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Wind farm site selection using GIS-based mathematical modeling and fuzzy logic tools: a case study of Burundi

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Introduction: The electricity generated from nuclear plants and petroleum-based products has a negative influence on the environment as a whole. It has shown the utility to search out and promote the utilization of renewable, environmentally friendly, and sustainable energy sources such as solar, wind, and geothermal. Nowadays, Wind energy resource has quickly emerged as the world's fastest-growing energy source.

Methods: However, the selection of the most suitable places for developing a wind farm is a crucial challenge that can be seen as a problem of site selection, which involves numerous conflicting variables. Therefore, it is classified as an MCDM (multi-criteria decision-making) problem. The main objective of this research is to determine the best locations in Burundi for the installation of wind farms. The Fuzzy Analytic Hierarchy Process (FAHP) was used to weigh the criteria considering their relative importance. This study considers several key factors when determining the optimal location for a wind farm. These factors include wind speed, slope, proximity to the grid network, distance to roads, and land use/land cover (LULC). Furthermore, a geographic information system (GIS) is utilized to generate the final suitability wind farm locations map.

Results and Discussion: The obtained results indicate that 20.91% of the whole study area is suitable nevertheless, only 1.96% is tremendously suitable for wind turbine placement. The western part of Burundi is the optimal area for constructing a wind farm, and the most is in Lake Tanganyika.

KEYWORDS

fuzzy theory, wind farm location, decision-making, fuzzy-analytic hierarchy process, restriction factors

1 Introduction

Energy is a major factor in any country's sustainable development and prosperity. However, the growing trend in energy demand is followed by an increase in the global use of fossil fuels, which results in significant climate, environmental, and health costs. (IEA, 2021; Mohammadzadeh et al., 2018). With this rapid increase in energy demand, the development of technologies for harvesting renewable energy has also accelerated. Wind energy, as stated by the Global Wind Energy Council (GWEC), is a renewable energy source that has experienced remarkable and rapid development. The global wind power capacity reached 743 GW by the end of 2020, with an addition of 93 GW in the same year. By 2021, it

surpassed 840 GW, and by 2022, it reached 906 GW with 9% growth (Rajendran et al., 2022; Global Wind Energy Council, 2023).

Wind energy represents one of the most promising, mature, and rapidly expanding renewable energy sources (Saraswat et al., 2021; Shahid et al., 2019). Its fastest growth is explained by the fact that it is considered a clean, reliable, and renewable energy resource that positively contributes to minimizing the issue of worldwide concerns about climate change and energy sources (Diffendorfer et al., 2021). Furthermore, the utilization of wind energy not only generates employment opportunities but also contributes to the reduction of CO₂ emissions. According to research, wind energy use is anticipated to increase in Canada, Sweden, China, and Germany by 2025 (Sadorsky, 2021). This clean and affordable energy source not only appeals to investors but also provides a practical solution for reducing dependency on fossil fuels. Studies have demonstrated that combining wind turbines with other energy sources can effectively decrease carbon emissions (Yousefi et al., 2022).

Moreover, wind resources are intrinsically unpredictable because of their dependency on geographic and climatic factors as well as the time of the region under consideration. This results in different values from one place to another for daily and seasonal changes. Therefore, there is a clear need for an effective assessment of suitable placements for the installation of wind turbines to maximize wind energy production while minimizing the effects of different challenges (Wu et al., 2018; Damousis et al., 2004).

At a given scale, wind energy is generated by installing wind farms in the windy areas. Selecting the right type of turbine is vital for establishing a sustainable wind farm. It must be able to seamlessly adjust to the diverse topography, climate, and time conditions of the site. The process of making a choice is often influenced by various factors, where multiple decision criteria conflict with each other (Rediske et al., 2021; Seyed et al., 2022; Badi et al., 2023). These factors include the following key technical requirements (Yousefi et al., 2022):

- Sustained wind speed that is adequate for generating substantial power;
- Sufficient area to accommodate wind turbines and related infrastructure;
- Ground conditions that are suitable for constructing and operating the wind farm;
- Access to the electricity grid, enabling the distribution of the generated power;
- Feasibility of providing access for oversized loads that may be required during construction or maintenance;
- Terrain and topography suitable for optimal wind turbine placement and operation.

Several strategies can be employed to effectively tackle the challenges of selecting turbines considering their multi-criteria nature. They fall under the domain of multi-criteria decision-making (MCDM). MCDM is an operation sub-discipline that assesses several operational competing factors in decision-making.

MCDM methods are used to handle decision problems involving multiple factors in the decision-making process. These criteria conflict with each other and are mutually in-

commensurable. Incommensurability refers to a scenario where the decision criteria have different units and magnitudes. Numerous MCDMs have been developed by researchers and each has advantages as well as disadvantages; therefore, the choice of which one to use is also an important decision. Common techniques include the weighted sum method, PROMETHEE, TOPSIS, VIKOR, ELECTRE, goal programming, AHP, Grey relation analysis, minimum manhattan distance (MMD) approach and Fuzzy logic, among others. (Mardani et al., 2015; Gr, 2020; Łaska, 2020; Indrajayanthan and Mohanty, 2022).

Numerous research studies have been conducted worldwide to identify the best areas for wind power facilities, using various MCDM methods. To determine the most effective approach for this study, previous works on the subject are thoroughly examined. Table 1 provides a comprehensive overview of prior research on wind farm site selection, prominently showcasing the MCDM-FAHP method as the premier decision-making tool for identifying the best location. The MCDM-FAHP method has not only been widely used for selecting wind farm sites but has also demonstrated its usefulness in other domains like solar farms, urban planning and resource allocation (Seyed et al., 2022; Barakat et al., 2019; Li et al., 2022). What sets it apart from other methods is its capacity to handle intricate decision-making situations and yield dependable outcomes. Therefore, it can be confirmed that the FAHP method represents unrivaled effectiveness and efficiency, making it the ideal choice for implementation in the present study.

MCDM methods have a significant limitation in their applicability, particularly when it comes to decision-making based on both 'AND' and 'OR' operations between criteria. In such situations, these approaches become ineffective. However, the Fuzzy logic theory provides a viable solution as it can handle decision rules involving 'AND' or 'OR' operations and effectively manage complex scenarios that combine 'AND-OR' type rules. This is why the implementation of Fuzzy logic is highly advantageous in developing and executing multiple decision criteria for wind farm site selection.

The fuzzy logic tool is based on Zadeh's fuzzy set theory, which he proposed in 1965 (Zimmermann, 2010). The fuzzy set theory offers a framework in which several conceptual phenomena can be precisely and rigorously analyzed. Furthermore, it can also be considered as a modelling language, fitting for cases in which fuzzy relations, criteria, and phenomena exist. A fuzzy logic tool is an essential tool in risk assessment in the way it compensates for the lack of knowledge and ambiguity faced when assessing the risks related to complex technological systems. It is also more useful when working with fuzzy linguistic concepts like low, medium, high, etc. (Gr, 2020; Nguyen et al., 2022).

The main steps in the fuzzy-logic method procedure are depicted in Figure 1 (Badran et al., 2011; Abdelmassih et al., 2021; Mustafa and Barabadi, 2022):

- Rule base: it contains all the rules and conditions defined by experts to control the decision-making system;
- Fuzzification process: in this step, the input variable values are provided by experts. It permits to convert crisp inputs into fuzzy sets that correspond to the intuitive perception of the system's status;

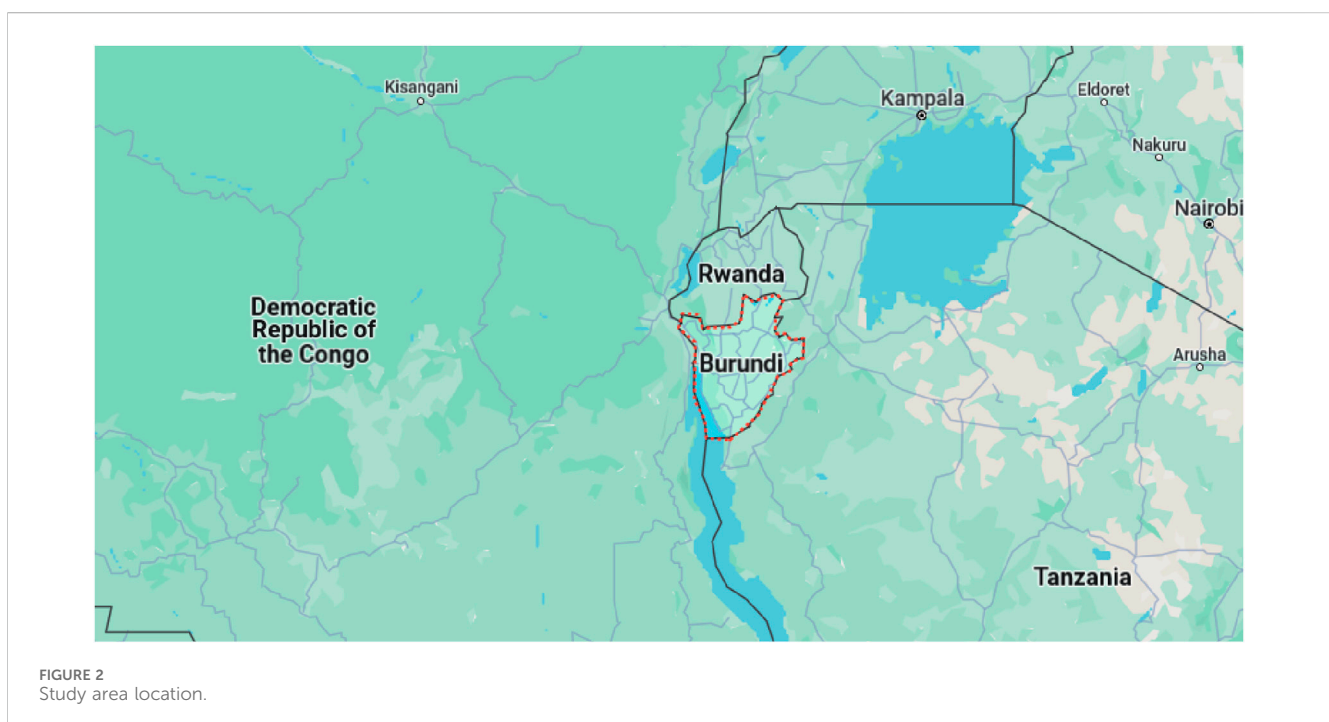
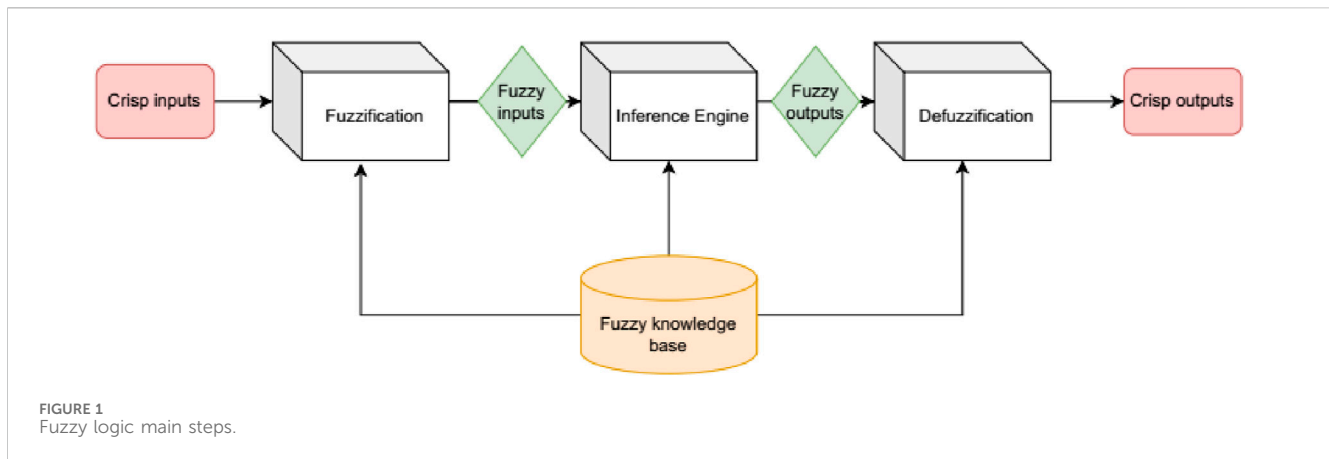
TABLE 1 Wind resource site selection previous research of some countries.

Ref	Location	Chosen criteria	Site selection type	Research approach
Alhuyi et al. (2020)	Shahrood, Khorramdareh, Zabol, and Abadeh in Iran	Wind speed, power lines, land use/land cover, slope, roads, settlements	Wind farm site selection	Fuzzy TOPSIS
Ecer (2021)	Izmir, Turkey	Wind speed, slope, topography, Land use, buffers, farm areas	Onshore Wind farm site selection	MCDM-BWM
Yousefi et al. (2022)	Semnan Province, Iran	Slope, wind speed, power lines, urban areas, highways, roads	Wind Farm site selection	GIS-based AHP
Ifkirne et al. (2022)	Southeast France	Wind speed, protected areas, slope, elevation, electrical substations, road networks	Mapping suitable sites for onshore wind farms	Combined GIS-AHP
Gao et al. (2020)	China	Wind speed, power lines, slope, elevation, protected areas, accessibility, employment	Offshore Wind farm site selection	MCDM-ILAO
Li et al. (2020)	China	Slope, wind speed, main roads, transmission lines, building areas, bird sanctuaries	Wind farm site selection	MCDM-Fuzzy AHP
Saraswat et al. (2021)	Gujarat, India	Wind speed, terrain slope, substation locations, human factors, environmental factors	Wind farm site selection	MCDM-Fuzzy AHP
Zalhaf et al. (2022)	Sudan	Slope, wind speed, grid lines, roads/railways, lightning strike flash rate, elevation, airports, cities	Wind farm site selection	MCDM-Fuzzy AHP
Cunden et al. (2020)	Mauritius	Wind speed, aspect, elevation, slope, roads, national electrical grid, protected areas	Wind farm site selection	MCDM-AHP
Yousefi et al. (2022)	Semnan Province, Iran	Elevation, slope, wind speed, main roads, electric lines, rivers, airports, settlement zones, wetlands, and protected areas	Wind farm site selection	MCDM-Fuzzy AHP
Ayodele et al. (2018)	Nigeria	Wind speed, elevation, land cover/flood areas, airports, grid lines, protected areas, important bird areas, boundaries, roads, water bodies, rivers, settlements	Wind farm site selection	Type-2 Fuzzy AHP
Xu et al. (2020)	Wafangdian, China	Wind speed, slope, electricity grids, main roads, protected areas, urban areas, power plants, bird migration channels, chemical plants	Wind farm site selection	FAHP and stochastic VIKOR
Ajanaku et al. (2022)	West Virginia	Wind potential, slopes, electrical lines, major roads, airport, protected areas, lakes/rivers, critical wildlife habitat, residential development	wind farm site selection	Type-2 Fuzzy AHP
Shahid et al. (2019)	Songkhla, Thailand	Wind speed, solar potential, elevation, land use, airport, roads, transmission lines	Identifying the ideal location for solar and wind sites	GIS and AHP
Gil- et al. (2022)	Gulf of Maine	Wind speed, bathymetry, Substations, coast, water quality, ports, dismantling costs	Offshore wind farm site selection	Fuzzy AHP GIS-MCDM
Hussaini et al. (2022)	Southeastern Spain	Wind speed, protected areas, watercourses/streams, roads/railroad network, Mediterranean coast	Onshore wind farm site selection	Fuzzy AHP GIS-MCDM
Nasery et al. (2021)	Herat, Afghanistan	Annual average wind speed, slope, residential areas, power transmission lines, roads, LULC	Wind farm site selection	GIS-based fuzzy AHP
Noorollahi et al. (2016a)	Iran	Slope, urban areas, wind speed, power lines, substations, roads and highways	Solar farms Site Selection	GIS and FAHP
Li et al. (2022)	Nanjing, China	Elevation, slope, precipitation, temperature, aspect	Urban Parks Selection	F-AHP
Barakat et al. (2019)	Béni-Mellal, Morocco	Bare soil, arboriculture, arable fields, forest, built up	Land use and land cover change and its environmental impact	GIS and FAHP

- Inference engine: this component helps to determine the degree of match between fuzzy inputs and the rules. It is a main step because all information is treated in the inference engine. Based on the percentage match, it determines what control to perform in response to the different combinations of the input variables;

Defuzzification: this process is performed to convert significant fuzzy outputs into specific output variables.

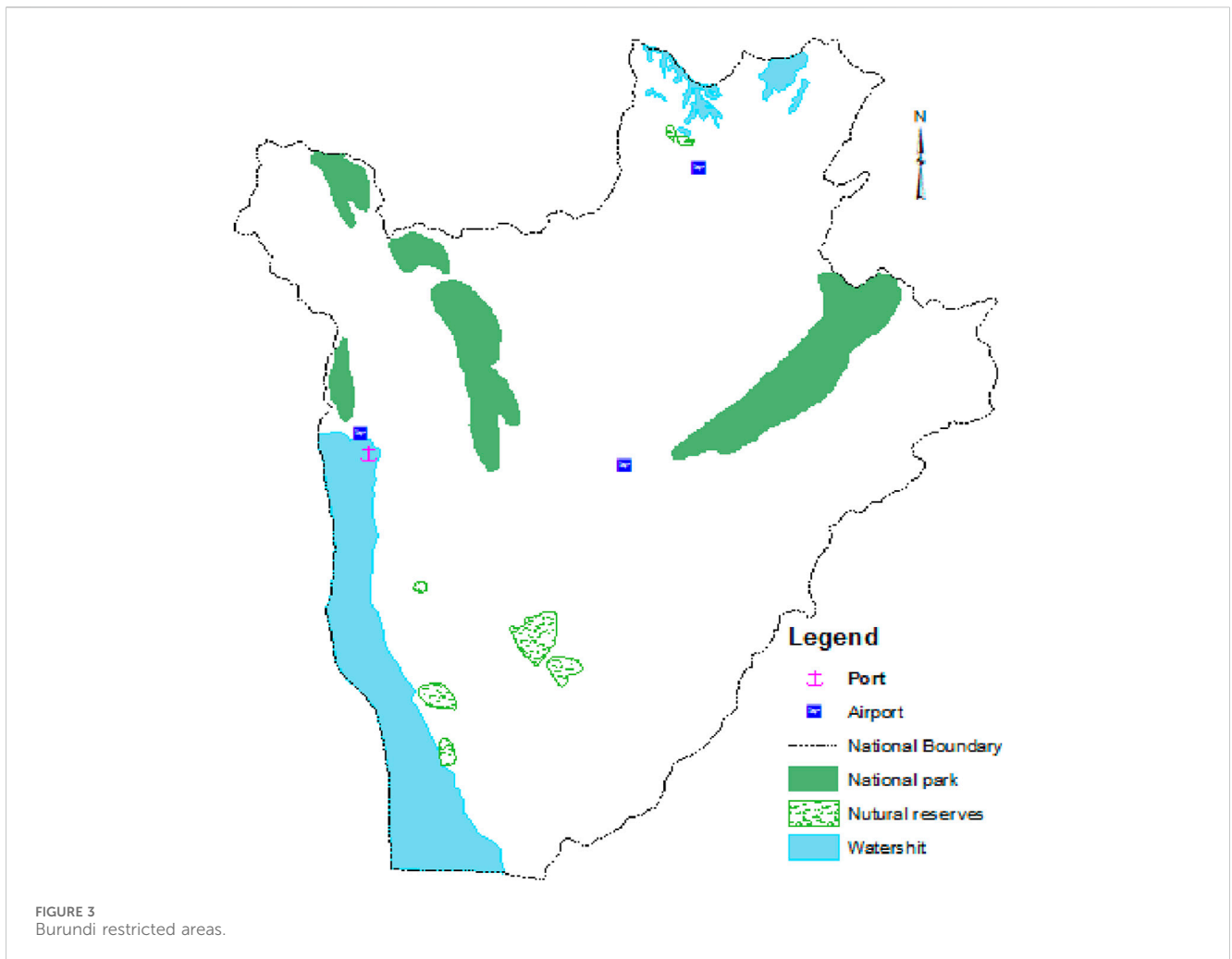
The economic viability of a wind project greatly depends on identifying the most suitable areas for wind farm development. There is a need to find a systematic approach to determine where these potential locations exist as well as the cost of power



production. With this objective, a fuzzy GIS-MCDM-based approach is recommended as the best tool for wind farm sitting based on prior research (Li et al., 2020; Cavazzi and Dutton, 2016; Villacreses et al., 2017; Ayodele et al., 2018; Kaya et al., 2019; Aliyev et al., 2020).

The F-AHP process is a combination of fuzzy logic theory and the classical AHP process. The analytic hierarchy process (AHP) provides a precise technique for determining the importance of different decision criteria. It is a highly systematic approach to evaluating complex judgments, allowing for effective organization and analysis of multiple factors. This process involves the construction of a pairwise matrix to assess the relative importance of decision criteria. The matrix is further normalized to establish the relative significance of each criterion, a vital component in the decision-making process. By integrating fuzzy theory, the AHP method effectively tackles scenarios where criterion weighting entails partial truth or uncertainty (Baalousha et al., 2023).

The FAHP method was selected for this study for site-selection problems due to several compelling reasons. Firstly, it is a highly regarded and widely used method known for its high computational efficiency and practicality. Moreover, it seamlessly integrates with GIS, a widely used tool for land analysis and site selection. Another advantage is its ability to conduct hierarchical modelling, enabling the incorporation of subjective judgments and consistency verification. Additionally, the FAHP method takes into consideration both quantitative and qualitative criteria, offering a comprehensive approach to problem interpretation. With the capability to perform various sensitivity analyses, FAHP provides flexibility in handling different criteria. Furthermore, it streamlines the decision-making process by facilitating pairwise comparisons among the criteria. Lastly, the method takes into account the consistency and inconsistency of alternatives, making it an invaluable tool (Mosadeghi et al., 2015; Perkin et al., 2015; Rehman and Khan, 2016; Sedaghat et al., 2019; Yunia and Rahmawati, 2020; Pang et al., 2021; Sánchez-Lozano et al., 2021).



In Burundi, the exploration of wind resource assessment remains relatively unmapped. This particular topic has been underexplored in previous studies, making it a significant gap that needs to be addressed. Although limited studies have been conducted in Burundi, including one conducted by (Bashahu et al., 2022), which examined 1 year of hourly wind speed data from two stations. This research offers invaluable insights for strategically organizing and executing wind energy conversion systems (WECS) in these areas. Furthermore, another study, (Bashahu and Buseke, 2016), performed a statistical analysis on a 4-year span of hourly wind speed data from four additional Burundian stations. Hence, it is of utmost importance to conduct further research on this matter to obtain general information on Burundi wind resource potential and its distribution throughout the territory. Unleashing the power of wind energy will revolutionize Burundi's energy landscape, providing a sustainable solution to the country's energy scarcity.

Furthermore, no research has focused on the selection of optimal wind farm placements and their classification. This will help decision-makers to know which type of wind farms fit well in Burundi and at which scale they can contribute to future projects.

The main objective of this research is to assess the feasibility of establishing wind farms in various locations across Burundi. The

study utilized the MCDM methodology, focusing on the fuzzy-AHP technique, to identify the optimal locations for wind farm projects using GIS software. Different criteria are taken into account to identify the best locations. These include factors like wind speed, slope, aspect, distance from transmission lines and power grids, distance from protected areas, distance from airports, elevation, and distance from major roads.

Finally, this study's main contributions and originality may be stated as follows: A cutting-edge wind farm suitability mapping method based on Fuzzy Analytic Hierarchy Process (FAHP) and Geographic Information System (GIS) methodologies is presented. This innovative approach takes into consideration technical, environmental, social, and spatial factors in the Burundi's territory. This research investigation is the first of its kind to identify the optimal locations for constructing wind power plants (WPPs) in Burundi.

The remainder of this paper is divided into the following sections: the second section is the research background, the third section describes the methodology used to solve the considered problem; the fourth section provides a comprehensive description, analysis, and discussion of both the GIS and the proposed decision problem; and the fifth section presents the results and engages in a thorough discussion of these findings. Finally, the sixth section succinctly outlines the main conclusions of this study.

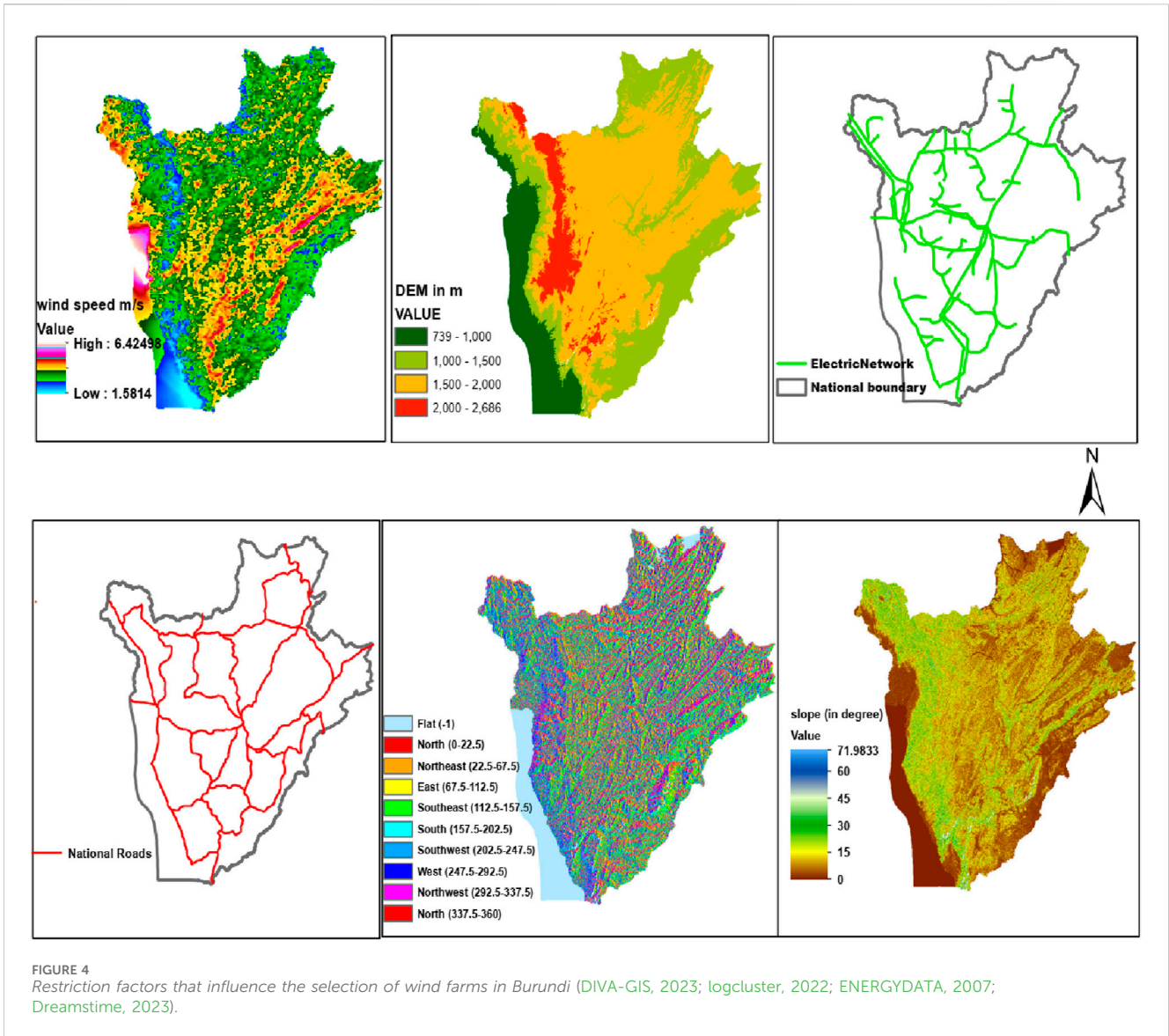


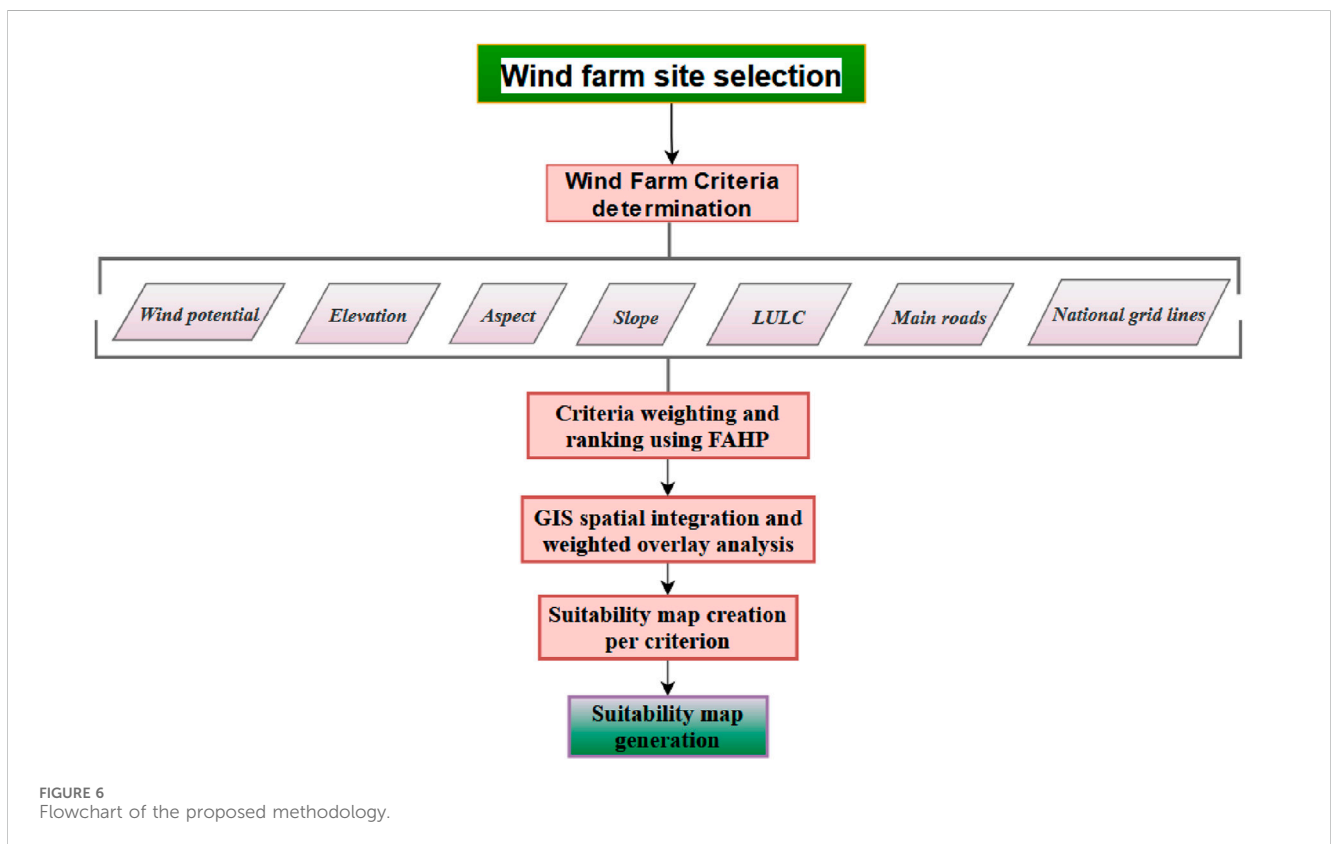
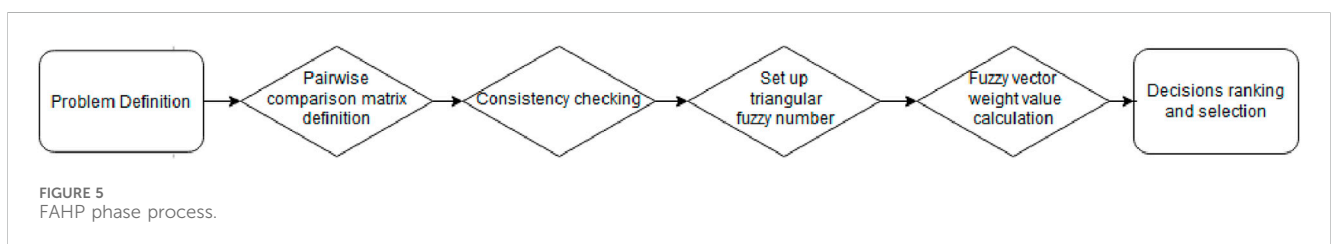
FIGURE 4 Restriction factors that influence the selection of wind farms in Burundi (DIVA-GIS, 2023; logcluster, 2022; ENERGYDATA, 2007; Dreamstime, 2023).

TABLE 2 The nine-point fuzzy conversion scale (Tripathi et al., 2022).

Linguistic terms	Crisp scale	TFN scale	Reciprocal TFN scale
Equally preferred	1	(1, 1, 1)	(1/1, 1/1, 1/1)
Equally to moderately preferred	2	(1, 2, 3)	(1/3, 1/2, 1/1)
Moderately preferred	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Moderately to strongly preferred	4	(3, 4, 5)	(1/5, 1/4, 1/3)
Strongly preferred	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Strongly to very strongly preferred	6	(5, 6, 7)	(1/7, 1/6, 1/5)
Very strongly preferred	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Very strongly to extremely preferred	8	(7, 8, 9)	(1/9, 1/8, 1/7)
Extremely preferred	9	(8, 9, 9)	(1/9, 1/9, 1/8)

TABLE 3 Fuzzy AHP pairwise comparison matrix.

Criteria	C1(Wind potential)			C2(Slope)			C3 (Distance to roads)			C4 (Distance to grids)			C5(Aspect)			C6 (LULC)			C7 (Elevation)		
C1	1	1	1	2	3	4	6	7	8	4	5	6	6	7	8	9	9	9	4	5	6
C2	0.25	0.33	0.5	1	1	1	4	5	6	2	3	4	4	5	6	6	7	8	2	3	4
C3	0.13	0.14	0.167	0.17	0.2	0.25	1	1	1	0.33	0.5	1	1	1	1	2	3	4	0.17	0.2	0.25
C4	0.17	0.2	0.25	0.25	0.3	0.5	1	2	3	1	1	1	2	3	4	4	5	6	0.25	0.33	0.5
C5	0.13	0.14	0.167	0.17	0.2	0.25	1	1	1	0.25	0.33	0.5	1	1	1	2	3	4	0.17	0.2	0.25
C6	0.11	0.11	0.111	0.13	0.1	0.17	0.25	0.33	0.5	0.17	0.2	0.25	0.25	0.33	0.5	1	1	1	0.13	0.14	0.17
C7	0.17	0.14	0.125	1.5	0.7	2	0.17	0.2	0.25	0.25	0.33	0.5	0.17	0.2	0.25	0.13	0.14	0.17	1	1	1



2 Methodology

Before development, manufacture, installation, commissioning and operation there is a need to process site selection at an

early stage to assess the feasibility of wind farms in light of environmental concerns, economic feasibility, and other criteria. This study’s methodology framework was developed in three key stages:

TABLE 4 F-AHP comparison matrix.

Fuzzy comparison matrix																					
Criteria	C1			C2			C3			C4			C5			C6			C7		
C1	1	1	1	2	3	4	6	7	8	4	5	6	6	7	8	9	9	9	4	5	6
C2	0.25	0.33	0.5	1	1	1	4	5	6	2	3	4	4	5	6	6	7	8	2	3	4
C3	0.13	0.14	0.17	0.17	0.2	0.25	1	1	1	0.33	0.5	1	1	1	1	2	3	4	0.17	0.2	0.25
C4	0.17	0.2	0.25	0.25	0.33	0.5	1	2	3	1	1	1	2	3	4	4	5	6	0.25	0.33	0.5
C5	0.13	0.14	0.17	0.17	0.2	0.25	1	1	1	0.25	0.33	0.5	1	1	1	2	3	4	0.17	0.2	0.25
C6	0.11	0.11	0.11	0.13	0.14	0.17	0.25	0.33	0.5	0.17	0.2	0.25	0.25	0.3	0.5	1	1	1	0.13	0.14	0.17
C7	0.17	0.14	0.13	1.5	0.67	2	0.17	0.2	0.25	0.25	0.33	0.5	0.17	0.2	0.25	0.13	0.14	0.17	1	1	1

TABLE 5 F-AHP criteria weighting and ranking.

	Geometric mean of fuzzy			Fuzzy weight			Average		Rank
	ri			Wi			Mi	Ni	
C1	3.074	3.514	3.904	0.438	0.4249	0.4063	0.423	0.4071	1
C2	1.739	2.091	2.479	0.248	0.2529	0.2581	0.253	0.2433	2
C3	0.543	0.638	0.774	0.077	0.0771	0.0806	0.078	0.0754	4
C4	0.855	1.104	1.369	0.122	0.1335	0.1425	0.133	0.1276	3
C5	0.521	0.602	0.701	0.074	0.0728	0.073	0.073	0.0706	5
C6	0.283	0.321	0.381	0.04	0.0388	0.0396	0.040	0.0381	6
C7	0.300	0.292	0.387	0.043	0.0353	0.0403	0.039	0.0379	7

- (a) The FAHP-MCDM approach was utilized in the initial stage to establish and prioritize the criteria for wind farm site suitability. A comprehensive evaluation of restriction and exclusion factors was conducted, leading to the definition of specific criteria for wind farms. These criteria were then ranked according to their level of importance.
- (b) To advance to the next stage, we conducted a comprehensive GIS analysis in order to identify the necessary GIS operations. This enabled the creation of classified digital map layers for each criterion, setting a solid foundation for the subsequent analysis.
- (c) In the final stage, wind farm suitability map was generated to identify the most suitable locations for wind farm development. Wind data collected over a 10-year period from several meteorological stations owned by the Geographical Institute of Burundi (IGE BU) was used to create an extensive wind map of the country of Burundi. Data from the World Bank and REGIDESO are used to create digital map layers for GIS software. These sources provided Burundi's main roads and electrical network maps (Devex, 2013).

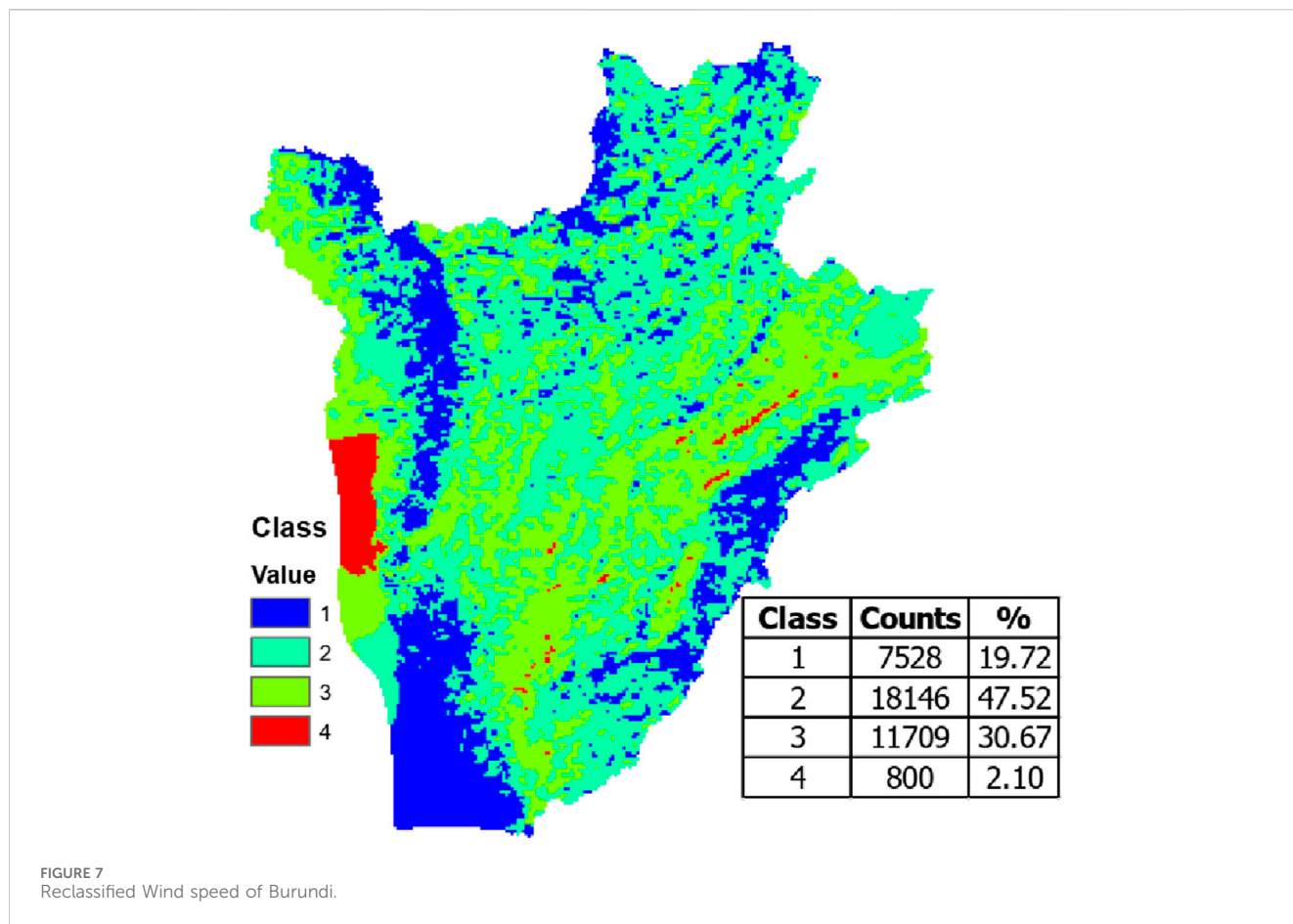
2.1 Study area

The main focus of this study lies on Burundi, Figure 2, an East African country that is entirely landlocked. Burundi shares

borders with Tanzania to the south and east, the Democratic Republic of Congo to the west, and Rwanda to the north. Its precise geographical coordinates are between 2° 15'– 4° 30'S and 28° 58'– 30° 53'E. Burundi is 27,834 square kilometers and is located in two major watersheds: the Nile basin (13,800km²) and the Congo River basin covering 14,034km². Being an East African country, Burundi's climate is mainly shaped by the North-South movement of the Intertropical Convergence Zone (ITCZ), and the El-Nino Southern Oscillation (ENSO). Consequently, the annual averages of climate parameters like precipitation, temperature, and wind speeds vary according to the specific climate zone (Heckmann et al., 2016; Nkunzimana et al., 2019; Tabutin and Schoumaker, 2020).

2.2 GIS-MCDM technique

GIS-MCDM combination allows evaluation of the criteria and their factors by the mean of characteristics within a specific range of decision rules and assessment. The technique is commonly used to select ideal site processes in a huge variety of scientific fields (Gr, 2020). Lots of the problems people have in suitable site selection are geographic and, thus, coupling GIS with the MCDM method has the potential to solve such complex decision-making problems



(Saraswat et al., 2021; Li et al., 2020). Concerning optimal wind farm site selection, the GIS-MCD methods have been standardized to effectively search for and select the best wind sites (Yousefi et al., 2022).

The main steps followed by the GIS-MCDM technique are (Ali et al., 2017):

- Problem definition. Try to define and understand the problem by fixing the goal or objective as clearly as possible;
- Criteria and limitations determination through a combination of experts' opinions and information from various sources;
- Transform values onto a relative scale to allow comparison between each of the criteria;
- Weight assignment to criteria in regards to the fixed objective and respect for each other;
- Combine, synthesize and aggregate criteria together;
- Analyze and then approve results.

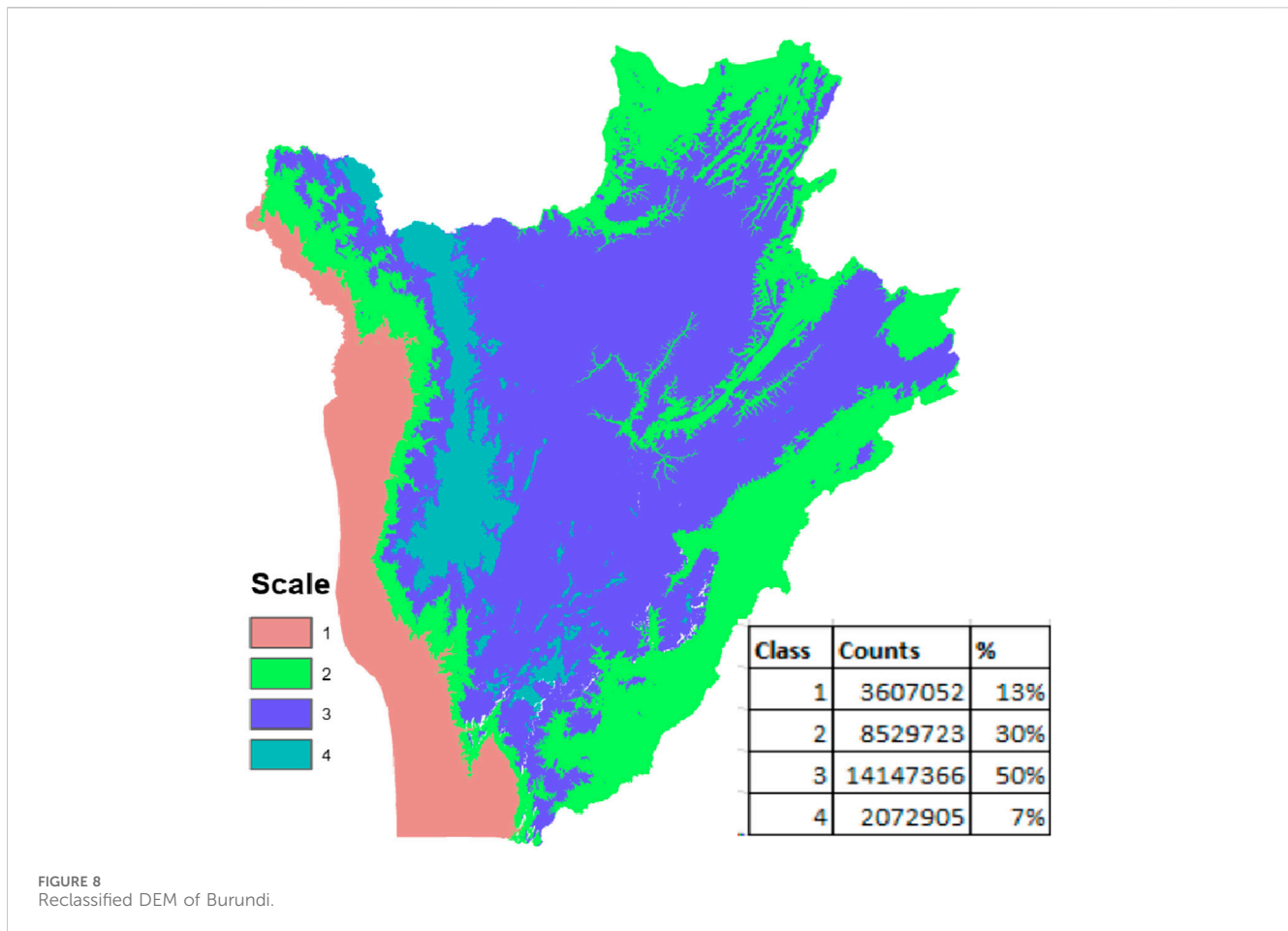
After the criteria determination, their hierarchy must be defined to calculate corresponding weights. All criteria are converted into standard values and combined using the weighted linear combination method, a widely used method (Balogun et al., 2017) that is based on the factors' weighted aggregation, to finally generate a suitability map.

2.3 Criteria determination

The optimal wind farm site selection problem depends on several criteria that include attributes and objectives. They can differ from the different areas and should have some properties to adequately represent the multi-criteria. Criteria must also be comprehensive and measurable (Yalcin et al., 2017; Dhunny et al., 2019). Consequently, to assess well the criteria, it is important to identify such relevant factors affecting the optimal wind farm site selection typically including topographic, geographic, climatic, socio-environmental, economic, location and political aspects.

For this study, the choice of evaluation criteria is based on previous various studies and is categorized into two main categories, restriction and exclusion criteria (See Table 3). The exclusion criteria comprise legally protected areas such as natural reserves, seaports, airports, and tourist sites. The areas dropping under this category are rejected and consequently not eligible for wind farm sites. Conversely, restriction criteria define a distance to be respected from the selected zone for the implementation of wind farms. The distance can be determined in terms of a buffer zone inside which the wind farm cannot be constructed. Some examples of those zones are found around settlements, water bodies, natural parks, airports, and aircraft landing corridors, among others (Refer to Figure 3 for this study).

The construction of wind energy facilities must consider that the selected location is not subject to any legal restrictions but



also has a set of factors influencing the decision. The choice of those factors is primarily dictated by the study area. Therefore, based on studies so far done, this study classified these factors into three general groups (geographical factors, climatological factors, and geographical location factors) (Xu et al., 2020; Sánchez-Lozano et al., 2014; Aksoy and San, 2019; Taoufik and Fekri, 2021). The factors are divided into a set of criteria that impact the selection of the wind turbine location and will make one site preferable rather than another (Caceoglu et al., 2022; Shafiee, 2022).

2.3.1 Wind speed

The local wind speed (intensity, direction, consistency, and uniformity) is the most important factor which plays a key role in wind farm project performance. A wind turbine's energy generation is directly proportional to the cube of the wind speed, and it is given by Eq. 1:

$$P = \frac{1}{2} \rho A v^3 \quad (1)$$

where P is the power produced by the wind turbine in watts (W), A is the area swept by the turbine blades in square meters, ρ is the air density in kg/m^3 , and v is the wind speed in m/s. Wind speed is the key factor of wind power development. Doubling the wind velocity gives eight times the wind power. Therefore, wind velocity is very important for optimal wind farm site locations.

2.3.2 Slope

Land slope influences the cost involved in wind farm implementation due to the difficulties in access and groundwork on slopy lands. In many studies, reference is taken in the range of $10^0 - 25^0$ (Yousefi et al., 2022; Zalhaf et al., 2022; Cunden et al., 2020; Sánchez-Lozano et al., 2016). Hence, high priority is given to flat grounds and locations with lower slopes when selecting regions for wind farm installation. Therefore, it is convenient the slope should not be too large to facilitate the accessibility of maintenance and installation equipment.

2.3.3 Elevation

Wind resource varies with altitude and is better at high altitudes but decreases at very high altitudes due to air density decrease. Elevation above 2000 m, is sometimes considered the cut-off altitude (Noorollahi Y. et al., 2016). Hence, ground elevation is also considered a factor in the choice of the best wind farm location. Therefore, flat terrain will be favourable for wind farm project construction, operation, and maintenance (Hoang et al., 2022).

2.3.4 Aspect

The better the aspect of the wind farm's location, the more straightforward it is to erect. As a result, the slope at the location of the wind farm should be oriented toward the prevailing

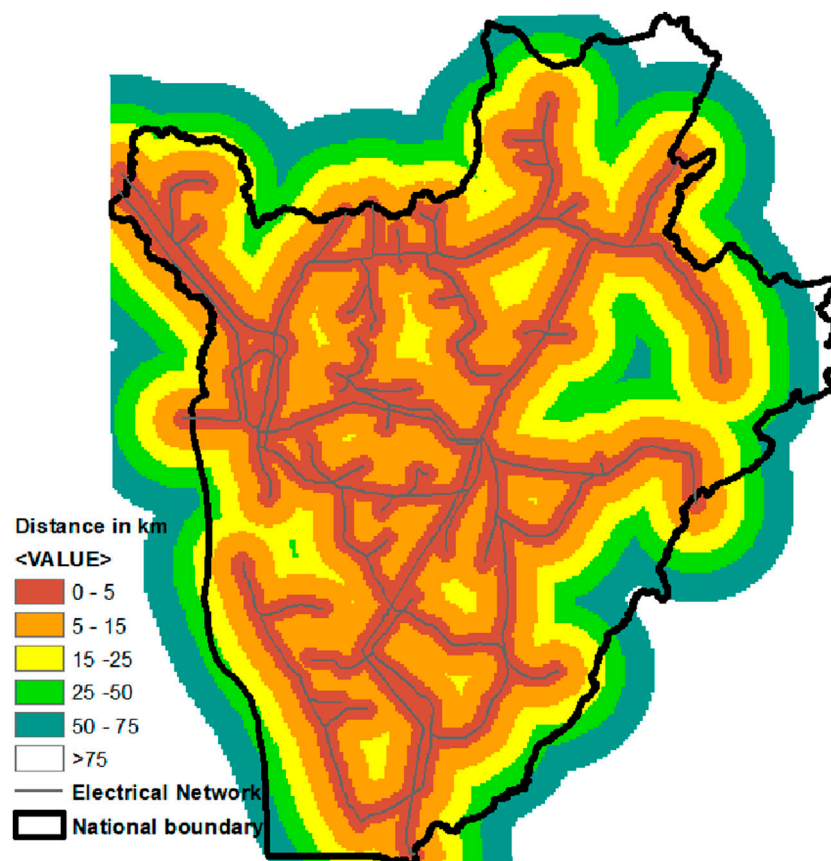


FIGURE 9
 Map of distance from the national electrical transmission line.

wind blow (Villacreses et al., 2017; Feng, 2021). In terms of wind potential, the slope orientation concerning wind direction is one of the crucial factors (Pamucar et al., 2017).

2.3.5 Distance to airports/sea ports

It is recommended to install wind farms at a distance from airports/seaports and similar facilities. It is highly recommended to install wind farms in locations that are at a considerable distance from airports and seaports (Sánchez-Lozano et al., 2014).

2.3.6 Proximity to main roads

Being close to the main road network is crucial in reducing transportation costs and facilitating material transport for wind turbine implementation (Hoang et al., 2022). The distance from the main roads is a significant economic factor, and therefore, the best location for a wind farm should be one that is near existing roads, rather than building new ones to access the site (Pamucar et al., 2017).

2.3.7 Proximity to national grids

Since wind energy must be connected to the grid, the proximity to the national grid affects the cost of a wind farm. Increasing the distance between the wind farm and the electrical grid will inevitably lead to higher

transmission costs (Alhuyi et al., 2020; Rehman and Khan, 2016). Hence, the power transport to consumers using the existing power transmission lines hugely reduces the project cost. Figure 4 illustrates a variety of maps that depict the restriction factors that affect the process of selecting suitable sites for wind farms. The Burundi maps of high voltage electric lines and national roads were obtained from the official reports published in Burundi country and are digitalized using ArcGIS software (Balogun et al., 2017; Yalcin et al., 2017; Dhunny et al., 2019).

The wind speed map is the outcome of the ArcGIS process obtained using weather research and forecasting model (WRF) output simulations. Wind speed data collected at a height of 12 m above the ground level was used for a wind potential simulation using the WRF model. However, modern wind turbines have hub heights ranging from 25 to over 100 m. Therefore, the WRF wind speed outcome was extrapolated to 60 m above ground level for a more comprehensive analysis (Baalousha et al., 2023; Van Sark et al., 2019; Benti et al., 2023). The slope, aspect and elevation map factors for this work were obtained using ArcGIS software and digital elevation model (DEM) data. The DEM is downloaded from the 'U.S. Geological Survey (USGS) EarthExplorer tool' (US Geological Survey, 2019).

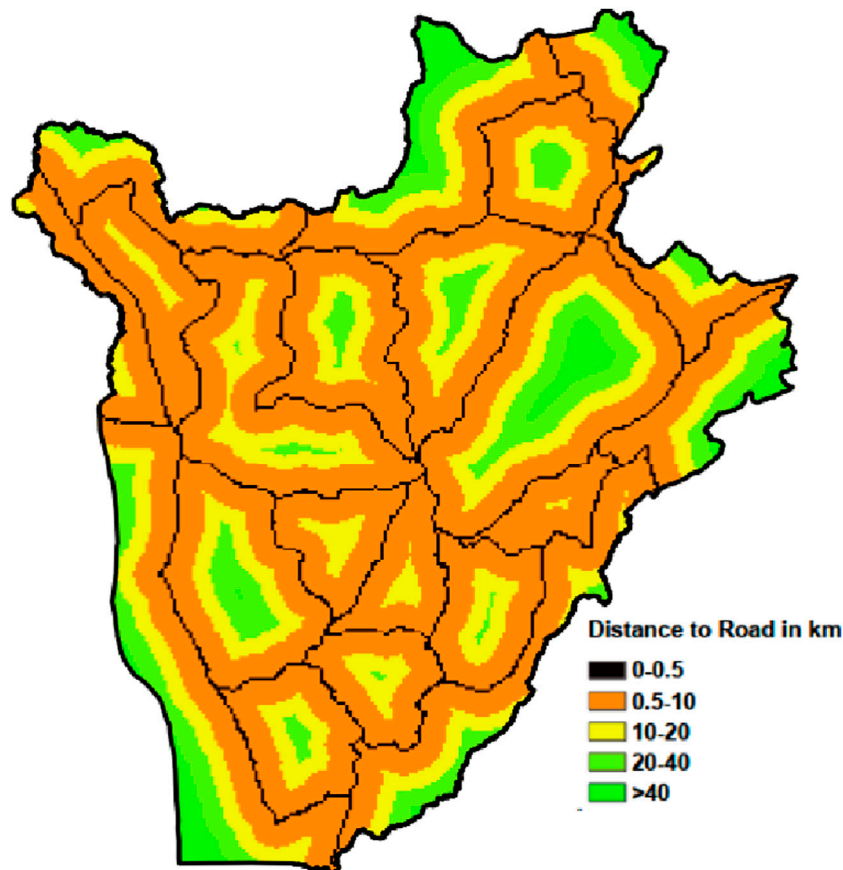


FIGURE 10
Map of distance from national roads.

2.4 Fuzzy AHP

The AHP methodology, first established by Saaty in 1980 (Cavazzi and Dutton, 2016), is widely acknowledged as a robust and flexible MCDM method for dealing with complex decision problems (Sánchez-Lozano et al., 2016). The decision maker can utilize it to effectively analyze complex decision problems that involve various criteria and obtain accurate results. The AHP enables a more comprehensive examination of the intricate facets of objective aspects related to a problem. Furthermore, it helps ensure the accuracy and constancy of their evaluation, thereby minimizing potential human errors during the decision-making procedure.

The AHP process through three main stages to get the final decision (Yousefi et al., 2022; Zalhaf et al., 2022):

- Develop complex problems in a hierarchy of goals, alternatives, and criteria to assess those alternatives;
- Comparison of alternatives at each level of the hierarchy, one criterion at a time;
- At last, generate a vertically oriented decision-making matrix that spans across the multiple levels of the hierarchy.

Despite its strengths, AHP does have some weaknesses. For instance, there is a mutual dependency among alternatives, which

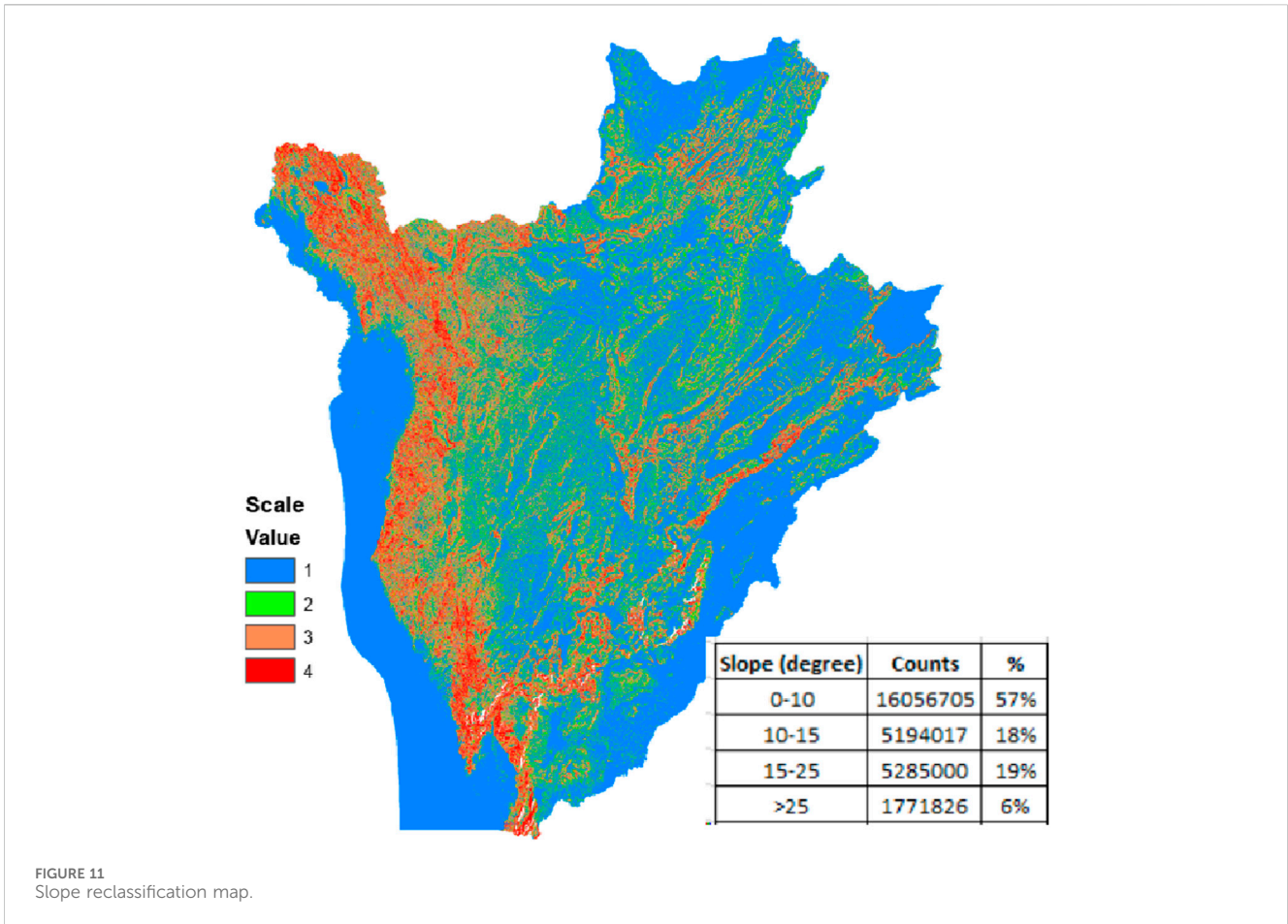
can occasionally result in relatively less accurate outcomes. Additionally, when multiple decision-makers with different perspectives are involved, defining criterion weights can become more complex. Furthermore, AHP relies on opinions and experience-based data collection, which may introduce some limitations. The main problem encountered when utilizing the AHP lies in the presence of uncertain, biased, and vague opinions expressed by experts (Gr, 2020; Sánchez-Lozano et al., 2021; Zalhaf et al., 2022).

The classical AHP method was extended to the fuzzy sets theory and the fuzzy AHP (FAHP) has been developed to handle complex decision problems accurately and more systematically than the simple AHP scheme. This technique integrates the fuzzy set theory concept with basic AHP. It displays the elaboration of a standard AHP into a fuzzy domain by applying fuzzy numbers rather than real numbers (Ali et al., 2017).

The FAHP application process is summarized below (Havle and Kılıç, 2019; Özdemir et al., 2018):

Step 1: This step consists of defining a fuzzy pairwise comparison matrix. This matrix consists of the main criteria that may have an impact on the problem under investigation. Diagonal matrices are built using the hierarchical structure's sub-criteria.

Decision-makers utilize fuzzy linguistic terms to assign the significance of one criterion over another. To achieve this, the decision-makers refer to Table 2 (In Table 2, TFN stands for



Triangular Fuzzy Number). The conversion scale displayed illustrates the nine-point scale utilized in converting responses into fuzzy numbers. The resulting pairwise comparison matrix is given by Eq. 2:

$$\tilde{A} = \begin{pmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \dots & \dots & \tilde{a}_{2n} \\ \dots & \dots & \ddots & \dots \\ \tilde{a}_{m1} & \dots & \dots & 1 \end{pmatrix} \quad (2)$$

Where \tilde{A} is the pairwise comparison matrix and \tilde{a}_{mn} is the joined comparison value of the criteria m and n .

Step 2: The comprehensive assessment is generated by combining the pairwise comparison matrices in this stage. This investigation employs fuzzy triangular numbers to calculate the judgment matrix. The results of this calculation can be found in Table 3. To accurately calculate the TFNs, Excel software has been employed. Each triple value represents the preference score of the considered criterion relative to other criteria as defined in Table 2.

Land use and land cover (LULC) refers to the standard restriction areas such as archaeological sites, forests, wetlands, seaports, aviation zones, military zones, water bodies, and urban areas from which wind turbines should be placed at a specific distance.

The decision-makers are aggregated using Eq. 3:

$$l_{ij} = \left(\prod_{k=1}^K l_{ijk} \right)^{1/K}, m_{ij} = \left(\prod_{k=1}^K m_{ijk} \right)^{1/K}, u_{ij} = \left(\prod_{k=1}^K u_{ijk} \right)^{1/K} \quad (3)$$

where $\tilde{A} = (l_{ij}, m_{ij}, u_{ij})$, with l_{ij}, m_{ij}, u_{ij} stand for the lower, middle, and upper values of support of a fuzzy number, i and j are respectively the row and column, and K represents the number of decision-makers. In this study $K = 7$ corresponding to the number of considered criteria.

Step 3: This computes the fuzzy weights matrix. The fuzzy comparison values are first calculated in this stage using Eq. 4:

$$\tilde{r}_i = \left(\prod_{j=1}^n \tilde{a}_{ij} \right)^{1/n}, i = 1, 2, \dots, n \quad (4)$$

Next, fuzzy weights \tilde{w}_i of the criteria are calculated as follows using the following equation, (Eq. 5):

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1} \quad (5)$$

Where \tilde{r}_i denotes the geometric mean of the fuzzy comparison values and \tilde{w}_i are the criteria weights.

Step 4: The center-of-area approach is used to defuzzify fuzzy weights using Eq. 6:

$$w_i = (l\tilde{w}_i + m\tilde{w}_i + u\tilde{w}_i)/3 \quad (6)$$

Step 5: Crisp weights normalization using Eq. 7:

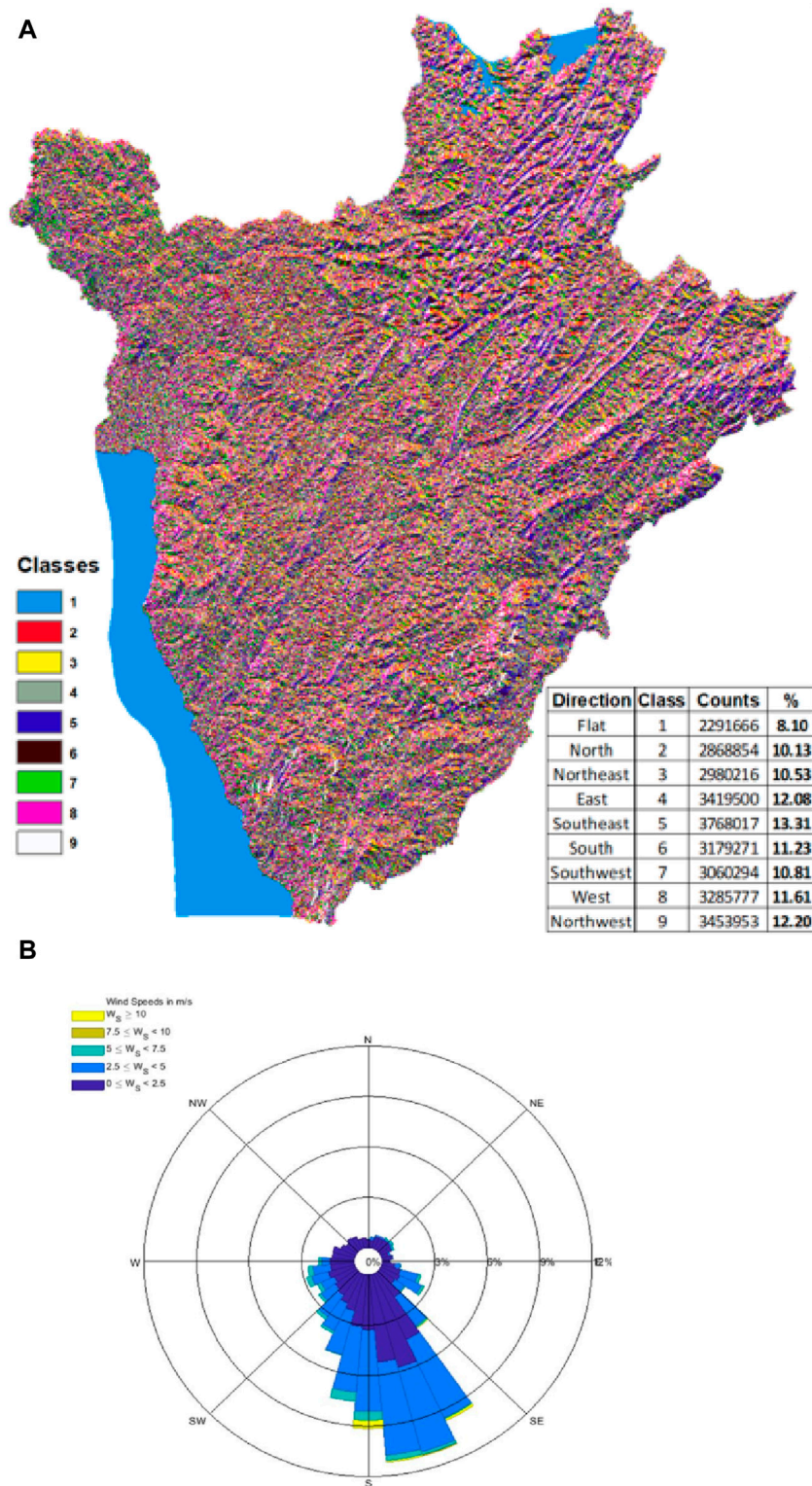


FIGURE 12 (A) Burundi Aspect Model Classification and (B) Burundi average annual wind rose.

$$w_r = \frac{w_i}{\sum_{i=1}^n w_i} \tag{7}$$

Figure 5 displays the six steps that are integral to the F-AHP phase process. These steps guide the way in defining the problem accurately and ultimately establishing the solution that is most

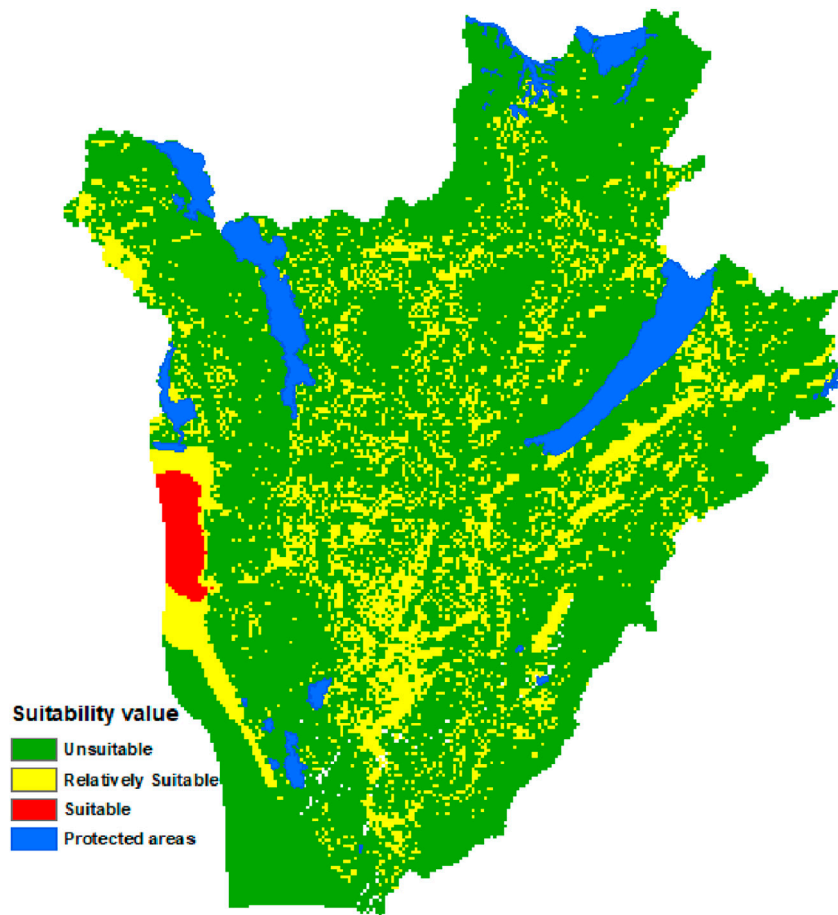


FIGURE 13
Map of wind farm suitability placements.

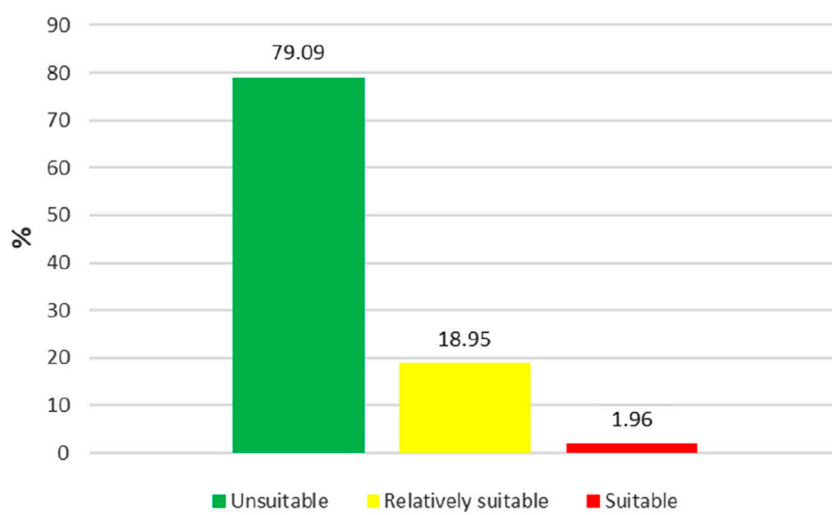


FIGURE 14
Share of the suitability based on the restriction factors.

TABLE 6 Estimated potential wind energy (EPWE).

Turbine	EPWE (MW)	AEPWE (MWh)	Reduction in CO ₂ /year (kg)
Vestas V63 (1.5 MW)	0.397	3.481	2,492.4
Enercon E-58/10.58 (1 MW)	0.337	2.953	2,114.6
Bonus B39/500 (500 kW)	0.149	1.305	933.9

desired. These steps are computed using R-4.3.2 (R package for fuzzy AHP computation) and Excel software in this study.

Figure 6 provides a concise summary of the proposed research methodology, incorporating all the previously mentioned details.

3 Results and discussion

This section will present and discuss the FAHP-GIS results in terms of spatial analysis of optimal wind turbine locations in Burundi. This includes the numerical values representing the optimal weight of the evaluation factors and the suitability map for the optimal wind sites.

3.1 FAHP results

In this study, the optimal weights of restriction factors mentioned in section Figure 5 are obtained using the FAHP-based MCDM method. Tables 4, 5 provides the numerical weights for each criterion (CRI), obtained through the use of Fuzzy pairwise comparison matrices. After obtaining the weight values for each criterion from the F-AHP pairwise comparison matrix presented in Table 3, this study utilized Buckley's algorithm to calculate the geometric mean of fuzzy values (r_i) and fuzzy weights (W_i) (Abdullah et al., 2021; Wang et al., 2021). To refine the results further, the averaged weight criterion (M_i) was normalized, resulting in the final normalized weight (N_i) for each criterion. The obtained weights corresponding to the criteria are given in Table 4.

According to the findings, the wind potential carries the greatest weight among other factors, amounting to an impressive 41% percentage. This means the wind potential has a high priority in the selection of the optimal areas for the implementation of wind farms. It is followed by the slope, proximity to the grids, distance from the roads, aspect, LULC and elevation with 24%, 13%, 8%, 7.3%, 4% and 4% respectively.

3.2 Land suitability mapping for wind farm site placement

Mapping wind suitability involves a meticulous and systematic process, where each criterion is classified into specific categories (Benti et al., 2023). The approach thoroughly evaluates each criterion's suitability level and ranks them accurately, from highest to lowest, to ensure precise results. This section introduces the classification of criteria and factors that are

essential for evaluating suitable locations for wind farms. In this work, "Counts" represents the number of records of each class.

3.2.1 Wind potential reclassification

As mentioned on the map, Figure 7, the wind speed is classified into four scales: very good, good, moderate, and poor. About 2.10% of the land area registered very high, 30.67% high, 47.52% moderate and 19.72% low wind speed. The cut-in wind speed typically ranges between 2.5 and 4 m/s (Loukatou et al., 2018; Satymov et al., 2022; Wind-Energy, 2023). Approximately 32.77% of total land area is considered highly suitable for wind turbines, which are classified as class 3 and 4 exclusively based on wind speed.

3.2.2 Elevation model reclassification

According to the map of the DEM of Burundi, Figure 8, 13%, 30% and 50% are situated in the elevation ranging from 739 to 1000 m, 1000–1500 m and 1,500–2000 m a.g.l respectively. These regions correspondingly represent extremely, very strongly, strongly preferred places for the implementation of wind farms (Cunden et al., 2020; Chikoto et al., 2015). As it has been mentioned in section 2.3.3, the altitude of 2000m is considered the cut-off favourite elevation for wind resources. Accordingly, for Burundi, about 7% of the land area has an elevation above 2000 m making it an unsuitable or less preferred place for wind farm placement. More than 90% of Burundi's land is suitable for wind farms due to its elevation being less than 2000 m.

3.2.3 Distance from major electrical transmission lines

Figure 9 displays the distance in km from the main national electric network. The area within a distance less than 5 km from the electrical lines is strongly suitable and the land areas between 5 km and 15 km are relatively suitable for wind site selection. However, it is considered impractical to implement wind farms in areas that are more than 15 km away from the national electric grid.

3.2.4 Distance from main roads

The maps of connectivity to main roads, Figure 10, show different categories of the distance from the national roads (logcluster, 2022). The land area situated at a distance of less than 0.5 km and a distance greater than 20 km is considered an exclusion zone for wind farm installation and represents 36% of Burundi. The Burundi land areas located at a distance in the range of 0.5–10 km away from the main roads are considered a strongly suitable location for wind farms. Furthermore, the land areas located at a distance ranging from 10 to 20 km are considered suitable for wind farm projects. In contrast, the land areas sited at a distance of 20 km or farther away from the main road network are unsuitable or less preferred for the implementation of wind farms.

3.2.5 Slope model reclassification

Figure 11 displays the slope value distribution through Burundi. More than 70% of the Burundi area is dominated by slope values below 15° with about 57% from 0°–10° and 18% from 10°–15°. These areas are considered to be the most excellent places for wind farm installation considering the construction cost (Zalhaf et al., 2022; Baalousha et al., 2023). Places with slopes varying between 15° and 25° represent 19% and they are considered relatively favourable for wind turbine siting. The remaining areas which have slopes >25° are not appreciated for the wind farm locations.

3.2.6 Aspect model reclassification

The two main attributes of wind are its speed and direction. These attributes impact the wind farm implementation to optimize its energy production. The prevalent wind blows direction and aspect orientation are two linked factors influencing wind turbine production. As it has been mentioned before, flat terrains are highly recommended when choosing the locations of wind turbines. Therefore, in this work, the aspect of Burundi is evaluated and the percentage aspect distribution is given for each direction. The map of the aspect model of Burundi, Figure 12A, revealed that the aspect orientation consists of flat terrain by 8.1%, the north by 10.13%, the northeast by 10.53%, the east by 12.08%, the southeast by 13.31%, the south by 11.23%, the southwest by 10.81%, the west by 11.61% and the northwest by 12.2%. The wind rose of Burundi, Figure 12B is produced using on-field data obtained from the meteorological institution Institut Géographique du Burundi (IGEBU) through Matlab software. As shown in previous studies, Burundi's predominant wind blow is from southwest to southeast (Placide et al., 2021). Consequently, the southeast, south and southwest aspect orientations are the fitting direction for wind farm implementation in Burundi. To this is added the flat land to totalize 43.45% of potential locations for wind farm construction in Burundi in terms of direction consideration.

3.3 Identification of the optimal locations for the wind farm

This study used GIS to locate optimal sites for wind farms using raster and vector data sets as inputs. The weighted values are utilized to determine the degree of suitability for the wind turbine site selection of Burundi. Based on the annual average wind values and other factors, the wind farm site suitability map, Figure 13, displays three classes of sites. Locations with an average wind speed of less than 2.5 m/s are deemed inappropriate for the installation of wind farms. On the map, the land area in green colour is unsuitable to be a candidate for a wind farm at any scale.

The area in yellow colour represents the relatively suitable locations for wind farm siting. The region in red colour is highly recommended as a suitable area to be a candidate for wind turbine siting.

The main part of the suitable region is located in Lake Tanganyika, in the western part of Burundi. This area encompasses both the prime locations for wind farm siting and the majority of the relatively suitable locations. This region is ideal for harnessing wind energy due to its strong and consistent ideal conditions for wind farm project development. Wind farms in this

region could greatly boost renewable energy production in Burundi and aid in sustainable development. The region's ample wind resources also have the potential to support global efforts against climate change. Apart from unsuitable areas, there also exist exclusion zones which cannot be eligible for wind farm installation. Such zones are found as protected areas on the Burundi wind farm site suitability map (Figure 12). They include forests, an airport, port, natural reserves and north lakes.

The GIS generates a useful attribute table that displays the area corresponding to each class. According to Figure 14, the outcomes show that just 1.96% (546 km²) of Burundi's land is suitable for wind power plant constructions. In contrast, 18.95% (5275 km²) of the regions analyzed demonstrate relative potential for such installations. This also means that 79.09% (22014 km²) of the land in issue is judged unsuitable for wind turbine installation. Hence, it clearly demonstrates that a significant portion of Burundi's land is not suitable for wind farm installations. This underscores the crucial need for careful deliberation when choosing the sites for wind turbines. Furthermore, this clearly demonstrates the importance of evaluating the availability of alternative options for other types of renewable energy sources.

3.4 Potential energy generation and environmental benefits

The suitable area experiences wind speeds exceeding 7 m/s, which leads to a significant amount of potential energy generation. Table 6 further strengthens this point by showcasing the projected energy output for three selected wind turbines.

The estimated wind energy is for a single turbine, yet envisioning a wind farm comprised of hundreds of turbines, it becomes clear that deploying wind farms in appropriate locations can substantially enhance energy access in Burundi. For example, the Kenyan wind farm, boasting 365 wind turbines, each with an outstanding 850-kW capacity, holds a total capacity of 310 MW. In Burundi, a similar wind farm with Vestas V63 (1.5 MW) turbine type could generate 240 MW of power. The estimated capacity greatly exceeds the capacity of the largest existing power plant, Rwegura Hydropower, which has a capacity of only 18 MW (Nsabimana, 2020). With wind turbine implementation in place, total potential energy generation could increase exponentially, making it possible to meet a significant portion of Burundi's energy demands. This would not only ensure a more reliable power supply but also contribute to reducing carbon emissions and promoting sustainable development in the country.

Burundi's power supply is largely dominated by hydropower plants, making it heavily reliant on seasonal rainfall. This dependence results in major shortages during dry seasons, from June to August and December to January. To overcome this energy shortage, REGIDESO, a Burundi company in charge of electricity supply, owns diesel generators used as a backup power source to supplement the hydroelectric supply during dry seasons. The use of diesel has negative environmental impacts due to its high carbon emissions and contribution to air pollution.

The unit CO₂ emission per MWh generated from fuel is estimated at 716 kg – CO₂ (JAPAN INTERNATIONAL COOPERATION AGENCY, 2010). By multiplying the annual

energy production of wind farms with this unit, we can precisely evaluate the environmental impact and determine the annual reduction in CO₂ emissions. The estimated reduction in CO₂ emission for the selected wind turbines is presented in Table 6.

The Estimated potential wind energy (EPWE) is determined by the following equation, Eq. 8:

$$EPWE = \frac{1}{2} \rho \times A \times v^3 \text{ [in W]} \quad (8)$$

Where A represents the area swept by the wind turbine blades, and ρ is the density of air which is approximately 1.23 kg/m³. The variable v represents the average wind speed.

Every wind turbine generator has a maximum efficiency limit when it comes to converting the energy of the wind into useable energy. Albert Betz, a renowned German physicist, discovered this limit. He calculated that no wind turbine could convert more than 59.3% of its kinetic energy into mechanical energy. This is known as the Betz Limit and represents the theoretical maximum coefficient of power that any wind turbine can achieve (Ranjbar et al., 2019; De et al., 2018). Considering the Betz Limit, Eq. 8 can be refined as follows, Eq. 9:

$$EPWE = \frac{1}{2} \rho \times A \times v^3 \times \frac{59.3}{100} \text{ [in W]} \quad (9)$$

The annual EPWE (AEPWE) is given by Eq. 10:

$$AEPWE = EPWE \times 365 \times 24 \times 10^{-6} \text{ [in MWh]} \quad (10)$$

4 Conclusion

This study used the MCDM system coupled with GIS to produce the wind suitability map of Burundi. The WRF model simulation outputs over Burundi territory were employed to classify the regions in terms of wind speed potential. Topographical, climatological, and location restriction factors were established. These restrictions such as aspect, slope, elevation, distance from major electrical transmission lines, distance from main roads and the protected zones divided the Burundi country into suitable and unsuitable areas for wind power facilities placement.

The results indicate that the Burundi territory has highly favourable areas for extracting wind energy, making it suitable for implementing medium-scale wind farms. The western part of the country has the highest potential for wind farms. The results signify about 1.96% of the hall country with the highest wind farm potential. At the same time, approximately 19% of the study area registers relatively suitable wind farm potential.

As it is the first time this kind of study has been used to evaluate the optimal wind site selection over Burundi, it is recommended that

further research focus on additional methods for optimal wind site selection to compare the results. Additionally, the study did not distinguish between onshore and offshore wind farm site assessments. To achieve this, the authors plan to conduct a techno-economic analysis to evaluate the unit cost of wind energy in various locations throughout Burundi.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

GP: Conceptualization, Writing–review and editing. ML: Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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