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A Comparison of Results from Two Multi-Criteria Decision-Making Methods for Solar Photovoltaic Plant Site Location: Case Study Rio De Janeiro

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ABSTRACT

Photovoltaic (PV) energy has become a low-cost, renewable, and environmentally friendly alternative to meet increasing energy demand. Nevertheless, there is still a lack of projects in this field in Brazil. Therefore, this study compares the results of two studies on the optimal site selection of PV in the Brazilian state of Rio de Janeiro. These studies used different methodologies to reach the conclusions and the resulting map. First, the final map of both studies was divided into a grid, and then the results of each cell were weighted for PV site selection. To compare the results using the maps, an intersection of the 10% of the grid cells with the best results from each study was formed. The results showed an 83% similarity between the different Multi-Criteria Decision-Making (MCDM) methods. The other part of the comparison focused on the following rank similarity coefficients: Spearman Correlation Coefficient, WS Coefficient, Spearman Weighted Correlation Coefficient, and Blest Correlation Coefficient. All these coefficients had values greater than 0.9, indicating a high degree of correlation between the results of the studies. Therefore, the two studies have a high degree of

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similarity and a high potential for installing photovoltaic solar power plants in Rio de Janeiro, especially in its intersection zones.

Keywords: GIS, multi-criteria decision making (MCDM), Rio de Janeiro, site selection, solar photovoltaic (PV)

INTRODUCTION

One of the main issues of sustainable development lies in the innovations and technological advances for transforming and using natural resources (Pereira et al., 2017). According to the Intergovernmental Panel on Climate Change (IPCC), the temperature increase has reached about 1°C. It is important to keep it below 1.5°C, considering the values from before the Industrial Revolution, to mitigate the consequences of global warming. Therefore, it is necessary to reduce the use of fossil fuels, including in energy production (Allen et al., 2018).

Several studies show that solar energy has numerous advantages compared to other renewable energy sources. Moreover, photovoltaics is one of the best options to meet the increasing energy demand in the future (Razykov et al., 2011; Uyan, 2013). For example, solar energy is everywhere on Earth, accounting for 99.8% of the total energy reaching Earth's surface. It also comes from the sun, making it an accessible and inexhaustible source of energy (Al-Shamisi et al., 2013; Jain et al., 2011; Ramedani et al., 2013), and if only 0.1% of this energy were converted into electricity at an efficiency rate of 10%, this amount would be sufficient to meet the planet's needs several times over (Thirugnanasambandam et al., 2010). In addition, the cost of solar photovoltaics is decreasing; for example, between 2010 and 2019, it decreased by 82%, making PV competitive with traditional energy sources (IRENA, 2020). In 2020, the estimated cost of new PV projects is 0.057 USD/kWh, while fossil fuel costs range from 0.055 to 0.236 USD/kWh, and the 2030 target is 0.02 USD/kWh, according to the Office of Energy Efficiency & Renewable Energy (https://www.energy.gov/eere/solar/articles/2030-solar-cost-targets; La Camera, 2020).

On the demand side, electricity consumption in Brazil is expected to increase by about 30% by 2030 and about 95% by 2050. In addition, Brazil recently experienced an unprecedented drought, a serious problem since most of its electricity generation comes from hydropower (http://www.ons.org.br/paginas/energia-agora/reservatorios; EPE, 2020a, 2020b, 2016). Therefore, clean, reliable renewable energy sources are needed to meet the increasing demand projected for the coming years.

Rio de Janeiro, one of the 27 federative units of Brazil, is a state with an area of 43,752 km² (CEPERJ, 2022a), a GDP of BRL 758 billion, which is about 10.8% of the total GDP of the country, and the second largest economy (CEPERJ, 2019), with a population of 17.4 million people, the third largest in Brazil (IBGE, 2022). The state is divided into seven regions, which are very different from each other. The metropolitan area of Rio de

Janeiro, the capital, concentrates 70% of the population and most of the economic and industrial resources (CEPERJ, 2022b). The state's geography is very heterogeneous, with high cliffs, hills, and valleys, as well as an extensive plateau that covers the entire western part of the territory and several areas of the Atlantic Forest (Ribeiro & Nunes, 2019). Regarding solar irradiation, the state has excellent levels, averaging between 4 and 5.5 kWh/m^2 across different regions (EGPEnergia & PUC-Rio, 2016). Despite the potential, Rio de Janeiro generated only 65 GWh of energy from solar PV in 2019, less than 1% of its total electricity generation (EPE, 2020a).

Various factors must be considered when determining the best locations for solar photovoltaic plants, including solar irradiation, existing infrastructure, and surrounding terrain characteristics (San Cristóbal, 2011; Zoghi et al., 2017). These factors range from the proximity of the grid and the road to the azimuth and slope of the terrain, apart from many restriction zones, i.e., locations where PV plant projects cannot be implemented. For this reason, searching for the most suitable sites for Rio de Janeiro requires the right tools and methods.

Multi-Criteria Decision-Making (MCDM) methods find extensive application across diverse fields, aiding decision-makers in navigating complex and often conflicting criteria (Figueira et al., 2005; Roy, 2016; Sałabun & Piegat, 2017). To this end, the result of the MCDM methods usually ranks the available alternatives, with the best ones in first place (Bandyopadhyay, 2016). These methods are commonly used for various problems, including renewable energy (Kolios et al., 2016; Sałabun & Piegat, 2017). Due to the complexity of this issue, renewable energy site selection often involves multiple alternatives based on a variety of criteria (Shao et al., 2020).

Mapping is an important method of analysis in the arts, humanities, and sciences that uses geospatial technologies to collect data about people and places (Manson et al., 2017). A Geographic Information System (GIS) is a computerized system based on cartography, geography, and remote sensing that can perform multiple functions, such as collecting, storing, analyzing, and presenting large data sets as maps (Das & Bhuyan, 2017; Wang et al., 2019). There are several examples where GIS is combined with MCDM. One of the main advantages of this tool is its excellent ability to perform an analysis of optimal locations for renewable energy plants through the possibility of using multiple layers (e.g., slope and solar irradiation) that provide maps and numerical information in one database (Janke, 2010; Sánchez-Lozano et al., 2016a; Van Haaren & Fthenakis, 2011). For example, according to Shao et al., of the 85 papers on renewable energy siting that their study reviewed, 52 used GIS (Shao et al., 2020).

Multi-criteria Decision-Making methods have become progressively popular in renewable energy power plant site selection (Shao et al., 2020). Recently, many studies have been conducted in different countries to evaluate the suitability of solar PV plants by combining GIS with MCDM: Yushchenko et al. (2018) in West Africa (ECOWAS region), Aly et al. (2017) in Tanzania, Uyan (2013) for the Konya Region in Turkey, Al Garni and Awasthi (2017) for Saudi Arabia, Kwak et al. (2021) for the state of Ilinois in the United States, Sánchez-Lozano et al. (2016b) for Murcia region in Spain, Zoghi et al. (2017) for Isfahan region in Iran, Qiu et al. (2022) in China, Sindhu et al. (2017) for the Haryana region in India, Janke (2010), Doorga et al. (2019) for Mauritius, Palmer et al. (2019) for the United Kingdom and several others. There is no single MDCM method in these studies, although AHP (Analytical Hierarchical Process) is the most commonly used (Shao et al., 2020).

Many MCDM methods exist, but none is perfect and suitable for every decision-making situation. Moreover, different approaches may lead to different results (Guitouni & Martel, 1998; Zanakis et al., 1998), and several factors may explain this divergence, such as the adoption of different weights for the selected criteria or the differences between the methods and algorithms themselves (Zanakis et al., 1998). Researchers and decision-makers should consider the trade-offs between various MCDM models (Shao et al., 2020). Therefore, by comparing the results of a variety of MCDM models, the merits and weaknesses of these different models for a given problem can be determined (Shao et al., 2020). For that reason, comparing the results of these methods for the same topic is important to obtain consistent results.

There are several ways to validate the results of the renewable energy site selection problem, including comparison with existing sites, sensitivity analysis—varying the criteria weights, comparison with other MCDM methods, and other less-used methods (Shao et al., 2020).

Numerous studies compare the results of different MCDM methods. However, only a fraction of them compare renewable energy projects, and even fewer compare the results of different studies applied to the same issue. A large proportion of these studies perform sensitivity analysis, essentially scenarios in which the weighting of the criteria is changed, and the results are compared through maps or tables (Aly et al., 2017).

Abdel-Basset et al. (2021) applied a Multi-Criteria Decision-Making approach to determine the best locations for PV solar plants in Egypt. First, the Delphi method was applied by various specialists to determine the criteria used. These criteria were described in the study as core dimensions and sub-indicators. In the next step, the importance of the selected criteria was determined using the DEMATEL (Decision-Making Trial and Evaluation Laboratory) method. Then, the VIKOR (Višekriterijumsko Kompromisno Rangiranje) method was applied to rank seven sites for photovoltaic plants. The final step compared the results with the AHP-TOPSIS and the SWARA-WASPAS methodology. The methods were compared in two ways: with the direct rank comparison and with the Spearman Rank Correlation. In both cases, the greatest agreement was found with the method AHP-TOPSIS.

Ohunakin and Sacaracoglu (2018) compared five MCDM methods to determine the most suitable location for installing Concentrated Solar Power Plants (CSP) in Nigeria. The selected methods were the Analytic Hierarchy Process (AHP), Consistency-Driven Pairwise Comparisons (CDPC), Decision Expert for Education (DEXi), Elimination, and Choice Translating Reality (ELECTRE III and IV). The study compared the ranks of nine factors on the selected MCDM without using a rank similarity coefficient. Instead, a direct comparison was made using a summary table. The study concluded that the ranks generated by the MCDM methods showed significant differences, with the highest degree of similarity observed between AHP and CDPC.

Sánchez-Lozano et al. (2016a) aimed to find the most suitable site for a PV plant in the Murcia region, Spain. The study used GIS to generate the maps and AHP to determine the weights of the selected criteria. Then, the TOPSIS and ELECTRE methods were selected to analyze the most suitable sites. Finally, comparing the best alternatives from both methods revealed the similarity. No rank similarity coefficient was used, but the analysis was based on maps and tables.

Kizielewicz et al. (2020) analyzed the criteria for determining the best locations for a wind farm using several decision support models (TOPSIS, VIKOR and COMET). They compared the results for each model using Spearman's rank correlation and the WS similarity coefficient. In addition, three scenarios were elaborated by eliminating one, two, and three of the selected criteria for comparison purposes.

Giamalaki and Tsoutsos (2019) searched for suitable sites for solar PV and CSP plants in the Mediterranean region of Rethymno using AHP and GIS. In order to verify the results, a sensitivity analysis was performed in three of the following scenarios: all criteria with equal weighting; equal weighting of techno-economic criteria and no weighting of socio-environmental criteria; equal weighting of socio-environmental criteria and no weighting of techno-economic criteria. Finally, a comparison of these scenarios was made using maps.

Villacreses et al. (2017) studied suitable sites for wind farms in Ecuador. The study used four Multi-Criteria Decision-Making methods combined with GIS. For this, they developed a standardization process. The MCDMs that were compared were AHP, OCRA (Occupational Repetitive Actions), VIKOR, and TOPSIS. Finally, the Pearson correlation coefficient was used to analyze the mutual agreement between these methods through the raster map values for the processing of each pixel for all sites and the best sites only, showing a greater correlation for all methods for the best sites.

Sánchez-Lozano et al. (2016a) compared the TOPSIS and ELECTRE methods to find the best locations for PV plants in the Murcia region, Spain. The study used the AHP to determine the weights of the selected criteria and ranked the results using the TOPSIS and ELECTRE methods. A remarkable similarity of the results was found in the comparative analysis of the maps. In addition, a detailed comparison was made between the results of the top 10 alternatives from TOPSIS and ELECTRE, which was presented in a table without applying a correlation coefficient.

Shorabeh et al. (2019) studied the most suitable sites for a PV plant in the Iranian provinces of Mazandaran, Kermanshah, Razavi Khorasan and Yazd. The study combined the Ordered Weighted Averaging (OWA) model with GIS for different levels of decision risks. The last step was to perform a sensitivity analysis on the results, changing the weights of the selected criteria to check the impact on the results. This analysis showed that the slope and road network criteria had the greatest impact on the area ranked as highly desirable.

Rios and Duarte (2021) searched for ideal sites for developing large-scale solar PV projects in Peru. The analysis in the study involved the integration of AHP with GIS, and a sensitivity analysis was performed at the end. Three scenarios were analyzed: equal weighting, weighting of the literature review, and weighting associated only with the technical factors. In these different scenarios, the percentage of adequacy of the area was compared, and the resulting maps were drawn.

Through this overview of the applications of different MCDM methods in the renewable energy field and their comparability, it is clear that they are very useful tools for solving problems related to the search for suitable sites for PV plants. Therefore, this study will compare two studies in which the best locations for PV plants in Rio de Janeiro were analyzed using different MCDM methods. It is relevant because the intersection of the two studies reaffirmed excellent potential sites for installing PV plants, making it a solid result for both studies and validating them.

These two papers (De Souza et al., 2019; De Souza et al., 2021a) were selected to elaborate on the studies presented and relate complementary research. In addition, there are few researches on the location of solar photovoltaic plants in Rio de Janeiro. It makes this relationship even more relevant.

LITERATURE REVIEW

Similarity Coefficients

In a simple way, correlation is a measure of association between variables and is one of the most used and reported statistical methods for summarizing scientific research data (Schober et al., 2018; Schober & Schwarte, 2018). A correlation coefficient with the value of zero indicates that no association exists between the variables, and as it gets closer to ± 1, the stronger the association. A positive correlation means that an increase in one variable will lead to an increase in the other criteria. In contrast, a negative correlation means that an increase in one variable will lead to a decrease in the other. Hypothesis tests and confidence intervals should be used to analyze the statistical significance of the results (Rodgers & Nicewander, 1988).

The concept of measuring rank correlation has been applied in several studies, and its utility is to compare results from different sources and determine how similar they are. In the MCDM, they prove to be very useful, as the alternatives are ranked at the end according to the selected criteria (Fagin et al., 2003; Figueira et al., 2016; Sałabun et al., 2020; Shekhovtsov & Kolodziejczyk, 2020; Shieh, 1998). This study will compare the ranking obtained by two studies using the following correlation coefficients: Spearman Correlation Coefficient, Spearman Weighted Correlation Coefficient, WS Coefficient, and Blest Correlation Coefficient.

Kendall and Goodman-Kruskal correlation coefficients are not used because they directly compare the number of matched pairs, i.e., equal pairs (Sałabun & Urbaniak, 2020). Since the number of cells generated by the grid is very large, more than 27 thousand cells were analyzed, so only a few pairs are equal.

Spearman Correlation Coefficient. The Spearman rank correlation coefficient (r_s) is one of the most popular tools to evaluate and analyze the similarity of rankings (Ceballos et al., 2016; Ishizaka & Siraj, 2018; Ivlev et al., 2016; Mulliner et al., 2016; Sałabun et al., 2020; Sałabun & Urbaniak, 2020) and can be used as a measure of monotonic association between ranks instead of raw data. The data is ordered and converted into ranks (Asuero et al., 2006; Schober et al., 2018; Zar, 2005). The rank correlation coefficient (r_s) is expressed as Equation 1 (Zar, 1972).

$$Spearman\ Rank\ Correlation\ Coefficient, r_s = 1 - 6\sum \frac{d_i^2}{(N^3 - \mathrm{N})} \qquad [1]$$

The number of measurements of the two variables is N, and d_i is the difference between the ranks of these variables ($di=R_{xi}-R_{yi}$). When two or more data have the same value, i.e., are of equal rank, each can be set as the mean of the ranks of the positions (Zar, 2005). This rank is the percentage of the rank variance of one variable explained by the other (Sałabun & Urbaniak, 2020).

Spearman Weighted Correlation Coefficient. Da Costa and Soares (2005) developed and proposed this rank. According to their study, the Spearman rank is unsuitable for some applications because it treats all ranks equally. Therefore, they developed the Spearman Weighted Correlation Coefficient (r_w), where the higher ranks (best positions) have more weight than the lower ranks (worst positions). Equation 2 shows the formula for the r_w Coefficient.

$$Spearman\ Weighted\ Correlation\ Coefficient, r_W = 1 - 6\sum \frac{(R_{xi} - R_{yi})^2((N - R_{xi} + 1) + (N - R_{yi} + 1))}{\mathrm{N}.(N^3 + N^2 - \mathrm{N} - 1)} \qquad [2]$$

The coefficient is r_w, the length of ranking is N and R_{xi} and R_{yi} are the positions in the rank order for each element in rank order x and rank order y, respectively.

WS Coefficient. The development of this coefficient has shown that the ranks are used to find the best solutions; therefore, the differences between the higher positions should be more significant; thus, the higher ranks are more relevant than the lower ranks (Sałabun & Urbaniak, 2020). Equation 3 shows the formula for the WS Coefficient.

$$WS\ Coefficient, WS = 1 - \sum \left(2^{-R_{xi}} \cdot \frac{|R_{xi} - R_{yi}|}{max\{|1 - R_{xi}|,\ |N - R_{xi}|\}}\right) \quad [3]$$

The similarity coefficient value is WS, the length of ranking is N, and R_{xi} and R_{yi} are the positions in the rank order for each element in rank order x and rank order y, respectively.

Blest Correlation Coefficient. Blest Correlation Coefficient (V_n) was published by Blest (2000). As the other rank similarities presented in this study, the Blest Correlation Coefficient shows that higher ranks are more important than lower ones. Equation 4 shows the formula for the V_n Coefficient.

$$Blest\ Correlation\ Coefficient,\ V_n = 1 - \frac{12\sum(N+1 - R_{xi})^2 R_{yi} - N(N+1)^2(N+2)}{N(N+1)^2(N-1)} \quad [4]$$

The similarity coefficient value is V_n, the length of ranking is N, and R_{xi} and R_{yi} are the positions in the rank order for each element in rank order x and y, respectively.

METHODOLOGY

Conceptual Framework

This study aims to analyze and compare the results of two different studies (De Souza et al., 2019) in which the best locations for solar PV plants in Rio de Janeiro were determined using different MCDM methods. De Souza et al. (2019) applied the AHP to find the optimal locations, while De Souza et al. (2021a) used the COPPE-COSENZA method to pursue the same objective. To this end, the study developed the following framework (Figure 1).

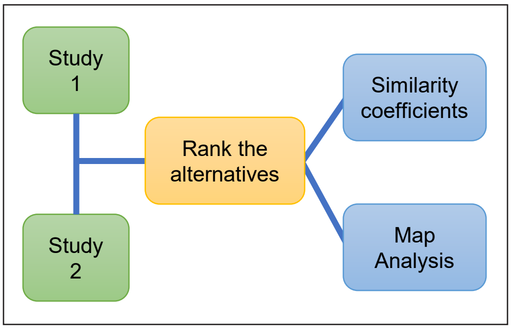

Figure 1. Framework for the research

The first step is to compare and analyze the two studies to rank the alternatives for the most suitable sites, i.e., the result of each study. When combined through GIS, the different criteria selected to determine the best locations for PV plants resulted in a georeferenced layer for each study showing these optimal locations within Rio de Janeiro. This layer was called the “resulting map.”

For each of these resulting maps, the data were converted to a raster format, which means that a grid was generated, and each grid cell contains a numeric attribute corresponding to the georeferenced location of the resulting map. For this article, each grid cell is 1 km × 1 km and has a unique ID.

It is possible to rank each location and compare studies using the grid cells. These ranks, therefore, form the basis for comparing results, i.e., for calculating the results of the map analysis and the similarity coefficients.

In the map analysis, the GIS was used to compare and superimpose each study’s top 10% ranks, making it possible to examine the intersections, the suitable regions in both studies and the regions indicated as suitable by only one of the MCDM methods. The rank of the alternatives in each grid cell was also used to apply the following similarity coefficients: Spearman Correlation Coefficient, Spearman Weighted Correlation Coefficient, WS Coefficient, and Blest Correlation Coefficient.

Map Analysis

According to Visser and de Nijs (2006), there are several reasons to compare maps, such as to compare different models, methodologies, or scenarios and to validate land use models. Map analysis provides ways to deal with data and understand spatial patterns. There are four main methods to analyze data presented in maps: Point Pattern, Autocorrelation, Proximity, and Correlation. These types of analysis differ by the focus of investigation (location and/or attribute), the geometric feature (point and/or area), and a number of topics (Manson et al., 2017).

Spatial analysis can be performed using a variety of techniques using statistics or even visual examination, although a more formal approach is often required (Paramasivam & Venkatramanan, 2019; Scott, 2015). For example, statistical spatial analysis is the most common type of spatial analysis performed with georeferenced data (Bishop & Giardino, 2021).

For this study, correlation analysis was used, i.e., determining the spatial relationship between the attributes of studies 01 and 02, in other words, how they are spatially related (Manson et al., 2017).

There are few examples in the literature of systematic methodologies for analyzing the similarity of maps that fit the proposed problem of this study; in this sense, the most common application of map comparison is land use. Usually, studies select the best sites for each MCDM method and only compare the maps visually. The objective of this study is to go further.

A selection process was conducted to identify the most promising sites for PV plants using the resulting map and the overlaid grid cells. Specifically, the top 10% of grid cells that showed the most favorable results were selected. As shown in Figure 2, a 10 × 10 grid with a total of 100 cells, only the 10 highest scores were selected. It is important to emphasize that this selection procedure was applied to the resulting maps from both studies analyzed.

The maps were then superimposed, and the intersection of results was achieved using a unique identifier for each cell. An example of this procedure can be found in Figure 3, where a total of 7 grid cells represent the overlap of results.

The reason for comparing only the best sites is that the studies are looking for locations for a PV plant, so matching these is essential.

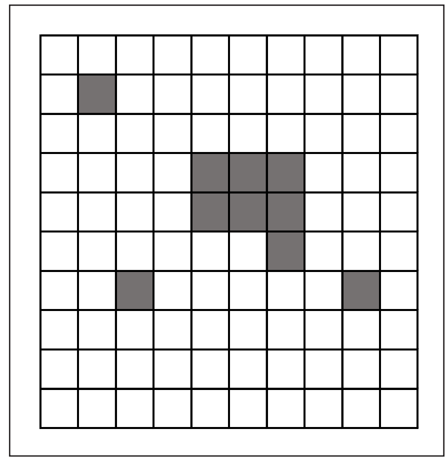

Figure 2. Example of the 10% best results on the grid cells

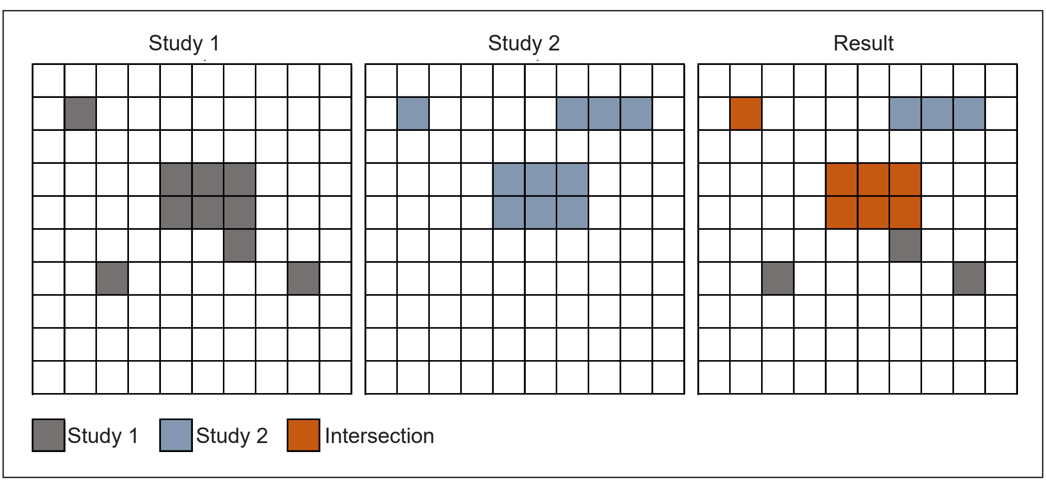

Figure 3. Intersection of the 10% best cells example

Study Analysis

It is worth mentioning that both papers used the same restriction zones, the same criteria, the same grid base, and the same sources or databases for the GIS layers. The main differences are the MCDM methods, the year the study was conducted, and the interviewing of specialists. In addition, the result of the studies, a suitability map, was merged into a grid base with 1 km of range, which means that they became cells in the form of squares with a length of 1 km.

Study 1

Study 01 (De Souza et al., 2019; De Souza et al., 2021b) was published in 2019 and then presented at a congress in 2021. The study took the following steps to identify the best sites for the PV plant in the state of Rio de Janeiro:

1. Several academic papers were reviewed to define the criteria for the plant's location.
2. The papers in which the AHP method was used were selected to determine the weight of these criteria (the degree of importance).
3. The average weight of the selected criteria was calculated and then normalized so that the sum of all weights was one.
4. The restriction zones, i.e., the sites where the plant cannot be established, were determined.
5. The final GIS layer that weighted all factors were generated, thus showing the best sites for the PV plant.

The selected criteria and the respective degree of importance are the following: Solar irradiation (42.42%), average temperature (11.34%), distance to transmission lines (9.12%), distance to transport links (5.33%), distance to urban centers (5.68%), slope (13.69%), azimuth (8.50%) and land use (3.92%).

The coverage level in each grid cell weighted the degree of importance of the criteria. Then, the fuzzy membership functions determined the degree of suitability to produce the map of the most suitable sites for PV plants (Figure 4).

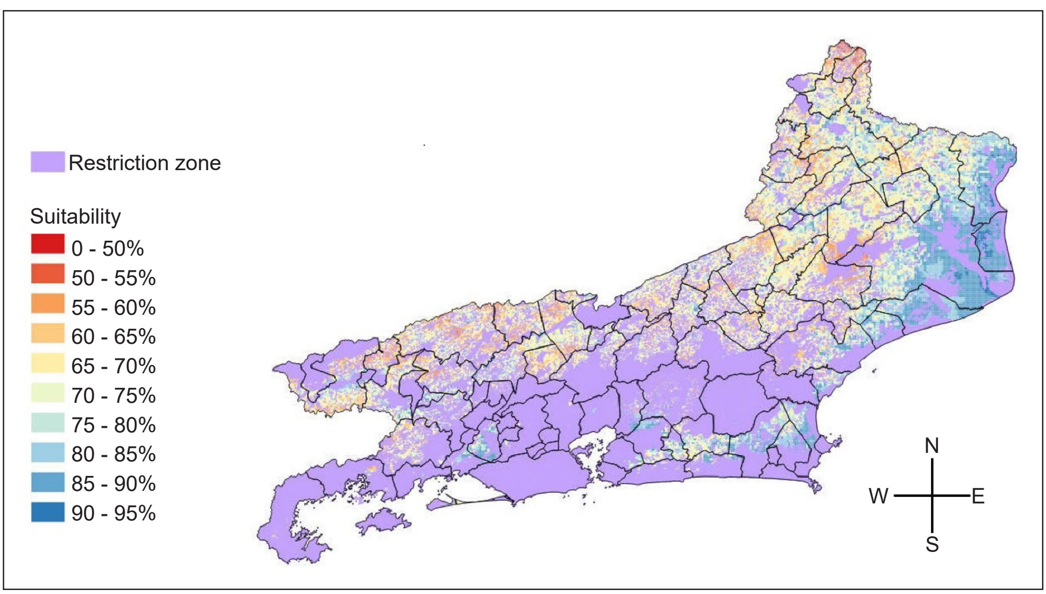

Figure 4. Suitability map—Study 01

Study 2

The Study 02 (De Souza et al., 2019; De Souza et al., 2021a; De Souza et al., 2021c) was published and presented at a congress in 2021. The study used the method COPPE-COSENZA and took the following steps to identify the best sites for the PV plant in the state of Rio de Janeiro:

1. Twenty academic papers were reviewed to determine the criteria for the plant's location.
2. The degree of importance of the selected criteria was determined through questionnaires completed by 14 specialists using the Google Forms tool. They were asked to rank the importance of the criteria as "critical," "conditional," "non-restrictive," or "irrelevant."
3. The restriction zones, i.e., locations where the plant cannot be established, were determined.
4. The COPPE-COSENZA method was applied by combining the specialists' responses with the coverage level of selected criteria for each grid cell.
5. The final GIS layer, which weights all factors, was created, indicating the best sites for the PV plant.

The final GIS layer, which weights all factors, was created, indicating the best sites for the PV plant. Table 1 shows the ranking of the criteria according to the questionnaires used. Most specialists ranked solar irradiation as the most decisive criterion, but the others are also important, such as distance to transmission lines and slope. In contrast, the specialists ranked land use and distance from urban centers less important.

The weighting of the selected criteria that resulted from the interviews was compared with the degree of coverage in each grid cell. Then, the degree of suitability was determined using fuzzy membership functions to map the most suitable locations for the PV plant (Figure 5). In the COPPE-COSENZA method, when the proposed index is equal to or greater than one, all factors are offered at the level required for the project, which means that the region is suitable for the proposed project, in this case, a solar PV plant (Cosenza et al., 2015).

Table 1
Importance criteria

	Solar Irradiation	Average Temperature	Distance to Transmission Lines	Distance to Transport Links	Distance to Urban Centers	Slope	Azimuth	Land Use
Critical	10	2	6	3	1	5	2	0
Conditioning	3	3	7	4	1	3	5	5
Not Restrictive	1	8	0	5	7	4	5	5
Irrelevant	0	1	1	2	5	2	2	4

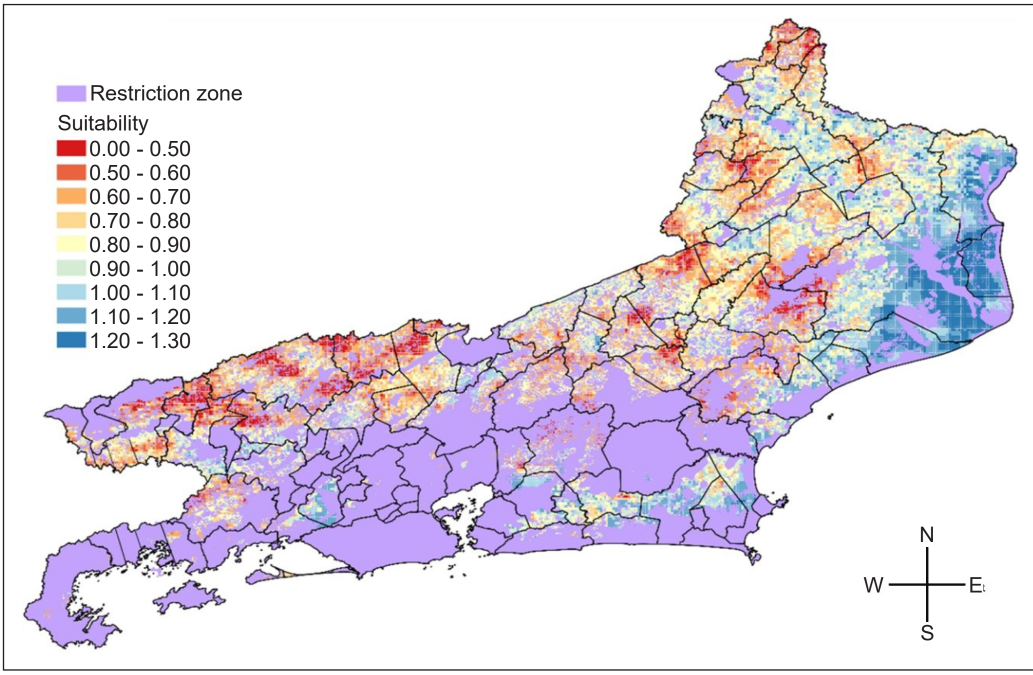

Figure 5. Suitability map—Study 02

RESULTS AND DISCUSSION

The results of the proposed approach are explained to compare two studies that identified the best sites for PV plants in Rio de Janeiro using different MCDA techniques (AHP and COPPE-COSENZA). The results were organized into two parts: the map analysis, in which the results of both studies were presented and compared through a map overlapping the results, and the second part is the calculation of the four similarity coefficients, namely Spearman, Weighted Spearman, WS, and Blest.

As previously mentioned, the maps resulting from both studies were first divided into 27,159 grid cells of 1 km^2 (1 km × 1 km), and each of these georeferenced cells was the basis for comparing the maps and applying the similarity coefficients.

Map Analysis

The first step was mapping analysis. Of the 27,159 base grid cells generated, 2,716 (10%) of the cells that presented the best results for suitable sites for PV plants were selected for comparison for each study. It means that 2,716 cells that presented the best results from Study 1 (De Souza et al., 2019) were selected, and the same was done for Study 2 (De Souza et al., 2021a), as shown in Figure 6.

Visually, both maps have a high degree of similarity, but it is important to know how similar they are. Analysis of the maps shows that of these 2,716 cells, there is an intersection of 2,242 cells, i.e., an 83% similarity between the results of the AHP (de Souza et al., 2019) and COPPE-COSENZA (De Souza et al., 2021a) methods. This result shows a high level of agreement between the studies in terms of the most suitable sites alone. Analysis of the results presented in Figure 7, which is an overlap map of the two results, shows that most of the intersections of the data are located near the state's northern coast.

The region where the best results were obtained has excellent solar irradiation—the best in Rio de Janeiro—is flat and has good infrastructure for electricity transmission and roads. Based on the studies evaluated, solar irradiation is probably the most important factor in determining the best locations for PV plants. On the other hand, the central region has a mountainous landscape and low solar irradiation, so there were no suitable sites in this area.

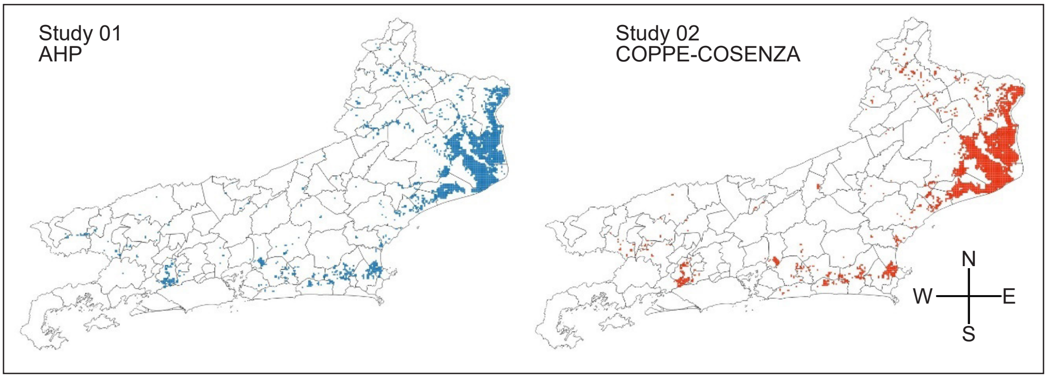

Figure 6. 10% of the best sites of both studies

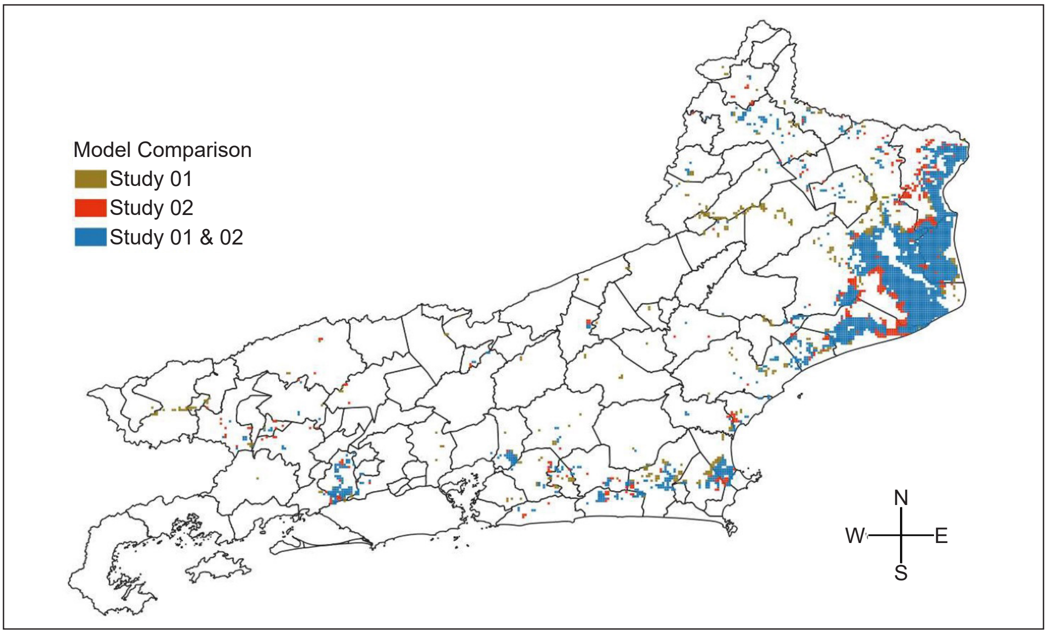

Figure 7. Comparison of the maps for Rio de Janeiro

Similarity Coefficients

In this step, several correlation coefficients were applied using the 27,159 grid cells, that is, all cells. The Spearman Correlation Coefficient (r_s) is 0.9036, indicating a very strong correlation between the results of the studies (Asuero et al., 2006; Schober et al., 2018). Due to the large number of samples, the resulting p-value was zero. The WS Coefficient is 0.9577, indicating a very strong correlation, especially for the best sites for the PV plant (Sałabun & Urbaniak, 2020). The Spearman Weighted Correlation Coefficient (r_w) value is 0.9118, indicating a very strong correlation. The Blest Correlation Coefficient (V_n) is also 0.9264, a very strong correlation. Thus, all the similarity coefficients showed a very high degree of correlation above 0.9. Table 2 shows the value for each of the coefficients.

By comparing the maps and applying the similarity coefficients, the results of the two studies, each using different analytical approaches, show a consistent result. While the Multi-Criteria Decision-Making technique requires the expertise of specialists to determine the results, the similarity coefficients, as nonparametric indices, do not require prior assumptions. It led to a comprehensive evaluation of the results and allowed for a solid and unbiased evaluation.

Table 2
The similarity coefficients results

Coefficient	Value
Spearman Correlation Coefficient	0.9036
WS Coefficient	0.9577
Spearman Weighted Correlation Coefficient	0.9118
Blest Correlation Coefficient	0.9264

CONCLUSION

Environmental issues are becoming increasingly important worldwide, and global warming is central to these concerns. In this scenario, solar energy emerges as an environmentally friendly alternative that has become financially competitive with traditional generation sources (fossil fuels, hydropower, and nuclear).

The generation of photovoltaic energy in Brazil, including the state of Rio de Janeiro, still occupies a small percentage of the energy matrix. However, all the basic requirements for operation on a larger scale have been met. Several studies use different MCDM methods to search for the optimal siting of PV plants in a variety of countries using different MCDM methods, and each of these methods has its peculiarities that can affect the result.

Although there are many studies on finding better sites, few compare the site selection results for renewable energy projects. Therefore, the objective of this study was to compare the results of two studies that identified the most suitable sites for a PV plant in Rio de Janeiro. This comparison was carried out in two ways: by map analysis and by applying different correlation coefficients. It is worth noting that in the reviewed papers, the MCDM results are usually compared using only one of the following options: Tables, one or two correlation coefficients, and graphs.

The map comparison showed a high similarity of results; 83% of the best sites were identical in studies 01 and 02. It is relevant because the intersections of this study show great potential for PV plants as different methods validated them. The four coefficients used had a very high degree of correlation, with all of them above 0.9. Thus, the consistency of all the ranks also validates the results of both studies since they gave similar results, although they were tested in different ways. Therefore, the consistency of the results of the analyzed studies indicates the potential for installing photovoltaic solar power plants in Rio de Janeiro and validates the methods used and the results themselves.

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REFERENCES

Abdel-Basset, M., Gamal, A., & ELkomy, O. M. (2021). Hybrid multi-criteria decision making approach for the evaluation of sustainable photovoltaic farms locations. *Journal of Cleaner Production, 328*(July), Article 129526. https://doi.org/10.1016/j.jclepro.2021.129526

Al-Shamisi, M. H., Assi, A. H., & Hejase, H. A. N. (2013). Artificial neural networks for predicting global solar radiation in Al Ain City - UAE. *International Journal of Green Energy, 10*(5), 443-456. https://doi.org/10.1080/15435075.2011.641187

Al Garni, H. Z., & Awasthi, A. (2017). Solar PV power plant site selection using a GIS-AHP based approach with application in Saudi Arabia. *Applied Energy, 206*, 1225-1240. https://doi.org/10.1016/j.apenergy.2017.10.024

Allen, M. R., Pauline Dube, O., Solecki, W., Aragón-Durand, F., Cramer France, W., Humphreys, S., Dasgupta, P., Millar, R., Dube, O., Solecki, W., Aragón-Durand, F., Cramer, W., Humphreys, S., Kainuma, M., Kala, J., Mahowald, N., Mulugetta, Y., Perez, R., Wairiu, M., … & Waterfield, T. (2018). *Special Report: Global warming of 1.5 °C*. The Intergovernmental Panel on Climate Change. https://www.ipcc.ch/sr15/

Aly, A., Jensen, S. S., & Pedersen, A. B. (2017). Solar power potential of Tanzania: Identifying CSP and PV hot spots through a GIS multicriteria decision making analysis. *Renewable Energy, 113*, 159-175. https://doi.org/10.1016/J.RENENE.2017.05.077

Asuero, A. G., Sayago, A., & González, A. G. (2006). The correlation coefficient: An overview. *Critical Reviews in Analytical Chemistry, 36*(1), 41-59. https://doi.org/10.1080/10408340500526766

Bandyopadhyay, S. (2016). Ranking of suppliers with MCDA technique and probabilistic criteria. In *2016 International Conference on Data Science and Engineering (ICDSE)* (pp. 1-5). IEEE Publication. https://doi.org/10.1109/ICDSE.2016.7823948

Bishop, M. P., & Giardino, J. R. (2021). Technology-driven geomorphology: introduction and overview. *Treatise on Geomorphology, 1*, 1-17. https://doi.org/10.1016/B978-0-12-818234-5.00171-1

Blest, D. C. (2000). Theory & methods: Rank correlation - An alternative measure. *Australian and New Zealand Journal of Statistics, 42*(1), 101-111. https://doi.org/10.1111/1467-842X.00110

Ceballos, B., Lamata, M. T., & Pelta, D. A. (2016). A comparative analysis of multi-criteria decision-making methods. *Progress in Artificial Intelligence, 5*, 315-322. https://doi.org/10.1007/s13748-016-0093-1

CEPERJ. (2019). *Fundação Estadual de Estatísticas, Pesquisas e Formação de Servidores do Estado do Rio de Janeiro*. [Foundation for Statistics, Research, and Training of Civil Servants of the State of Rio de Janeiro]. https://www.ceperj.rj.gov.br/wp-content/uploads/2021/07/PIB-ESTADUAL2018.pdf

CEPERJ. (2022a). *Histórico e Características | CEPERJ*. Fundação Estadual de Estatísticas, Pesquisas e Formação de Servidores Do Estado Do Rio de Janeiro [Foundation for Statistics, Research, and Training of Civil Servants of the State of Rio de Janeiro]. https://www.ceperj.rj.gov.br/?page_id=260

CEPERJ. (2022b). *Regiões | CEPERJ*. Fundação Estadual de Estatísticas, Pesquisas e Formação de Servidores Do Estado Do Rio de Janeiro [Foundation for Statistics, Research, and Training of Civil Servants of the State of Rio de Janeiro]. https://www.ceperj.rj.gov.br/?page_id=262

Cosenza, C. A. N., Doria, F. A., & Pessôa, L. A. M. (2015). Hierarchy models for the organization of economic spaces. *Procedia Computer Science, 55*, 82-91. https://doi.org/10.1016/j.procs.2015.07.010

Da Costa, J. P., & Soares, C. (2005). A weighted rank measure of correlation. *Australian and New Zealand Journal of Statistics, 47*(4), 515-529. https://doi.org/10.1111/j.1467-842X.2005.00413.x

Das, A. K., & Bhuyan, P. K. (2017). Hardcl method for defining LOS criteria of urban streets. *International Journal of Civil Engineering, 15*, 1077-1086. https://doi.org/10.1007/S40999-017-0207-6

de Souza, M. P., Moura, L. C. B., & Cosenza, C. A. N. (2019). Analysis to determine the most suitable location for a photovoltaic solar plant in the state of Rio De Janeiro, Brazil. *International Journal of Development Research*, *09*(11), Article 17462.

de Souza, M. P., Moura, L. C. B., Cosenza, C. A. N., Brasil, C. N. F., Cosenza, H. J. S. R., Amaral, S. de M., & Dias, S. M. P. (2021a). Analysis to determine the most suitable location for a photovoltaic solar plant using coppe-cosenza method: Case study Rio De Janeiro. *International Journal of Development Research, 11*(04), 46378-46382.

de Souza, M. P., Moura, L. C. B., & Cosenza, C. A. N. (2021b). Análise para a localização ótima de uma usina solar fotovoltaica no estado do Rio de Janeiro [Analysis for the optimal location of a photovoltaic solar plant in the state of Rio de Janeiro]. *Revista Brasileira de Energia, 27*(4), 8-37. https://doi.org/10.47168/rbe.v27i4.491

de Souza, M. P., Moura, L. C. B., Cosenza, C. A. N., Dias, S. M. P., & Barata, P. R. (2021c, October 18-21). Determinação da Localização de uma Usina Solar Fotovoltaica com o Auxílio de Método de Decisão Multicritério [Determination of the location of a solar photovoltaic plant with the aid of a multicriteria decision method]. In *Proceedings of the National Production Engineering Meeting - Enegep* (pp. 1-12). Paraná, Brazil. https://doi.org/10.14488/enegep2021_tn_sto_362_1872_41849

Doorga, J. R. S., Rughooputh, S. D. D. V., & Boojhawon, R. (2019). Multi-criteria GIS-based modelling technique for identifying potential solar farm sites: A case study in Mauritius. *Renewable Energy, 133*, 1201-1219. https://doi.org/10.1016/j.renene.2018.08.105

EGPEnergia, & PUC-Rio. (2016). *Atlas Rio Solar - Atlas Solarimétrico do Estado do Rio de Janeiro* [Rio Solar Atlas - Solimeric Atlas of the State of Rio de Janeiro].

EPE. (2020a). *Balanço energético nacional 2020* [National energy balance 2020]. Empresa de Pesquisa Energética. https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/balanco-energetico-nacional-2020

EPE. (2020b). Plano decenal de expanção de energia 2029 [Ten-year energy expansion plan 2029]. Empresa de Pesquisa Energética. https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/plano-decenal-de-expansao-de-energia-2029

EPE. (2016). *Estudos da demanda de energia: Demanda de energia 2050* [Energy Demand Studies: Energy Demand 2050]. https://www.epe.gov.br/sites-pt/publicacoes-dados-abertos/publicacoes/PublicacoesArquivos/publicacao-227/topico-458/DEA 13-15 Demanda de Energia 2050.pdf

Fagin, R., Kumar, R., & Sivakumar, D. (2003). Comparing top k lists. *Journal on Discrete Mathematics, 17*(1), 134-160. https://doi.org/10.1137/S0895480102412856

Figueira, J., Greco, S., & Ehrogott, M. (2005). *Multiple Criteria Decision Analysis: State of the Art Surveys*. Springer. https://doi.org/10.1007/b100605

Figueira, J. R., Mousseau, V., & Roy, B. (2016). ELECTRE methods. In S. Greco, M. Ehrgott & J. Figueira (Eds.), *Multiple Criteria Decision Analysis. International Series in Operations Research & Management Science* (Vol. 233; pp. 155-185). Springer. https://doi.org/10.1007/978-1-4939-3094-4_5

Giamalaki, M., & Tsoutsos, T. (2019). Sustainable siting of solar power installations in the Mediterranean using a GIS/AHP approach. *Renewable Energy, 141*, 64-75. https://doi.org/10.1016/j.renene.2019.03.100

Guitouni, A., & Martel, J. M. (1998). Tentative guidelines to help choosing an appropriate MCDA method. *European Journal of Operational Research, 109*(2), 501-521. https://doi.org/10.1016/S0377-2217(98)00073-3

IBGE. (2022). *Cidades e Estados* [Cities and States]. *IBGE*. https://www.ibge.gov.br/cidades-e-estados/rj.html

IRENA. (2020). *Renewable Power Generation Costs in 2019 - Key Findings.* International Renewable Energy Agency. https://www.irena.org/publications/2020/Jun/Renewable-Power-Costs-in-2019

Ishizaka, A., & Siraj, S. (2018). Are multi-criteria decision-making tools useful? An experimental comparative study of three methods. *European Journal of Operational Research, 264*(2), 462-471. https://doi.org/10.1016/j.ejor.2017.05.041

Ivlev, I., Jablonsky, J., & Kneppo, P. (2016). Multiple-criteria comparative analysis of magnetic resonance imaging systems. *International Journal of Medical Engineering and Informatics, 8*(2), 124-141. https://doi.org/10.1504/IJMEI.2016.075757

Jain, A., Mehta, R., & Mittal, S. K. (2011). Modeling impact of solar radiation on site selection for solar pv power plants in India. *International Journal of Green Energy, 8*(4), 486-498. https://doi.org/10.1080/15435075.2011.576293

Janke, J. R. (2010). Multi-criteria GIS modeling of wind and solar farms in Colorado. *Renewable Energy, 35*(10), 2228-2234. https://doi.org/10.1016/j.renene.2010.03.014

Kizielewicz, B., Wątróbski, J., & Sałabun, W. (2020). Identification of relevant criteria set in the MCDA process - Wind farm location case study. *Energies, 13*(24), Article 6548. https://doi.org/10.3390/en13246548

Kolios, A., Mytilinou, V., Lozano-Minguez, E., & Salonitis, K. (2016). A comparative study of multiple-criteria decision-making methods under stochastic inputs. *Energies, 9*(7), 1-21. https://doi.org/10.3390/en9070566

Kwak, Y., Deal, B., & Heavisides, T. (2021). A large scale multi-criteria suitability analysis for identifying solar development potential: A decision support approach for the state of Illinois, USA. *Renewable Energy, 177*, 554-567. https://doi.org/10.1016/j.renene.2021.05.165

La Camera, F. (2020). *Renewable Power Generation Costs in 2019*. International Renewable Energy Agency. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2018/Jan/IRENA_2017_Power_Costs_2018.pdf

Manson, S., Matson, L., Kernik, M., DeLuca, E., Bonsal, D., & Nelson, S. (2017). *Mapping, Society, and Technology*. Libraries Publishing.

Mulliner, E., Malys, N., & Maliene, V. (2016). Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. *Omega, 59*(Part B), 146-156. https://doi.org/10.1016/j.omega.2015.05.013

Ohunakin, O. S., & Saracoglu, B. O. (2018). A comparative study of selected multi-criteria decision-making methodologies for location selection of very large concentrated solar power plants in Nigeria. *African Journal of Science, Technology, Innovation and Development, 10*(5), 551-567. https://doi.org/10.1080/20421338.2018.1495305

Palmer, D., Gottschalg, R., & Betts, T. (2019). The future scope of large-scale solar in the UK: Site suitability and target analysis. *Renewable Energy, 133*, 1136-1146. https://doi.org/10.1016/j.renene.2018.08.109

Paramasivam, C. R., & Venkatramanan, S. (2019). Chapter 3 - An introduction to various spatial analysis techniques. In *GIS and Geostatistical Techniques for Groundwater Science* (pp. 23-30). Elsevier. https://doi.org/10.1016/B978-0-12-815413-7.00003-1

Pereira, E. B., Martins, F. R., Gonçalves, A. R., Costa, R. S., Lima, F. J. L. de, Rüther, R., Abreu, S. L. de, Tiepolo, G. M., Pereira, S. V., & Souza, J. G. de. (2017). *Atlas Brasileiro Energia Solar 2ª Edição* [Brazilian Solar Energy Atlas 2nd Edition]. Instituto Nacional de Pesquisas Espaciais.

Qiu, T., Wang, L., Lu, Y., Zhang, M., Qin, W., Wang, S., & Wang, L. (2022). Potential assessment of photovoltaic power generation in China. *Renewable and Sustainable Energy Reviews, 154*, Article 111900. https://doi.org/10.1016/j.rser.2021.111900

Ramedani, Z., Omid, M., & Keyhani, A. (2013). Modeling solar energy potential in a Tehran province using artificial neural networks. *International Journal of Green Energy, 10*(4), 427-441. https://doi.org/10.1080/15435075.2011.647172

Razykov, T. M., Ferekides, C. S., Morel, D., Stefanakos, E., Ullal, H. S., & Upadhyaya, H. M. (2011). Solar photovoltaic electricity: Current status and future prospects. *Solar Energy, 85*(8), 1580-1608. https://doi.org/10.1016/j.solener.2010.12.002

Ribeiro, M. A., & Nunes, N. da S. (2019). *Geografia do Estado do Rio de Janeiro* [Geography of the State of Rio de Janeiro]. CECIERJ. https://canal.cecierj.edu.br/022020/6a6bfdba31d1653c8e1cb37b757a531a.pdf

Rios, R., & Duarte, S. (2021). Selection of ideal sites for the development of large-scale solar photovoltaic projects through analytical hierarchical process – Geographic information systems (AHP-GIS) in Peru. *Renewable and Sustainable Energy Reviews, 149*, Article 111310. https://doi.org/10.1016/j.rser.2021.111310

Rodgers, J. L., & Nicewander, W. A. (1988). Thirteen ways to look at the correlation coefficient. *American Statistician, 42*(1), 59-66. https://doi.org/10.1080/00031305.1988.10475524

Roy, B. (2016). Paradigms and challenges. In S. Greco, M. Ehrgott & J. Figueira (Eds.), *Multiple Criteria Decision Analysis* (pp 19-39). Springer. https://doi.org/10.1007/978-1-4939-3094-4_2

Sałabun, W., & Piegat, A. (2017). Comparative analysis of MCDM methods for the assessment of mortality in patients with acute coronary syndrome. *Artificial Intelligence Review, 48*, 557-571. https://doi.org/10.1007/s10462-016-9511-9

Sałabun, W., & Urbaniak, K. (2020). A new coefficient of rankings similarity in decision-making problems. In V. Krzhizhanovskaya, G. Závodszky, M. H. Lees, J. J. Dongarra, P. M. A. Sloot, S. Brissos & J. Teixeira (Eds.), *Computational Science - ICCS 2020. ICCS 2020. Lecture Notes in Computer Science* (pp. 632-645). Springer. https://doi.org/10.1007/978-3-030-50417-5_47

Sałabun, W., Watróbski, J., & Shekhovtsov, A. (2020). Are MCDA methods benchmarkable? A comparative study of TOPSIS, VIKOR, COPRAS, and PROMETHEE II methods. *Symmetry, 12*(9), Article 1549. https://doi.org/10.3390/SYM12091549

San Cristóbal, J. R. (2011). Multi-criteria decision-making in the selection of a renewable energy project in Spain: The Vikor method. *Renewable Energy, 36*(2), 498-502. https://doi.org/10.1016/j.renene.2010.07.031

Sánchez-Lozano, J. M., García-Cascales, M. S., & Lamata, M. T. (2016a). Comparative TOPSIS-ELECTRE TRI methods for optimal sites for photovoltaic solar farms. Case study in Spain. *Journal of Cleaner Production, 127*, 387-398. https://doi.org/10.1016/j.jclepro.2016.04.005

Sánchez-Lozano, J. M., García-Cascales, M. S., & Lamata, M. T. (2016b). Comparative TOPSIS-ELECTRE TRI methods for optimal sites for photovoltaic solar farms. Case study in Spain. *Journal of Cleaner Production, 127*, 387-398. https://doi.org/10.1016/j.jclepro.2016.04.005

Schober, P., & Schwarte, L. A. (2018). Correlation coefficients: Appropriate use and interpretation. *Anesthesia and Analgesia, 126*(5), 1763-1768. https://doi.org/10.1213/ANE.0000000000002864

Scott, L. M. (2015). Spatial pattern, analysis of. In J. D. Wright (Ed), *International Encyclopedia of the Social & Behavioral Sciences: Second Edition* (Vol. 22). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.72064-2

Shao, M., Han, Z., Sun, J., Xiao, C., Zhang, S., & Zhao, Y. (2020). A review of multi-criteria decision-making applications for renewable energy site selection. *Renewable Energy, 157*, 377-403. https://doi.org/10.1016/j.renene.2020.04.137

Shekhovtsov, A., & Kolodziejczyk, J. (2020). Do distance-based multi-criteria decision analysis methods create similar rankings? *Procedia Computer Science, 176*, 3718-3729. https://doi.org/10.1016/j.procs.2020.09.015

Shieh, G. S. (1998). A weighted Kendall's tau statistic. *Statistics and Probability Letters, 39*(1), 17-24. https://doi.org/10.1016/s0167-7152(98)00006-6

Shorabeh, S. N., Firozjaei, M. K., Nematollahi, O., Firozjaei, H. K., & Jelokhani-Niaraki, M. (2019). A risk-based multi-criteria spatial decision analysis for solar power plant site selection in different climates: A case study in Iran. *Renewable Energy, 143*, 958-973. https://doi.org/10.1016/j.renene.2019.05.063

Sindhu, S., Nehra, V., & Luthra, S. (2017). Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India. *Renewable and Sustainable Energy Reviews, 73*, 496-511. https://doi.org/10.1016/j.rser.2017.01.135

Taylor, R. (1990). Interpretation of the correlation coefficient: A basic review. *Journal of Diagnostic Medical Sonography, 6*(1), 35-39. https://doi.org/10.1177/875647939000600106

Thirugnanasambandam, M., Iniyan, S., & Goic, R. (2010). A review of solar thermal technologies. *Renewable and Sustainable Energy Reviews, 14*(1), 312-322. https://doi.org/10.1016/J.RSER.2009.07.014

Uyan, M. (2013). GIS-based solar farms site selection using analytic hierarchy process (AHP) in Karapinar region Konya/Turkey. *Renewable and Sustainable Energy Reviews, 28*, 11-17. https://doi.org/10.1016/j.rser.2013.07.042

Van Haaren, R., & Fthenakis, V. (2011). GIS-based wind farm site selection using spatial multi-criteria analysis (SMCA): Evaluating the case for New York State. *Renewable and Sustainable Energy Reviews, 15*(7), 3332-3340. https://doi.org/10.1016/J.RSER.2011.04.010

Villacreses, G., Gaona, G., Martínez-Gómez, J., & Jijón, D. J. (2017). Wind farms suitability location using geographical information system (GIS), based on multi-criteria decision making (MCDM) methods: The case of continental Ecuador. *Renewable Energy, 109*, 275-286. https://doi.org/10.1016/j.renene.2017.03.041

Visser, H., & De Nijs, T. (2006). The map comparison kit. *Environmental Modelling and Software, 21*(3), 346-358. https://doi.org/10.1016/j.envsoft.2004.11.013

Wang, H., Pan, Y., & Luo, X. (2019). Integration of BIM and GIS in sustainable built environment: A review and bibliometric analysis. *Automation in Construction, 103*, 41-52. https://doi.org/10.1016/J.AUTCON.2019.03.005

Yushchenko, A., de Bono, A., Chatenoux, B., Patel, M. K., & Ray, N. (2018). GIS-based assessment of photovoltaic (PV) and concentrated solar power (CSP) generation potential in West Africa. *Renewable and Sustainable Energy Reviews, 81*(Part 2), 2088-2103. https://doi.org/10.1016/j.rser.2017.06.021

Zanakis, S. H., Solomon, A., Wishart, N., & Dublish, S. (1998). Multi-attribute decision making: A simulation comparison of select methods. *European Journal of Operational Research, 107*(3), 507-529. https://doi.org/10.1016/S0377-2217(97)00147-1

Zar, J. H. (1972). Significance testing of the Spearman rank correlation coefficient. *Journal of the American Statistical Association, 67*(339), 578-580. https://doi.org/10.1080/01621459.1972.10481251

Zar, J. H. (2005). Spearman rank correlation. In *Encyclopedia of Biostatistics*. Wiley. https://doi.org/10.1002/0470011815.B2A15150

Zoghi, M., Ehsani, A. H., Sadat, M., Amiri, M. J., & Karimi, S. (2017). Optimization solar site selection by fuzzy logic model and weighted linear combination method in arid and semi-arid region: A case study Isfahan-IRAN. *Renewable and Sustainable Energy Reviews, 68*(Part 2), 986-996. https://doi.org/10.1016/j.rser.2015.07.014