

Renewable Energy Site Assessment with Multi-Criteria Decision-Making

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Abstract - With global demand for renewable energy increasing, the search for suitable locations for renewable power plants has intensified. This paper presents a comprehensive site suitability assessment for solar power plants and wind farms using the Analytical Hierarchy Process (AHP) in conjunction with Geographic Information Systems (GIS). The Analytic Hierarchy Process forms the basis for the analysis of criteria while considering their relative importance, making it suitable for multi-criteria decision-making scenarios. Graphical Information Systems provide spatial analysis capabilities that enable the integration of various geographic information layers and facilitate informed decision-making. By combining AHP with GIS, this study offers a systematic approach for decision-makers and stakeholders in renewable energy industries worldwide to identify optimal locations for renewable power plants. The methodology encompasses data collection from reputable sources, extracting useful information from these sources and using them within the AHP framework, all within various Python software libraries. Through the integration of the aforementioned methodologies, this research contributes to the advancement of renewable energy site suitability assessment methodologies and supports the transition towards a more sustainable energy future.

Keywords - renewable energy, solar power plants, wind farms, site suitability assessment, Analytical Hierarchy Process, Geographic Information Systems, multi-criteria decision-making.

I. INTRODUCTION

The global energy landscape is undergoing a significant transformation driven by concerns over climate change, energy security, and sustainable development. The country of focus for this paper, South Africa, is dealing with an energy crisis [1] and is thus acutely aware of the need for diversification of energy sources to increase energy security. Renewable energy sources, such as wind and solar, have emerged as promising alternatives to the traditional fossil fuels used in the majority of power plants in South Africa [2], offering environmentally friendly and economically viable solutions [3] to meet the country's ever-growing energy requirements. However, the widespread adoption of renewable energy technologies necessitates strategic planning and careful consideration of various factors,

including resource availability, geographical limitations and infrastructure concerns, environmental impacts, and socio-economic considerations [4]. This statement becomes increasingly self-evident as one takes notice of the increased usage of renewable energy technologies by global powers. Norway, Sweden, and Brazil are standouts, with 71.63%, 53.31%, and 48.74% of their energy consumed from renewable energy sources [5]. Additionally, global renewable energy production increased from 2864.09TWh as of 2000, to 8538.50TWh as of 2022 [5]. Wind and solar energy sources saw the largest proportional increase during that time period, as wind and solar power grew from 31.41TWh and 1.06TWh to 2104.84TWh and 1322.62TWh, respectively – an increase from approximately 1.10% and 0.037% to 24.65% and 15.49%, respectively.

Amidst this backdrop, the identification of suitable locations for renewable power plants has become a pressing challenge faced by policymakers, energy developers, and environmental stakeholders alike, as it is a complex and multi-faceted process, requiring the integration of diverse spatial data, governmental and corporate stakeholder inputs, and decision-making frameworks to adequately consider the various factors at play. Additionally, the transition towards renewable energy necessitates the deployment of robust methodologies that are able to consider a wide variety of criteria put forth by the various stakeholders to ensure the effective utilisation of resources and the minimisation of environmental impacts brought about by the construction of renewable power plants.

Various economic, climatic, environmental, and logistic criteria are taken into account when determining site suitability. Any one of these criteria may make a given site an unwise investment if any hard limitations are faced during site selection. This may come in the form of selecting an otherwise ideal site, rich with the desired renewable energy resource, but it is too close to an ecological conservation zone, or the local electrical grid lacks additional connection capacity. In response to these challenges, this research paper aims to contribute to the field of renewable energy planning by proposing a comprehensive analysis of site suitability assessment for renewable power plants. By leveraging Geographic Information Systems (GIS) and the Analytical Hierarchy Process (AHP), this study offers a systematic approach to identifying optimal locations for renewable energy infrastructure development. The integration of GIS provides spatial analysis capabilities, allowing for the integration, visualisation, and analysis of

diverse geographic datasets. Meanwhile, the utilisation of AHP facilitates the systematic evaluation and prioritisation of these criteria, considering their relative importance as laid out by Thomas L. Saaty in his seminal paper *How to Make a Decision: The Analytic Hierarchy Process* [6].

II. LITERATURE REVIEW

A. What is GIS?

A Geographic Information System is a system designed for capturing, managing, analysing, and visualising geographic data from a variety of sources. This geographic data is typically paired with attribute data that provides additional information or context for spatial features, allowing for meaningful analysis of the geographic data in question [7]. Visualisation of this combined data further deepens insights into the data, revealing patterns and relationships, allowing for more informed decision-making [8], and this increased with the use of additional GIS tools. GIS allows for the combination and overlaying of data from various data structures (vector vs. raster data), data types (spatially-referenced data vs. attribute tables), and file formats [9]. Integration of these data sets requires setting a common Coordinate Reference System for the data, which defines the position of spatial features in two-dimensional (projected) or three-dimensional (geographic) space [10]. The data used in this paper consists entirely of projected data, and reprojection to a common Projected Coordinate Reference System was required to integrate the data. Spatial joins, which refers to the use of geographical proximity to combine attributes between two different data sets [11], allow for the extraction of additional information from the integrated data. This concept is particularly useful with regard to site suitability assessment, as information about the relevant criteria can be extracted from the integrated data, and the use of additional GIS tools increases the quality and quantity of information that can be extracted. One such GIS tool that is not often discussed is geospatial clustering, which typically uses unsupervised machine learning algorithms to identify areas of statistical significance, geographic areas which share similar attribute values, and spatial outliers [12].

B. Criteria Considerations in Renewable Power Plant Siting

The siting of power plants is a critical decision-making process that involves assessing various criteria to identify suitable locations for electrical infrastructure development. While the specific criteria may vary depending on factors such as geographic location, environmental regulations, and energy needs, several common considerations are typically evaluated during the siting process, regardless of the type of power plant. These criteria encompass a range of factors, such as geographic features, environmental impacts, and infrastructure accessibility. Geographic features such as topography and proximity to water bodies often influence the selection of power plant sites, especially for hydropower and thermal power plants, and less so for solar power plants and wind farms. Environmental considerations, such as emissions regulation and environmental conservation zones, play a crucial role in ensuring compliance with regulatory standards and minimising environmental impacts. Additionally, infrastructure

accessibility, such as proximity to roads and transmission lines, is essential for efficient operation and grid integration.

However, it is important to note that the criteria considered in power plant siting can vary significantly across different countries and power plant types. For example, countries prone to geological hazards, such as earthquakes and tsunamis, must prioritise geological factors in their siting decisions to mitigate risks and ensure the safety and resilience of power infrastructure. For example, In Japan, seismic considerations are of utmost importance due to their susceptibility to earthquakes and tsunamis [13], necessitating rigorous geological assessments and engineering standards for power plant siting.

C. WHAT IS AHP?

The Analytic Hierarchy Process, developed by Thomas L. Saaty, is a multi-criteria analysis framework designed to assess the relative weight of multiple criteria intuitively. It eases the load of decision-making as policymakers can readily determine relative importance between criteria and obtain results that determine the overall importance of each criterion, rather than directly determining overall criteria importance from the outset [14]. The AHP methodology used in this paper is as follows:

1. Identify the objective and the criteria. For this paper, the objective is site selection. The criteria used herein include global tilted irradiance and wind speed, national grid transmission voltage, provincial grid capacity, the average distance to the national grid, the average distance to the national road network and, the average distance to major cities.
2. Determine the relative weights on a scale from 1 – 9, where 1 denotes equal criteria importance, and 9 denotes extreme importance of one criterion over another [15].
3. Create a pair-wise comparison matrix of the selected criteria. This matrix consists of the selected criteria and is filled with the relative importance of each criterion.
4. Sum the values in each column and divide the values in each column by their respective columnal sum – this represents the normalised pair-wise comparison matrix. Finally, sum the values row-wise and divide by the number of criteria – this final value represents the criteria weight for the criterion pertaining to that row.
5. Multiply the values in each criterion column by their respective weights, then sum up the row-wise values. Divide the row-wise sum by the criterion weight that corresponds to that column. These values are known as the consistency vectors [16].
6. Calculate $\lambda_{max} = \frac{\sum_{i=1}^n C_v}{n}$, where C_v represents the consistency vector, and n represents the number of criteria. Calculate the consistency index $CI = \frac{\lambda_{max} - n}{n - 1}$. Calculate the consistency ratio $CR = \frac{CI}{RI}$, where RI represents the randomness index, which is the consistency index of randomly generated pair-wise

comparison matrices. The randomness index for various values of n is provided by Saaty – for this research paper, for $n = 6$, $RI = 1.26$. As recommended by Saaty, a minimum consistency ratio value of 10% is required in order to accept the criteria weightings.

D. Multi-Criteria Decision-Making

Generally speaking, multi-criteria decision-making refers to the process of determining the most feasible solutions according to established criteria. All MCDM processes involve identifying and selecting criteria, determining the weights of these criteria, and creating rankings of objectives/options by using a suitable MCDM method [17]. This concept is useful in the context of site selection, as it allows one to determine which frameworks are best suited to derive criteria weights and how to use said weights to arrive at a site suitability score. This paper uses a linear model that is a weighted sum of the different criteria values. Two scaling factors A_1 and A_2 are used to scale the site suitability score at a geographic point. More specifically, if a point falls within an environmental conservation zone, A_1 is 0 and thus the site suitability score at that point is reduced to zero, otherwise it remains the same. This is much the same for A_2 , as A_2 is 0 for any geographic point that falls within an area with no additional grid connection capacity, which reduces the site suitability score at that point to 0, otherwise the score remains the same. This linear model takes the form of $Y = A_1 A_2 (B_1 x_1 + B_2 x_2 + \dots + B_n x_n)$, where Y represents the final suitability score, B represents the criteria weights, and x represents the normalised criteria values, with normalised criteria values expressed as a fraction of the maximum criterion value.

III. METHODOLOGY

A. Data Sourcing and Data Preparation

Data was largely gathered from authoritative sources, including the World Bank Group and their affiliates, and from open sources like Open Street Maps. This data was reprojected to the WGS84 CRS (geographic coordinates) as a common CRS for all data, and then projected to the EPSG:9221 CRS (projected coordinates) when performing Euclidean Distance calculations.

B. Criterion Considerations and Information Extraction

The chosen criteria, as mentioned in *What is AHP*, were chosen due to their relevance regarding power plants within the South African context. The grid connection capacity criterion serves as a prominent example of a criterion relevant to the South African context – our national grid is severely constrained and lacks the ability to add generation capacity in certain provinces and is thus a pertinent consideration in terms of power plant siting.

C. Information Collation and Site Suitability Scores

A final data set was collated, containing all the data pertinent to each criterion. From this, site suitability scores were calculated and visualised on a map of South Africa.

IV. RESULTS AND DISCUSSION

A. Maps of Criterion Data

The criterion data was mapped to illustrate how criterion data varied across the country, allowing for ease of interpretation of the data at hand.

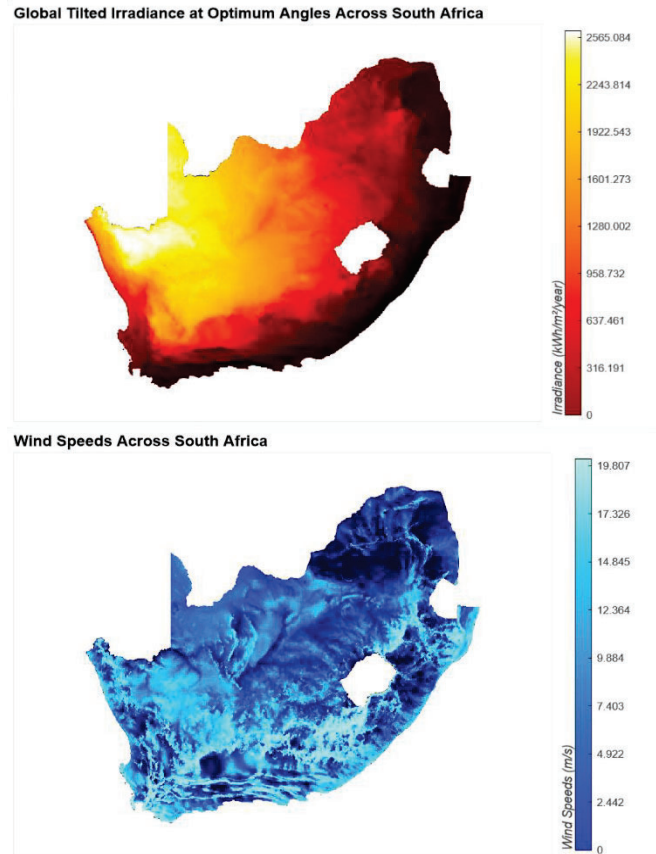


Fig. 1 Global tilted irradiance and wind speeds across South Africa

Figure 1 quite clearly shows that the Northern Cape and the municipalities immediately bordering the province have a wealth of solar irradiance, which would make them prime candidate locations if other criteria were not taken into consideration. As for wind speeds, the coastal provinces of the country, especially KwaZulu-Natal and the Eastern Cape, have the highest average wind speeds across the country, making them prime candidate locations before accounting for other criteria.

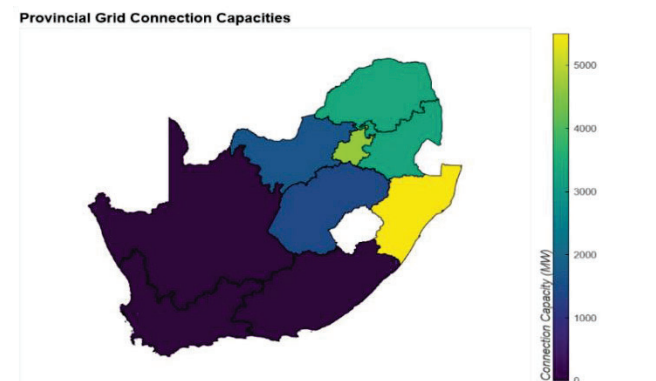


Fig. 2a. Provincial grid connection capacity and national transmission grid

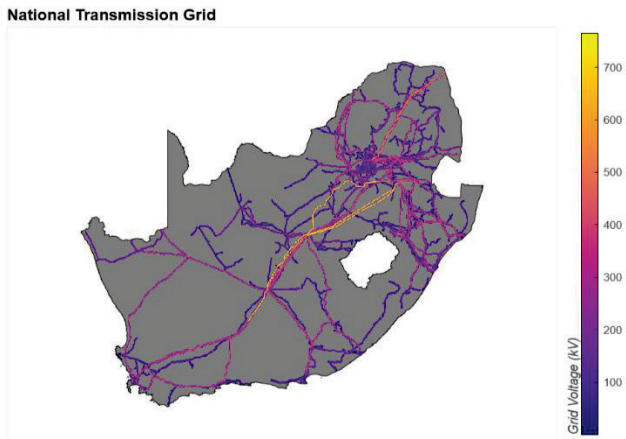


Fig. 2b. Provincial grid connection capacity and national transmission grid

Figure 2 illustrates South Africa’s constrained national grid, as the Northern, Western, and Eastern Cape lack any additional grid capacity. The remaining six provinces have adequate grid connection capacity, with Gauteng and Kwa-Zulu Natal having the largest capacity. The national transmission grid is also depicted here, with the highest-voltage transmission lines passing through Gauteng and the Free State, and lower-voltage transmission lines passing through the outlying provinces.

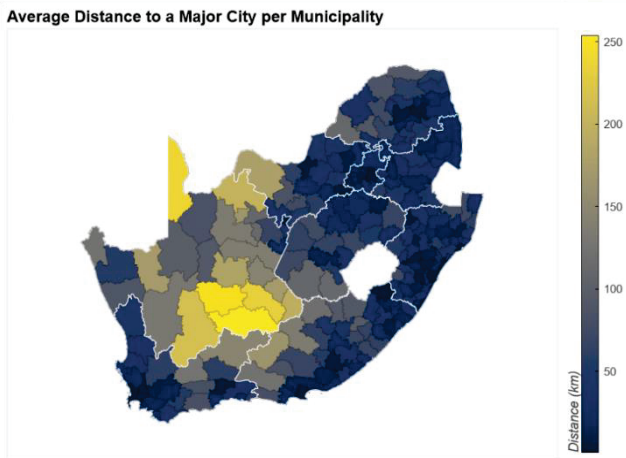
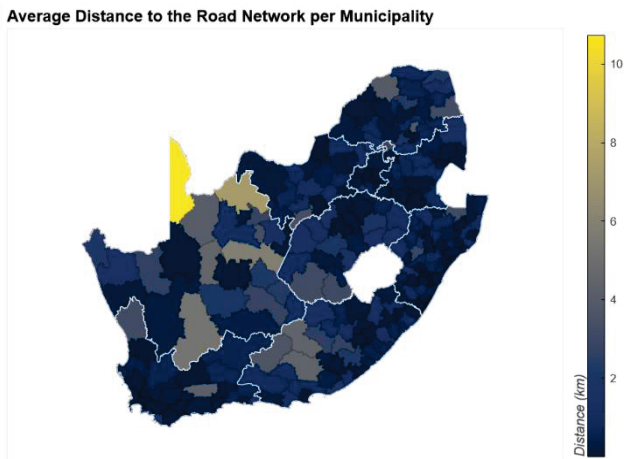


Fig. 3 Average distance to the national grid, to the national road network, and to major cities (per municipality)

Figure 3 shows that most municipalities are located relatively near the national grid and the national road network, with the Northern Cape municipalities being the most standout exception. Additionally, the Northern Cape municipalities require notably longer average travel times to reach major cities in comparison to nearby municipalities in neighbouring provinces. Municipalities in the Free State, Gauteng, and most municipalities located near the coast have good access to important infrastructure.

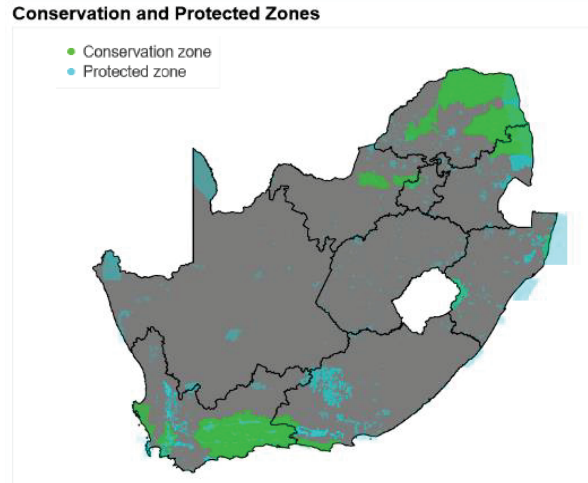


Fig. 4 South Africa’s conservation and protected zones

Figure 4 depicts conservation and protected zones originating within the country’s land borders. These zones have a 500m buffer radius and are areas in which power plants of any type may not be sited [18]. Large parts of the Western Cape and Limpopo are covered in these zones, thus making large swathes of these provinces unsuitable for solar power plants or wind farms.

B. AHP Criteria Weights

In the Analytic Hierarchy Process (AHP), criteria weights are assigned to the criteria presented in Table 1. These criteria are weighted based on their importance to the overall objective, such as selecting an optimal location for renewable energy development.

TABLE I. PI CONTROLLER GAIN

Criteria	Constraint Factor	Consideration
GTI/Wind Speed	Renewable Resource	Climatic
Grid Connection Capacity	Access	Logistic
Average Distance to the National Grid	Access	Logistic
Average Distance to Roads	Access	Logistic
Grid Transmission Voltage	Power Loss Minimisation	Economic
Average Distance to Cities	Power Loss Minimisation	Economic

The criteria above are represented in the table below as criteria C1 to C6.

TABLE II. PAIR-WISE COMPARISON MATRIX

	C ₁	C ₂	C ₃	C ₄	C ₅
C ₁	1	7	5	5	9
C ₂	1/7	1	1/3	1/3	2
C ₃	1/5	3	1	1	4
C ₄	1/5	3	1	1	4
C ₅	1/9	1/2	1/4	¼	1

$\lambda_{max} = 5.12, CI = 3\%, CR = 2.7\%$ are the obtained results. The consistency ratio is less than 10%, thus the resulting criteria weightings may be accepted.

C. Site Suitability Scores

The image on the left in Figure 5a depicts the reality of South Africa’s constrained electrical grid. The Northern Cape municipalities shown to have the greatest abundance of solar irradiation are also the municipalities located in a province with a constrained grid, thus eliminating and nullifying much of their initial suitability as power plant sites.

Solar Site Suitability Scores Across South Africa (Version 1)

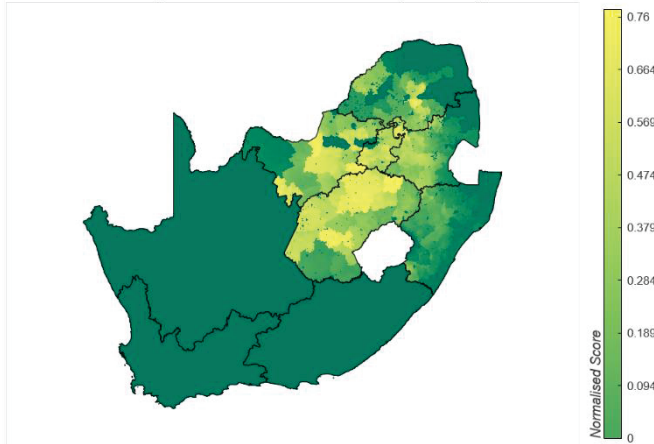


Fig. 5a. Solar site suitability scores across South Africa

Figure 5b depicts a more ideal reality than Figure 5a, depicting that the site suitability scores of the municipalities within grid-constrained provinces would be far higher if not for that constraint. Despite many infrastructural constraints working against the Northern Cape municipalities, some of them retain high site suitability scores. As for the other provinces, Gauteng and the Free State appear to be prime power plant sites, while most coastal municipalities in KwaZulu-Natal and the Eastern Cape are not as suitable as the inland municipalities, with only a few coastal municipalities in the Western Cape and the Northern Cape being an exception to this observation.

Figure 6 depicts a situation much like in Figure 5, showing that the site suitability scores of the municipalities within grid-constrained provinces would be far higher if not for the lack of additional connection capacity. It can be seen in the image on the right in Figure 6 that municipalities within KwaZulu-Natal

and the Eastern Cape have the lion’s share of suitable sites for wind farms, with municipalities within the Free State also having a respectable share of suitable sites.

Solar Site Suitability Scores Across South Africa (Version 2)

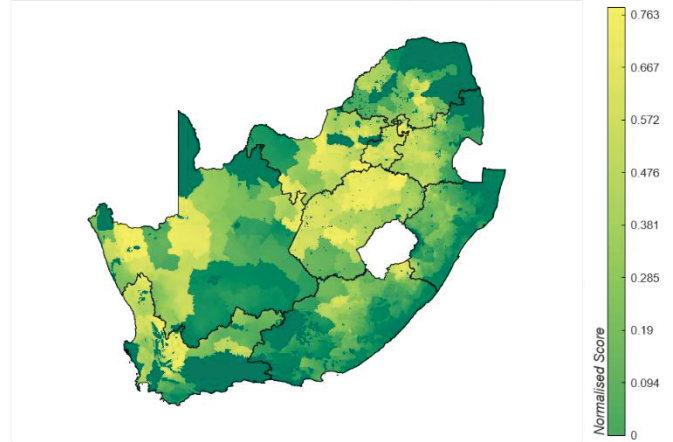


Fig. 5b. Solar site suitability scores across South Africa

Wind Site Suitability Scores Across South Africa (Version 1)

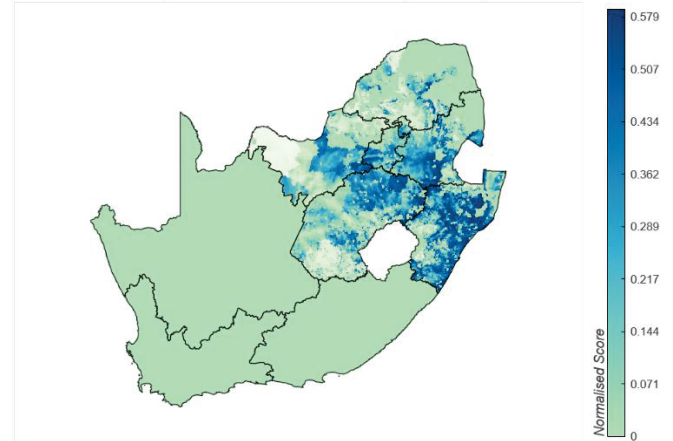


Fig. 6a. Wind site suitability scores across South Africa

Wind Site Suitability Scores Across South Africa (Version 2)

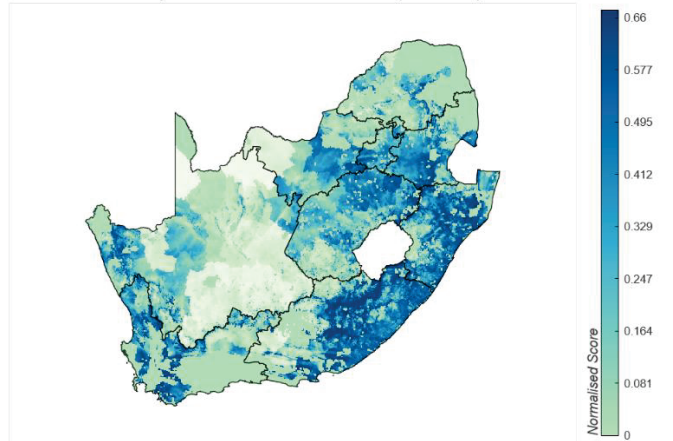


Fig. 6b. Wind site suitability scores across South Africa

CONCLUSION

In conclusion, this paper has outlined a systematic approach to multi-criteria decision-making (MCDM) using the Analytic Hierarchy Process. By deriving weights for criteria through pairwise comparisons, a structured framework for formulating linear models used to determine the final suitability score was established. While this methodology offers a structured approach to decision-making, it is essential to acknowledge the limitations and assumptions present in this approach. Factors such as data quality and subjective judgments in pairwise comparisons may introduce uncertainty into the process. Future research may further refine the methodology and explore advancements in MCDM frameworks to enhance the reliability of the findings. In summary, the analysis demonstrates the effectiveness of the AHP method in addressing complex decision-making problems by providing decision-makers with a systematic and transparent framework for evaluating power plant site options.

DATA AVAILABILITY

The code used to implement the models used in this paper can be found via the following link: <https://colab.research.google.com/drive/128BKYZh4KyfM9-TmK8cJtOCNm4BSez?usp=sharing>

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REFERENCES

- [1] R. Mathekgga, "Southern Africa's energy woes," GIS Reports, <https://www.gisreportsonline.com/tr/southern-africa-energy/> (accessed May 27, 2024).
- [2] "South Africa - Energy," International Trade Administration | Trade.gov, <https://www.trade.gov/country-commercial-guides/south-africa-energy> (accessed May 27, 2024).
- [3] "U.S. Energy Information Administration - EIA - independent statistics and analysis," Solar energy and the environment - U.S. Energy Information Administration (EIA), <https://www.eia.gov/energyexplained/solar/solar-energy-and-the-environment.php> (accessed May 27, 2024).
- [4] W. Strielkowski, "Critical factors in renewable energy generation," Encyclopedia, <https://encyclopedia.pub/entry/17147> (accessed May 27, 2024).
- [5] H. Ritchie, M. Roser, and P. Rosado, "Renewable energy," Our World in Data, <https://ourworldindata.org/renewable-energy> (accessed May 28, 2024).
- [6] T. L. Saaty, L. G. Vargas, U. Eco, E. Forman, and G. A. Miller, "How to make a decision: The Analytic Hierarchy Process," European Journal of Operational Research, <https://www.sciencedirect.com/science/article/abs/pii/0377221790900571> (accessed May 28, 2024).
- [7] "Research guides: Mapping and geographic information systems (GIS): What is GIS?," What is GIS? - Mapping and Geographic Information Systems (GIS) - Research Guides at University of Wisconsin-Madison, <https://researchguides.library.wisc.edu/GIS> (accessed May 28, 2024).
- [8] "What is GIS?" Esri South Africa, <https://www.esri-southafrica.com/what-is-gis/> (accessed May 28, 2024).
- [9] C. Dempsey, "Types of GIS data explored: Vector and Raster," Geography Realm, <https://www.geographyrealm.com/geodatabases-explored-vector-and-raster-data/> (accessed May 28, 2024).
- [10] "Geographic vs projected coordinate reference systems - GIS in python," Earth Data Science - Earth Lab, <https://www.earthdatascience.org/courses/use-data-open-source-python/intro-vector-data-python/spatial-data-vector-shapefiles/geographic-vs-projected-coordinate-reference-systems-python/> (accessed May 28, 2024).
- [11] "How spatial join works in GIS," GIS Geography, <https://gisgeography.com/spatial-join/> (accessed May 28, 2024).
- [12] "An overview of the mapping clusters toolset," An overview of the Mapping Clusters toolset-ArcGIS Pro | Documentation, <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/an-overview-of-the-mapping-clusters-toolset.htm> (accessed May 28, 2024).
- [13] Y. Ishiyama, "Earthquake damage and seismic code for buildings in ...," Earthquake Damage and Seismic Code for Buildings in Japan, http://ares.tu.chiba-u.jp/peru/pdf/meeting/120817/M6_Ishiyama.pdf (accessed May 28, 2024).
- [14] S. Singh, "Multi-criteria decision-making using AHP in python," Analytics Vidhya, <https://www.analyticsvidhya.com/blog/2023/05/multi-criteria-decision-making-using-ahp-in-python/> (accessed May 28, 2024).
- [15] M. A. Baseer, S. Rehman, J. P. Meyer, and M. Alam, "GIS-based site suitability analysis for wind farm development in Saudi Arabia," Energy, <https://www.sciencedirect.com/science/article/abs/pii/S0360544217316857> (accessed May 28, 2024).
- [16] L. Joselin, The Implementation of Analytical Hierarchy Process for Determining Best Employee, <https://iopscience.iop.org/article/10.1088/1742-6596/1230/1/012071/pdf> (accessed May 28, 2024).
- [17] H. Taherdoost and M. Madanchian, "Multi-criteria Decision making (MCDM) methods and concepts," MDPI, <https://www.mdpi.com/2673-8392/3/1/6> (accessed May 1, 2024).
- [18] GIS data downloads | Egis, https://egis.environment.gov.za/data_egis/data_download/current (accessed May 28, 2024).