criteria weighting is an important step in solving decision-making problems [52]. SWARA was developed in 2010 by Keršulienė et al., to help experts weight decision-making criteria. The main advantage of this method is not only that expert opinions are unconditionally included but, in comparison to other models, it has a higher degree of accuracy in evaluating the opinions of experts [53]. SWARA is much simpler to comprehend with fewer pair comparisons than similar methods such as AHP and ANP [54]. It also allows decision makers to interact and advise each other making the results more precise compared to other techniques [55].

The main criteria weighting steps of SWARA are as follows [54,56–58]:

- Stage 1: Arrange the criteria;
- Stage 2: Assign the respective significance of average value (S_j) for each criterion;
- Stage 3: Assign the coefficient K_j ; a function of S_j ; using the following equation:

$$K_j = S_j + 1 \tag{1}$$

- Stage 4: Account for the weight q_j using the following equation

$$q_j = \frac{q_{j-1}}{K_j} \tag{2}$$

where the most important criterion has a weight of 1.

- Stage 5: Account for normalised weight using the following equation

$$w_j = \frac{q_j}{\sum q_j} \tag{3}$$

4.2. ARAS

ARAS is based on the assumption that intricate events can be seen using simple relative comparisons [59,60]. The aggregate of weighted and normalised number of criteria for each alternative is divided by the aggregate of weighted and normalised number of criteria for the best alternatives to gain the degree of optimality coefficient. The stages of ARAS are as follows [59,61]:

Stage 1: Form an $m \times n$ decision matrix as follows:

$$X = \begin{bmatrix} x_{01} & \dots & x_{0j} & \dots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \dots & x_{ij} & \dots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mj} & \dots & x_{mn} \end{bmatrix} \quad i = \overline{0, m}; \quad j = \overline{1, n} \tag{4}$$

x_{0j} is the optimal value for the criterion j which, when unknown, can be determined as follows:

$$\begin{aligned} x_{0j} &= \max_i x_{ij} & , \text{ if } \max_i x_{ij} & \text{ is preferable,} \\ x_{0j} &= \min_i x_{ij}^* & , \text{ if } \min_i x_{ij}^* & \text{ is preferable} \end{aligned} \quad (5)$$

The performance of alternatives in the criteria (x_{ij}) and the weight of criteria (w_j) are derived from input from the decision-makers. However, the weights must first be made dimensionless which can be accomplished by dividing the weight by the optimal value obtained above.

Using the normalisation method, the primitive decision-making matrix values are converted to values in the (0, 1) or (0, ∞) range.

Stage 2: Normalise the primitive input values of all the criteria and convert into the matrix \bar{X} or \bar{x}_{ij} :

$$\bar{X} = \begin{bmatrix} \bar{x}_{01} & \dots & \bar{x}_{0j} & \dots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \dots & \bar{x}_{ij} & \dots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \dots & \bar{x}_{mj} & \dots & \bar{x}_{mn} \end{bmatrix} \quad i = \overline{0, m}; \quad j = \overline{1, n} \quad (6)$$

For positive criteria, normalisation is done using Equation (7):

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^m x_{ij}} \quad (7)$$

For negative criteria, normalisation is done using Equation (8):

$$x_{ij} = \frac{1}{x_{ij}^*} \quad \bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^m x_{ij}} \quad (8)$$

Stage 3: Apply the weights to the normalised matrix \bar{X} to obtain the matrix \hat{X} . The appointed weights must have the following specifications:

$$0 < w_j < 1$$

$$\sum_{j=1}^n w_j = 1 \quad (9)$$

$$\hat{X} = \begin{bmatrix} \hat{x}_{01} & \dots & \hat{x}_{0j} & \dots & \hat{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{i1} & \dots & \hat{x}_{ij} & \dots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \dots & \hat{x}_{mj} & \dots & \hat{x}_{mn} \end{bmatrix} \quad i = \overline{0, m}; \quad j = \overline{1, n} \quad (10)$$

$$\hat{x}_{ij} = \bar{x}_{ij} \times w_j; \quad i = \overline{0, m} \quad (11)$$

The value of the optimality function is obtained using Equation (12):

$$O_i = \sum_{j=1}^n \hat{x}_{ij}; \quad i = \overline{0, m} \quad (12)$$

To determine the utility degree of each alternative, it has to be compared with the best value O_0 . The utility degree for the alternative A_i ; denoted by K_i ; is given by:

$$K_i = \frac{O_i}{O_0}; \quad i = \overline{0, m} \quad (13)$$

where O_0 and O_i are given by Equation (12). It is clear that K_i is always in the range (0, 1). Alternatives are prioritised based on K_i .

5. Data Analysis

5.1. Identification of Suitable Provinces for Geothermal Projects

To begin with, the Afghan provinces with some geothermal project potential had to be identified. Since regions with hot springs are likely to have geothermal reservoirs [20], it was assumed that provinces that have hot springs and hot water resources would have good geothermal potential. The presence of faults, volcanic mountains, and volcanic rocks was considered geological criteria, the presence of hot springs and mud pools was considered geochemical criteria, and the presence of intrusive rocks was considered a geophysical criterion for geothermal potential evaluation [62]. These criteria were used to identify provinces that had potential for geothermal projects.

5.2. Decision Model Criteria

In order to choose locations with suitable potential for geothermal projects, a wide range of criteria have to be evaluated. First and foremost, these criteria must be specified. Therefore, the decision criteria for geothermal project implementation were identified by studying the literature review of geothermal energy and input from an expert panel. The shortlisted decision criteria are listed in Table 1.

Table 1. Criteria for estimating the suitability of a region for geothermal projects.

Code	Criteria	Definition	Reference
C ₁	Hot spring density	Hot springs are a significant and clear sign of hydro geothermal resources. Many of the world's geothermal regions have been identified by visible signs on the terrain such as hot springs created by volcanic activity. Therefore, the number of hot springs was used as a criterion for measuring geothermal potential.	[17,39,40,42,62–65]
C ₂	Fault density	Fault and heat transfer in the ground's surface is directly related to the presence of faults. Faults are a vital component of fluid upwelling that aids convective heat transfer. Therefore, the distance from faults as well as the density of fault layers are an indication of the proximity to a fracture and the presence of a geothermal reservoir. Fault-related criteria are important in terms of heat transfer as geothermal activity is related to faults and fault densities. Fault density is equal to the ratio of the fault length in the province area. While fault density increases the geothermal potential of a region, the geothermal power plant itself must be constructed in a place safe from natural disasters. Therefore, new technologies can be used in geothermal power plants to mitigate natural disasters.	[17,39,40,62–67]
C ₃	Volcanic dome density	Volcanic mountains and rocks can be considered geological criteria for geothermal potential evaluation as their surrounding areas have great potential for geothermal sources. Therefore, the number of volcanic domes was used as a criterion for measuring geothermal potential.	[17,39,40,62,64,66,67]
C ₄	Hot mineral spring density	Areas surrounding hot springs and mineral springs are very likely to be in high-temperature zones. The presence of mineral water springs is a visible indicator of a thermal water source. Therefore, the number of hot mineral springs was taken as a sign of geothermal activity in a region and used as a criterion for measuring geothermal potential.	[17,39,63,68–70]

Table 1. Cont.

Code	Criteria	Definition	Reference
C ₅	Drainage density	Drainage density, which refers to the number of drainage lines such as streams, rivers, and seasonal rivers, is an important criterion for geothermal site selection. Drainage density is determined by the length of drainage lines per unit area, sometimes given in square kilometres. Therefore, the higher the water density, the higher the geothermal potential.	[17,39,63,66]
C ₆	Intrusive rock density	The presence of intrusive rocks is a sign of volcanic activity and the highest heat flows are found near hot springs, large faults, and intrusive rocks. The location of geothermal energy sources is known to be associated with the presence of old volcanic and intrusive rocks. The density of intrusive rocks is an important geophysical criterion for measuring the geothermal potential of an area. It is measured as a ratio of the area of intrusive rocks to the area of the province.	[17,39,40,62,65]
C ₇	Population density	Population and work not only lead to the development of an area but lays the foundation for the improvement of businesses in the area. Population is often considered a principal indicator of employment. The implementation of geothermal projects in populous areas can offer electricity and energy to a larger number of people. Therefore, areas with a higher population density were considered to have higher geothermal potential.	[1,14]
C ₈	University density	Access to skilled labour is essential for the operation of geothermal power plants. Since the availability of talented labour directly correlates to the number of colleges and learning centres within a region, the number of universities in each region was also used as a criterion for evaluating the suitability of a region for geothermal projects.	[1,14]
C ₉	Area of the province	The area of a region significantly impacts the cost incurred from transportation, labour movement, and power transmission. This factor is considered a negative (cost type) criterion because as an area increases, so does the cost of transportation, labour movement, and power transmission. Therefore, smaller areas have higher potential for geothermal plant development.	[1,14]

The values of the decision criteria for the studied areas are outlined in Table 2.

Table 2. Values of the decision criteria for Afghan provinces.

	Province	The Number of Hot Springs [49,71]	Fault Density	The Number of Volcanic	The Number of Hydrothermal Mineral Waters	Drainage Density	Intrusive Rocks Density	Population of the Province [48]	The Number of Universities [48]	Area of the Province [48]
A ₁	Badakhshan	3	0.0219	0	5	0.0806	0.3777	950,953	1	44,836
A ₂	Badghis	1	0.0118	0	9	0.0757	0.0406	495,958	0	20,794
A ₃	Baghlan	4	0.0247	0	2	0.0543	0.2889	910,784	4	18,255
A ₄	Balkh	2	0.0117	0	2	0.0823	0.0256	1,325,659	10	16,186
A ₅	Bamyan	6	0.0457	0	12	0.0558	0.1923	447,218	1	18,029
A ₆	Daykondi	2	0.0179	0	6	0.0769	0.2896	424,339	0	17,501
A ₇	Farah	4	0.0103	2	12	0.0976	0.1853	507,405	0	49,339
A ₈	Ghazni	4	0.0389	10	6	0.0588	0.2047	1,228,831	1	22,460
A ₉	Chowr	1	0.0306	0	12	0.0612	0.2238	690,296	0	36,657
A ₁₀	Heart	8	0.0323	0	10	0.0619	0.1789	1,890,202	4	55,868
A ₁₁	Helmand	3	0.0123	0	45	0.0517	0.1098	924,711	2	58,305
A ₁₂	Kabul	0	0.0150	0	1	0.0464	0.3152	4,372,977	57	4524
A ₁₃	Kandahar	3	0.0148	0	7	0.0391	0.1540	1,226,593	2	54,844
A ₁₄	Logar	1	0.0354	0	1	0.0558	0.2921	392,045	0	4568
A ₁₅	Nimruz	0	0.0022	0	10	0.0930	0.0032	164,978	0	42,410
A ₁₆	Oruzgan	8	0.0289	0	8	0.0616	0.0503	386,818	0	11,474
A ₁₇	Pakitika	0	0.0136	0	2	0.0472	0.0439	434,742	0	19,516
A ₁₈	Parwan	6	0.0440	0	3	0.0435	0.3421	664,502	2	5715
A ₁₉	Sari pul	2	0.0101	0	0	0.0534	0.0339	559,577	0	16,386
A ₂₀	Wardak	9	0.0423	0	11	0.0469	0.2921	596,287	0	10,348
A ₂₁	Zabol	0	0.0154	0	1	0.0572	0.2438	304,126	0	17,472

5.3. Criteria Weighting Using SWARA

The selected decision criteria were weighted with the help of an expert panel of seven experienced and knowledgeable academic and working professionals. In line with the procedures of the SWARA method, experts sorted the shortlisted criteria in descending order of importance. Upon completion, the obtained weights were then normalised and the ultimate weights of the criteria were decided. These weights are displayed in Table 3.

Table 3. Criteria weights obtained using stepwise weight assessment ratio analysis (SWARA).

Criterion	Code	Comparative Significance of Average Value	K_j	q_j	w_j
The number of hot springs	C ₁	1.000	1.000	1.000	0.209
Fault density	C ₂	0.110	1.110	0.901	0.188
The number of volcanic	C ₃	0.210	1.210	0.745	0.156
The number of hydrothermal mineral waters	C ₄	0.250	1.250	0.596	0.125
Drainage density	C ₅	0.320	1.320	0.451	0.094
Intrusive rocks density	C ₆	0.310	1.310	0.344	0.072
Population of the province	C ₇	0.280	1.280	0.269	0.056
The number of universities	C ₈	0.080	1.080	0.249	0.052
Area of the province	C ₉	0.110	1.110	0.224	0.047

The obtained weights showed that hot spring density (0.209), fault density (0.188), and volcanic dome density (0.156) were the most important criteria. These findings are corroborated by numerous other studies [17,39,40,63,64,67–69].

5.4. Ranking of Afghan Provinces for Geothermal Projects

5.4.1. ARAS

Table 4 shows the ranking of Afghan provinces in terms of suitability for geothermal project implementation according to the ARAS method. The provinces of Ghazni, Wardak, and Herat were ranked most suitable for geothermal projects in that order.

Table 4. Ranking of Afghan provinces in terms of suitability for geothermal project implementation according to the additive ratio assessment (ARAS) method.

	Province	O_i	K_i	Rank
A ₁	Badakhshan	0.190	0.180	11
A ₂	Badghis	0.016	0.109	17
A ₃	Baghlan	0.052	0.184	10
A ₄	Balkh	0.034	0.135	16
A ₅	Bamyan	0.059	0.264	6
A ₆	Daykondi	0.046	0.149	14
A ₇	Farah	0.053	0.251	8
A ₈	Ghazni	0.032	0.587	1

Table 4. Cont.

	Province	O_i	K_i	Rank
A ₉	Ghowr	0.028	0.165	13
A ₁₀	Heart	0.021	0.281	3
A ₁₁	Helmand	0.014	0.254	7
A ₁₂	Kabul	0.050	0.276	4
A ₁₃	Kandahar	0.048	0.143	15
A ₁₄	Logar	0.013	0.168	12
A ₁₅	Nimruz	0.048	0.075	20
A ₁₆	Oruzgan	0.016	0.240	9
A ₁₇	Pakitika	0.031	0.066	21
A ₁₈	Parwan	0.050	0.264	5
A ₁₉	Sari pul	0.026	0.086	19
A ₂₀	Wardak	0.111	0.310	2
A ₂₁	Zabol	0.027	0.087	18

5.4.2. Comparison of ARAS, TOPSIS, VIKOR, and WASPAS Ranking Results

This study used four MCDM methods; ARAS, TOPSIS, VIKOR, and WASPAS; to rank Afghan provinces in terms of suitability for geothermal project implementation. The ranking of each province by each MCDM method is as follows: (1) ARAS: Ghazni, Wardak, and Herat, (2) TOPSIS: Ghazni, Wardak, and Helmand, (3) VIKOR: Ghazni, Wardak and Bamian, and (4) WASPAS: Ghazni, Wardak, and Parwan. The rankings obtained from the different MCDM methods are compared in Table 5.

5.5. Sensitivity Analysis

The rankings obtained from the four different MCDM methods strongly depend on the nature of the evaluation criteria as well as the weight assigned to each criterion. As criteria weights are usually assigned by the decision-maker or a team of experts, they are subjective and increase the likelihood of bias in weight assignment. This should, therefore, be taken into account. In this study, sensitivity analysis was used to determine the correlation between the ranking results and the weight criteria. This was accomplished by measuring the degree of a criterion's change in the rankings following a change in its weight, the results of which are presented in Table 5. The chart plotted in Figure 2 shows how a change in the weight of a criterion affects its ranking. In this chart, dark green rectangles represent weight changes that do not alter rankings while light green rectangles represent weight changes that have an effect on the rankings. Horizontal bar length represents the sensitivity of criteria to change: the shorter the bar, the higher the sensitivity. The sensitivity analysis of the four MCDM methods are presented on the top (ARAS, TOPSIS, VIKOR) and bottom (WASPAS) axes of this chart.

Table 5. Comparison of ARAS, similarity to ideal solution (TOPSIS), vlse kriterijumsk optimizacija kompromisno resenje (VIKOR), and weighted aggregated sum product assessment (WASPAS) Afghan provinces ranking results in terms of suitability for geothermal project executions.

	Province	ARAS	TOPSIS	VIKOR	WASPAS
A ₁	Badakhshan	11	13	8	7
A ₂	Badghis	17	17	17	17
A ₃	Baghlan	10	10	9	9
A ₄	Balkh	16	16	12	16
A ₅	Bamyan	6	5	3	5
A ₆	Daykondi	14	14	11	14
A ₇	Farah	8	8	7	8
A ₈	Ghazni	1	1	1	1
A ₉	Ghowr	13	12	15	13
A ₁₀	Heart	3	4	5	4
A ₁₁	Helmand	7	3	10	11
A ₁₂	Kabul	4	9	18	12
A ₁₃	Kandahar	15	15	13	15
A ₁₄	Logar	12	11	14	10
A ₁₅	Nimruz	20	20	20	20
A ₁₆	Oruzgan	9	6	6	6
A ₁₇	Pakitika	21	21	21	21
A ₁₈	Parwan	5	7	4	3
A ₁₉	Sari pul	19	19	16	19
A ₂₀	Wardak	2	2	2	2
A ₂₁	Zabol	18	18	19	18

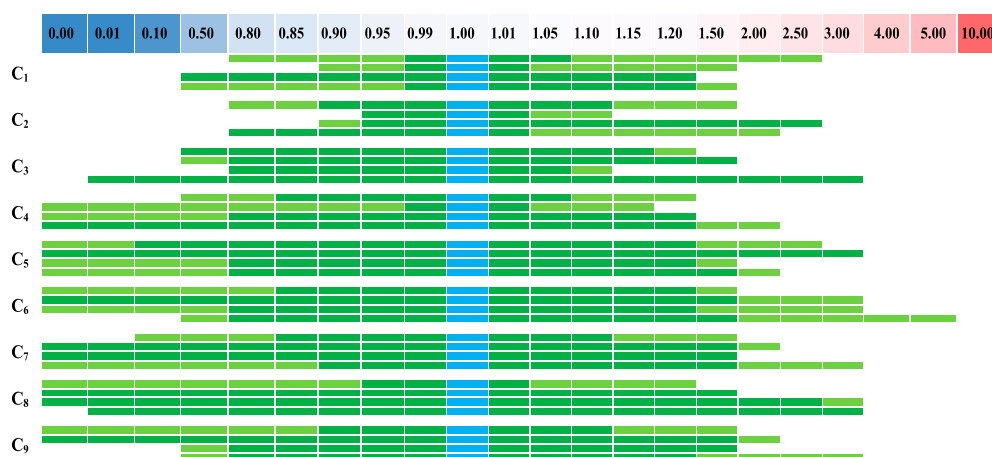


Figure 2. The sensitivity of rankings to changes in criteria weights.

As seen, both incremental and diminishing changes in the weight of one criterion proportionately changed the weights of the other criteria so that the total weight remained equal to one. Therefore, a coefficient of sensitivity was assigned to represent the sensitivity of each criterion in each method. The coefficient of sensitivity for the criterion C_j , denoted by SC_j^* , was calculated independently for

each method and showed that a 5% or 50% increase or decrease in criterion weight led to a change in ranking. The sensitivity coefficients calculated for the criteria are listed in Table 6.

Table 6. Distribution of the coefficient of sensitivity (SC^*) for the four multi-criteria decision-making (MCDM) methods.

MCDM Method	Change of Criterion Weight											
	−5%			+5%			−50%			+50%		
	Sensitivity Coefficient SC^*											
	0	1	>1	0	1	>1	0	1	>1	0	1	>1
	Occurrence of Sensitivity Coefficient Amongst 9 Criteria											
ARAS	8	1	0	8	5	1	0	2	2	0	6	3
TOPSIS	7	2	0	6	2	3	0	5	2	6	1	2
VIKOR	9	0	0	9	4	0	0	3	2	4	2	3
WASPAS	8	1	0	8	6	1	0	3	0	5	4	0

An analysis of the calculated coefficients of sensitivity showed that a 5% increment or reduction in the weights had an effect on the rankings of all methods except VIKOR.

The critical criterion in each MCDM method was then identified. The critical criterion was defined as C_j for which the smallest relative (percentage) change within the weight (the change D_j in the weight W_j) resulted in a change in the ranking. The sensitivity criterion SC_j was used to measure the sensitivity of the results to change in the weight of each criterion. As seen in Figure 3, the critical criteria in ARAS, TOPSIS, VIKOR, and WASPAS were C_1 , C_5 , C_2 , and C_2 , respectively. Overall, C_3 was identified as the critical criterion for the best alternative for all the methods used.

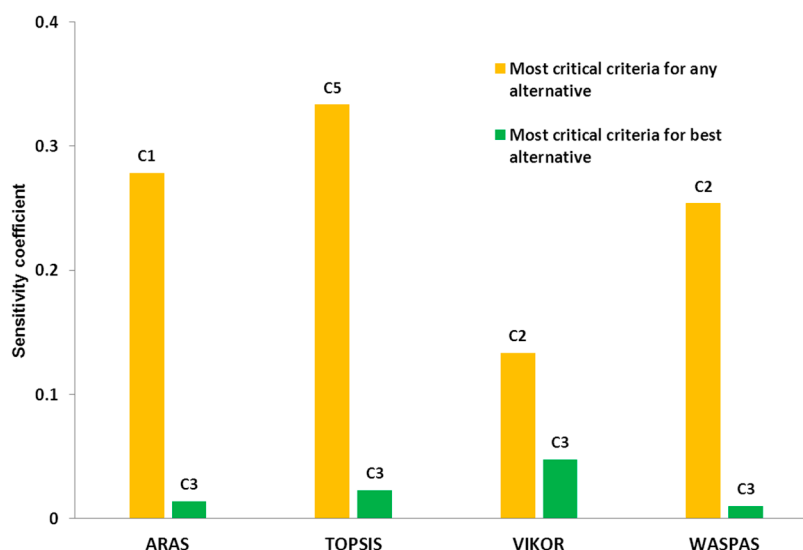


Figure 3. The critical criterion for each MCDM method and the critical criterion for best alternative.

6. Conclusions

Investment in renewable energy technologies can boost the efforts of developing countries to fulfil economic, environmental, and social objectives as well as serve as a springboard for achieving sustainable development. Geothermal energy is one of the most dependable and stable renewable energy sources as it can be harvested regardless of inclement weather and climate changes and it can be used to generate power for industrial, agricultural, and domestic applications. Due to significant

geothermal potentials in Afghanistan, ours was the first study to rank the provinces of this country in terms of geothermal project potential.

After assessing the literature review on the ranking of regions in terms of geothermal potential, it was discovered that most of these studies either used only one or a few MCDM methods and completely overlooked the fact that the results changed significantly according to the method and criteria used. To fill this gap, this study used multiple MCDM methods, namely SWARA, ARAS, TOPSIS, VIKOR, and WASPAS, to rank a number of provinces in terms of suitability for geothermal project implementation. SWARA was employed to assign a weight to each criterion while ARAS, TOPSIS, VIKOR, and WASPAS were utilised to rank the provinces. After comparing the results of all four methods, a sensitivity analysis was performed to determine how the criteria and methods used affected their ranking. The most significant points of this research are listed below:

- Nine criteria were used to evaluate the geothermal potential of each province.
- Hot spring density, fault density, and volcanic dome density were the most significant criteria for geothermal site location according to SWARA, which was used to weight the selected criteria.
- The studied provinces were ranked according to geothermal suitability using ARAS, TOPSIS, VIKOR, and WASPAS. Sensitivity analysis was performed to further analyse the results.
- Ghazni province was identified as the most suitable province for geothermal project implementation using ARAS, TOPSIS, VIKOR, and WASPAS.
- Sensitivity analysis indicated that a 5% change in criteria weight affected the rankings of all methods except VIKOR.
- Hot spring density C_1 , drainage density C_5 , fault density C_2 , and fault density C_2 were identified as the most important criteria in ARAS, TOPSIS, VIKOR, and WASPAS, respectively.
- Overall, volcanic dome density C_3 was identified as the critical criterion for the best alternatives in all methods.

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