

Optimal Site Selection using Geographical Information System (GIS) Based Multicriteria Decision Analysis (MCDA): A case study to Concentrated Solar Power Plants (CSP) in Brazil

Seleção Ótima de Locais usando Análise de Decisão Multicritério (MCDA) Baseada em Sistema de Informação Geográfica (SIG): Estudo de caso para Usinas de Concentração de Energia Solar (CSP) no Brasil

Eduardo Chiarani^{1,2} , Alzir Felipe Buffara Antunes¹ , Danielle Drago^{1,2} ,
Ana Paula Oening² , Luís Alexandre Catussi Paschoalotto³ 

¹Universidade Federal do Paraná, Departamento de Geomática, Programa de Pós-Graduação em Ciências Geodésicas, Curitiba, PR, Brasil

²Instituto de Tecnologia Para o Desenvolvimento, Curitiba, PR, Brasil

³Companhia Energética de São Paulo, São Paulo, SP, Brasil

E-mails: eduardooc@gmail.com; felipe@ufpr.br; danielle.drago@lactec.com.br; ana.oening@lactec.com.br; luis.paschoalotto@cesp.com.br

Corresponding author: Eduardo Chiarani; eduardo.chiarani@gmail.com

Abstract

Optimal site selection using multi-criteria decision analysis (MCDA) is an important step to support decision makers to locate places that benefit the maximum potential of technology's preconditions. As a new, emerging and renewable technology in Brazil, concentrated solar power (CSP) plays an important role in power generation mix, and it's crucial to indicate the viability of Brazilian regions to CSP power plants. To achieve this goal, a detailed workflow of multi-criteria analysis based on geographic information system (GIS based AHP) is set in free software, in which criteria are selected from literature, acquired as geospatial data, weighted with parity matrices through online questionnaires filled by experts, processed on QGIS with weighted linear combination (WLC), and the results validated by its AHP consistency, thematic accuracy and comparative analysis with VIKOR and TOPSIS methodologies. As a product, sites are mapped according to viability indices, with higher values in most of Northeast, Central-west and Southeast regions of Brazil, showing good stability by its validation. Thereby, the workflow with free software allows the methodology to be replicated to support decision makers in locating viable and restrictive places for technologies.

Keywords: Analytic Hierarchy Process (AHP); Map algebra; Geospatial data

Resumo

A seleção ótima de locais usando análise de decisão multicritério (MCDA) é uma etapa importante para apoiar a tomada de decisão na localização de regiões que beneficiam o máximo potencial de pré-condições de uma tecnologia. Como uma tecnologia nova, emergente e renovável no Brasil, a energia solar concentrada (CSP) desempenha um papel essencial à diversificação da geração de energia, sendo crucial indicar a viabilidade das regiões brasileiras para usinas CSP. Para alcançar este objetivo, um fluxo de trabalho detalhado de análise multicritério com base em sistema de informação geográfica (MCDA baseado em SIG) é aplicado em software gratuito, no qual critérios são selecionados na literatura, adquiridos como dados geoespaciais, ponderados com matrizes de paridade através de questionários online preenchidos por especialistas, processados no QGIS com combinação linear ponderada (WLC) e os resultados validados por consistência AHP, acurácia temática e análise comparativa com as metodologia VIKOR e TOPSIS. Como resultado, os locais são mapeados de acordo com os índices de viabilidade, com maiores valores em parte das regiões Nordeste, Centro-Oeste e Sudeste do Brasil, mostrando estabilidade através da validação. Desse modo, o fluxo de trabalho com software gratuito permite que a metodologia seja replicada para apoiar os tomadores de decisão na localização de locais viáveis e restritivos para tecnologias.

Palavras-chave: Processo de análise hierárquica (AHP); Álgebra de mapas; Dados geoespaciais



1 Introduction

Renewable energy sources are the main composition of the Brazilian electricity matrix. According to Brazilian Electricity Regulatory Agency (ANEEL 2019), in the first quarter of 2019, it accounted for 87% of total production, while the remaining 13% were generated by fossil fuels. Despite the favorable rate, about 80% is concentrated in hydraulic sources. This dependency related to extreme climatic phenomena, such as drought, requires energy compensation by fossil fuels, pollutants and often more expensive (Souza & Cavalcante 2017).

An alternative is diversifying Brazil generation matrix with emerging technologies as concentrated solar power (CSP). Brazil registers normal direct solar irradiation (DNI) values above the minimum necessary for effective performance of CSP technologies (Souza & Cavalcante 2017). CSP by Cylinder-parabolic collectors (CCP) produces electrical energy by the concentration of solar energy in a thermodynamic cycle composed by three subsystems: solar field, thermal storage and power pack (Pereira et al. 2014).

The first steps of planning CSP plants is locating viable sites to construct and operate it, in which the viability can be determined by decision-making analysis of multiple criteria based on geographic attributes (Pereira et al. 2014). There are several methods of multi-criteria decision-analysis (MCDA), but not all of them integrate geospatial data and a large set of alternatives. TOPSIS and VIKOR are two well-know methods that use normalization and aggregation functions representing alternatives closeness to the ideal solution (Opricovic & Tzeng 2004). But, due to their aggregation function that treats each alternative at a time, it's applied to a small set of alternatives compared to GIS based analysis. GIS based MCDA uses geographic information

systems (GIS) to work with large areas represented by geospatial data (Greene et al. 2011; Malczewski 2006).

One of the first studies to locate sites to solar power plants using GIS based MCDA was to North Africa (Broesamle et al. 2001), in which regions were ranked by its estimation cost to construct the technology. Two criteria, DNI and slope, were selected with equal weights and classified with equal intervals by discretization. Fluri (2009) also analyzed the potential of solar power with 4 criteria, its geospatial data were classified in equal intervals with binarization and discretization, overlaying the maps with weighted linear combination – WLC. In these papers, discrete and continuous data were treated with discretization that breaks the transition zones between its distributions, which leads to misinterpretation of the data. A solution was applying normalization, in which transition zones were represented with normalized values (Clifton & Boruff 2010; Effat 2016). However, normalization creates an inconsistency due to the difference in the amplitude values of each criterion. Azevêdo, Candeias and Tiba (2017) and Mokarram et al. (2020) added an amplitude threshold to continuous data before normalizing it, controlling the intervals of the data and reducing inconsistencies. The threshold values were selected through literature and experts. Weights were obtained with AHP with processes in proprietary software. Table 1 brings characteristics of cited papers.

The mentioned studies used similar weighting, ranking and validating MCDA methodologies, although, to our knowledge, there isn't a clear sequence of methods to apply GIS based MCDA with open source software. Because of this, the aim of this paper is to describe a detailed workflow with open source software of GIS based MCDA to locate viable sites to CSP plants in Brazil, validate and compare its results to another methodology and allow its replication to other technologies.

Table 1 Contribution of the reviewed papers.

Source	Title	MCDA	Methods	Software
Broesamle et al. (2001)	Assessment of solar electricity potentials in North Africa [...]	WLC	Discretization + WLC	STEPS
Fluri (2009)	The potential of concentrating solar power in South Africa	WLC	Binarization + WLC	
Clifton and Boruff (2010)	Assessing the potential for concentrated solar power	WLC	Normalization + WLC	ArcGIS
Effat (2016)	Mapping Solar Energy Potential Zones	WLC-AHP	Normalization + WLC	ArcGIS
Azevêdo, Candeias and Tiba (2017)	Location Study Solar Thermal Power plant [...]	WLC-AHP	Amplitude threshold + Normalization + WLC	ArcGIS and Spring
Mokarram et al. (2020)	A novel optimal placing of solar farms utilizing multi-criteria decisionmaking (MCDA)	WLC-AHP, WLC-ANP	Amplitude threshold + Normalization + WLC	ArcGIS

2 GIS Based AHP Methodology

2.1 Criteria Definition and Geospatial Data Acquisition

Firstly, the decision problem or main goal of the study must be set and the most important preconditions that lead to it, documented. For each precondition interpreted as a criterion, a geospatial data is obtained and standardized to the same geodetic reference system (GRS) and map projection.

2.2 AHP Weighting Method

GIS based AHP is a hybrid methodology of decision analysis. So, the five steps of classic AHP are applied to weight the criteria and the last two steps to rank the data are replaced by GIS approaches.

The classic AHP consists in a paired comparison of criteria applied with different levels of hierarchy to select the best alternatives (Saaty 2004). AHP can be applied through few steps: A. Define the decision problem or main goal of the study; B. Structure the decision-making hierarchy, starting from the top with the main goal, following with the most important criteria to reach the goal and subsequent lower level criteria, down to the last level where the alternatives are set; C. Construct pairwise matrices for each criteria level; D. Set the importance criteria values with experts opinion or indicators following the Fundamental Scale of Absolute Numbers; E. Calculate criteria weights and the matrix consistency; F. Compare alternatives according to each criterion; G. Rank the alternatives according to the objective.

The pairwise matrices can be structured on spreadsheets, in which each criterion is represented by a cell composed by a pair of line and column (Table 2). The expert’s opinion to fill the matrices usually are got with questionnaires to simplify the comparison between criteria, in which each comparison ‘line by column’ is one question. For example, to the cell (C₁, C₂) in Table 2, is applied a question: ‘How much (criterion 1) is more important than (criterion 2) to the objective?’ the answer value must be based on the fundamental scale of Saaty. The same is done

Table 2 Criteria pairwise matrix.

	C ₁	C ₂	C ₃
C ₁	1	C ₁ , C ₂	C ₁ , C ₃
C ₂	1/(C ₁ , C ₂)	1	C ₂ , C ₃
C ₃	1/(C ₁ , C ₃)	1/(C ₂ , C ₃)	1

to all cells on the top diagonal of each matrix. The bottoms of the diagonals were mirrored to the inverse of these values and the diagonals were composed by 1.

Weights to each criterion are defined by the eigenvector of the matrix (Equation 1). To ensure the consistency of the matrix values, the Consistency Ratio (CR) is calculated with Consistency Index (CI) and Randomness Index (RI) (Equation 2, 3 and 4). RI is obtained of an external table (Saaty 2004), according to the number of criteria of the respective matrix.

$$\text{Eigenvector}_i = \sum_{j=1}^n (A_{ij} f \sum_{j=1}^n A_{ij}) f \quad (1)$$

$$\text{Eigenvector}_i = \sum_{j=1}^n (\text{Eigenvector}_i * \sum_{j=1}^n A_{ij}) \quad (2)$$

$$\text{CI} = \left(\left(\sum_{i=1}^n \text{Eigenvalue}_i f \right) - n \right) f (n-1) \quad (3)$$

$$\text{CR} = \text{CI} f \text{ RI} \quad (4)$$

The CR should result within the interval suggested by Saaty (2004) of 0.1, which means that the process is consistent as it presents a maximum of 10% of inconsistency.

2.3 WLC Ranking Method

The GIS approach combines geospatial data with cartographic modeling and algebraic operators to rank the data. One of the most known models is WLC. It is applied to data structured in raster, in which each pixel had a location attribute with geographic coordinates and a numerical value that represents the feature. Then, the values of the pixels are normalized, and a weight is assigned to each image. The images are combined by map algebra resulting in a viability model (Malczewski 2000).

In WLC, the geospatial data must be in raster structure or transformed to it. The process called Rasterisation transform a vector feature into a raster with pixels values determined by a feature attribute value (Malczewski 2000). The feature attribute value can be set by many methods, three are described below:

- A. Data attribute: Selecting single or multiples values from the data attribute table;
- B. Binarization: Analyzing if the feature occurs in the cell, if it is true the pixel value is set to 1, otherwise, false, it is set to 0;
- C. Proximity analysis: Binarization is applied as above, and after that, the distances from each pixel to pixels with value equal to 1 are calculated and a new value of the shortest distance is set to the pixel.

Interoperability between discrete and continuous data is ensured with normalization, which enables logical modeling from inaccurate data. However, it can mask discrepant amplitudes of data, as observed in previous studies. So, a threshold must be applied to the data

$$\text{Model}_i = \sum_i = 1^n (\text{Criterion}_i * \text{Global weight}_i) * (1 - \text{Restriction criterion}) \quad (5)$$

2.4 Methods Validation

In addition to the AHP consistency, other validating methods based on comparative analysis can be proposed. Thematic accuracy is a validation method that compares same pixel in two different datasets, checking the percentage of similarity (IBGE 2017). Comparing the results obtained with the workflow to well-known methodologies based on different approaches, analyzing the trends and differences obtained. For both methods, points must be randomly sampled from the map as alternatives, and its criteria values are used to check the similarity and to calculate the ranking index with the methodologies.

2.4.1. VIKOR and TOPSIS, MCDA Ranking Methods

Two well-known not GIS based approaches are VIKOR and TOPSIS. VIKOR (*VlaseKriterijumska Optimizacija I Kompromisno Resenje*) is a ranking method based on an aggregation of all criteria, the relative importance of the criteria, and a balance between total and individual satisfaction to determine the compromise solution. The aggregation function uses the proximity of the alternative to the ideal solution, in which the closer to the ideal solution, the better the alternative. The ranking index is a distance between two solutions distinguished by a weight applied to balance a majority decision by the decision makers or vetoes from a presence of conflicting criteria.

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is based on the distance from the ideal point and from the negative-ideal point. The method assumes that each criterion increases or decreases continuously until reaching its ideal and non-ideal value, maximum or minimum value of the criterion. Then, the Euclidean distance from the alternative criterion to both values are calculated. The best alternative must be next as possible of the ideal value and the worst alternative must be as far as possible. Finally, a similarity index between the best and the worst population distances are calculated, with values closest to 1 being ranked as the best alternatives (Opricovic & Tzeng 2004).

amplitude, with fixed minimum and maximum values, reducing unwanted weights, and subsequently normalization is applied.

After that, the standardized data representing the criteria is combined by WLC (Equation 5).

As it cannot be assumed that all criteria have the same importance, a weight can be applied to criteria in both methods. The main differences between them are the aggregation function as seen above and normalization function, where VIKOR uses linear normalization and TOPSIS uses vector normalization.

3 GIS Based MCDA Site Selection Framework: A case study of CSP in Brazil

In this work, GIS based AHP was applied to map Brazilian territory by its viability to the construction and operation of CSP by CCP technology. For that, preconditions were selected, classified as criteria (CR) and subcriteria (SC) and acquired as geospatial data. Then, criteria and subcriteria were weighted with AHP through parity matrices composed by online questionnaire created by the authors and applied to experts. Geospatial data treatment was done in open source software QGIS, in which the data was treated with diffuse logic and map algebra, resulting in a model of optimal site viability. Figure 1 describes the project workflow with stakeholders, MCDA, methods and tools applied.

3.1 Preconditions and Data Acquisition

In the definition of preconditions were analyzed 12 initial criteria, contemplating geographical, environmental and social attributes from a project of Brazilian Ministry of Science, Technology and Innovations (MCTI) with the German International Cooperation Agency (GIZ) (Pereira et al. 2014). From that, were chosen seven criteria composed by twenty three subcriteria based on characteristics of the Brazilian territory and the CSP technology, described on the first and second columns of Table 3. To each subcriteria were obtained a geospatial data and its metadata from reliable digital repositories and governmental data infrastructures, indicated in the third and fourth columns of Table 3.



Figure 1 GIS Based MCDA Site Selection Framework.

Table 3 Geospatial Data.

Criteria	Subcriteria	Source	Classification values and amplitude threshold	
C1 - Solar irradiation	C11 - DNI (annual average)	Solargis 2019	≤ 1785, 1785 – 6500 kWh/m ² /year	
C2 - Topography	C21 - Slope (DEM)	CGIAR 2020	0 – 20o, ≥ 20o	
C3 - Electricity infrastructure	C31 - Transmission lines;	EPE 2019	0 - 15 km, ≥ 15 km	
	C32 - Substation;	EPE 2019		
	C33 - Urban areas	IBGE 2018		
C4 - Water resources	C41 - Water availability	ANA 2013	1 (Available), 0 (Critical)	
C5 - Transport infrastructure	C51 - Highways;	DNIT 2019	0 – 15 km, ≥ 15 km	
	C52 - Railways;	MI 2017		
	C53 - Cargo airports;	INFRAERO 2010		
	C54 - Waterways.	MI 2017		
C6 - Land use	C61 - Open areas;	IBGE 2018	1, 2, 3, 4, 5	
	C62 - Pasture;			
	C63 - Agriculture;			
	C64 - Sparse vegetation;			
	C65 - Forest;			
C7 - Restrictions	Constructed area*;	Water*	Total restriction (viability reduced by 100%)	
	DNI threshold <1785 kWh/m ² /year;			Solargis 2019
	Conservation unit of integral protection;			MMA 2012
	Indigenous land;			FUNAI 2016
	Conservation unit of sustainable use;			MMA 2012
Quilombola;	INCRA 2018	Partial restriction (viability reduced by 30%)		
Rural settlement.				

3.2 Weighting Criteria with AHP

Parity matrices were made to subcriteria from criterion 3, 5 and 6 and between criteria. These were filled with experts opinions by questionnaires structured in a form template in free platform *Jotform*, available on <https://www.jotform.com/form-templates/questionario-ahp>. The form was organized in 5 pages: The first one contained an introduction to understand the methodology and instructions to fill the questions; the next four pages contained the four questionnaires with questions to the subcriteria and criteria. More than 34 forms were sent to experts, members of the project and externals. From these, 16 were selected based on its consistencies and according to the minimal forms suggested (Saaty 2004).

To fill the matrices were used the average of the answers of the 16 forms. To each parity matrix, the weights of the criteria or grouped subcriteria were calculated by the eigenvector of its corresponding line. The subcriteria global weight was obtained multiplying the grouped subcriteria weight by its respective criteria weight. The results are disposed on Table 4.

3.3 Ranking Alternatives with WLC and AHP

Firstly, geospatial data was projected to the geodetic reference system (GRS) SIRGAS 2000 and Polyconic map projection with central meridian at 54 degrees west. Data

in vector structure was transformed to raster structure with rasterisation. The pixel size was set to 180 meters to satisfy a scale map of approximately 1:1.000.000.

The pixel value was obtained according to the precondition to be represented, with three methods: A. Data attribute: The data processed were Solar Irradiation, Slope, Land Use and Water Availability. For example, to solar irradiation the pixel value was collected from the annual average attribute on its attribute table. While, land use attributes were assigned to numeric values from 1 to 5; B. Binarization: The data processed was the restrictive criteria; C. Binarization + proximity analysis: In this process the pixel was set to 1 or 0, as above, and calculated the distance from each pixel set with 1, with Manhattan equation (which defines the distance between two points as the sum of the absolute differences between their coordinates). The data processed were the proximity of transmission lines, substations, urban areas, highways, railways, waterways and cargo airports.

The interoperability between the data was ensured setting the amplitude threshold and normalizing them. Firstly, the amplitude threshold values were applied to the rasterized data, with values from Table 3 specified with experts through the project guidelines (Küster et al. 2021). After that, discrete and continuous data were normalized by linear normalization. The standardized data for each subcriterion are presented in Figure 2.

Table 4 Criteria and subcriteria calculated weights.

Criteria	Criteria weight (%)	Subcriteria	Grouped subcriteria weight (%)	Subcriteria global weight (gw) (%)
C1 - Solar irradiation	43.10	DNI	100	43.10
C2 - Topography	15.00	Slope	100	15.00
C3 - Proximity to electricity infrastructure	22.40	Transmission lines	37.9	8.49
		Substation	53.4	11.96
		Urban areas	8.6	1.93
C4 - Water resources	4.0	Water availability	100	4.00
		Highways	60.5	4.17
C5 - Proximity to transport infrastructure	6.90	Railways	12.6	0.87
		Cargo airports	6.3	0.43
		Waterways	20.6	1.42
		Open areas	46.8	4.02
C6 - Land use	8.60	Pasture	27.2	2.34
		Agricultural area	12.1	1.04
		Sparse vegetation	10.6	0.91
		Forest vegetation	3.3	0.28
C7 - Restrictions	n/a	8 subcriteria	n/a	n/a

The last step was combining the index from weight method with the ranking method (Equation 6). Each raster corresponding to a subcriterion (SC) was multiplied by its

global weight (gw) and combined, then multiplied to the restrictions raster reduced from one, resulting in a new raster, the viability model.

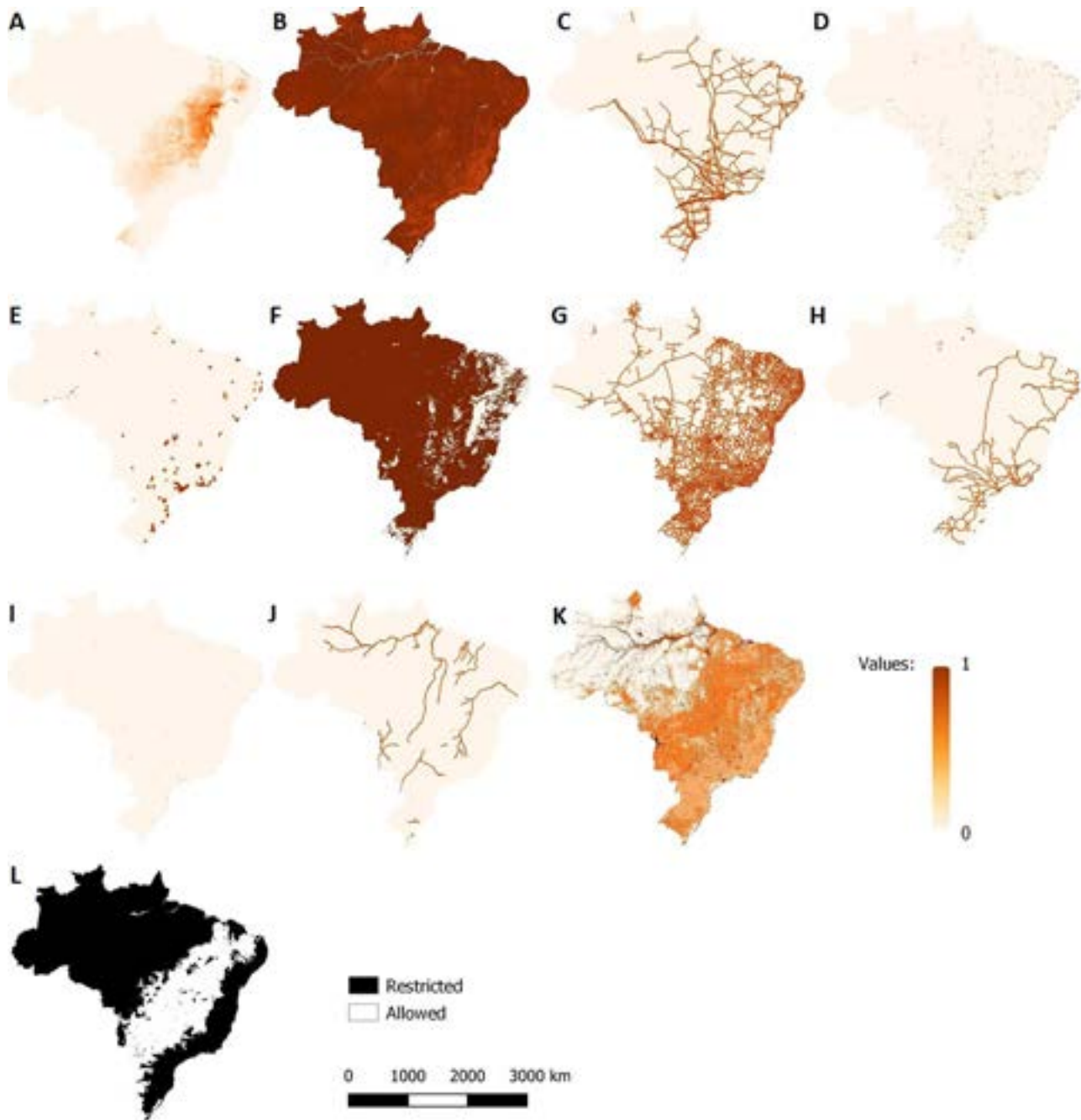


Figure 2 Standardized data: A. Direct solar irradiation; B. Topography; C. Proximity to transmission lines; D. Proximity to substations; E. Proximity to urban areas; F. Water resources; G. Proximity to highways; H. Proximity to Railways; I. Proximity to cargo airports; J. Proximity to waterways; K. Land use; L. Restrictions by environmental, traditional communities and DNI threshold.

Viability model =

$$\begin{aligned}
 & (\text{DNI} * 43.10 + \text{Slope} * 15.00 + \text{Proximity to transmission lines} * 8.49 + \text{Proximity to substation} * \\
 & 11.96 + \text{Proximity to urban areas} * 1.93 + \text{Water availability} * 4.00 + \text{Proximity to highways} * \\
 & 4.17 + \text{Proximity to railways} * 0.87 + \text{Proximity to cargo airports} * 0.43 + \text{Proximity to waterways} * \\
 & 1.42 + \text{Land use open areas} / 1 * 4.02 + \text{Land use pasture} / 2 * 2.34 + \text{Land use agricultural area} / 3 * \\
 & 1.04 + \text{Land use sparse vegetation} / 4 * 0.91 + \text{Land use forest vegetation} / 5 * 0.28) * \\
 & (1 - \text{Restrictions})
 \end{aligned}
 \tag{6}$$

3.4 Model Results and Validation

The result was a model with viability indices from 0 to 100%, restricted to ideal sites, to construct and operate CSP by CCP plants all over Brazil.

Figure 3 shows a large viability area to the technology mostly in Central-west, Southeast and Northeast of Brazil. Central-west and Southeast indices vary from 40% to 66%, while the Northeast brings the highest indices, reaching 70% in the state of Piauí (PI), and 80% in the state of Bahia (BA).

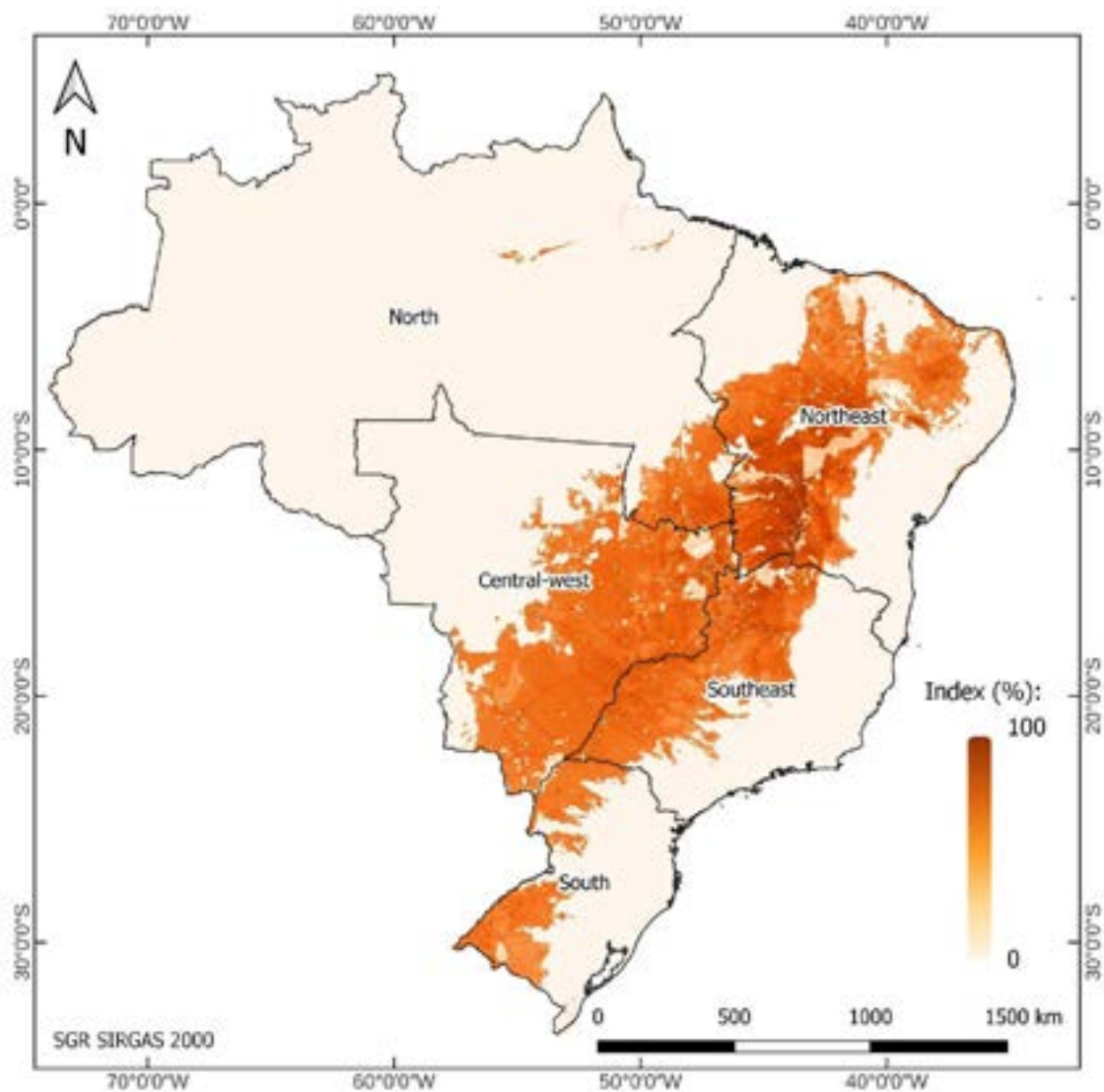


Figure 3 Viability to CSP power plants in Brazil.

3.4.1. Model Consistency

The AHP consistency index was calculated from the average of each parity matrix, resulting in values of Table 4, in which the highest one is equal to 0.10 meaning a general consistency of 90%, in agreement with Saaty's suggestion.

3.4.2. Thematic Accuracy of Standardized Data

Meanwhile, a validation of the data thematic accuracy was done pixel by pixel, comparing the standardized data index to another cartographic data external to the study (Table 5). Firstly, 80 areas with positive viability were randomly sampled and 20 manually in specific places. In each of the 100 areas, 5 items were sampled based on the 7 criteria (topography and water resources were not validated), resulting in 500 samples to compare with external data. Thereby, the validation obtained 96% of thematic accuracy.

3.4.3. Comparative Analysis of WLC, VIKOR and TOPSIS

In the comparative analysis were randomly sampled 10 points from the map as alternatives. Table 6 brings the alternatives indices and positions to the 3 methodologies.

For AHP+WLC and AHP+TOPSIS, the higher the index, the better, while for AHP+VIKOR, the lower the better. For ranking positions, all the methodologies follow the same tendency for first positions, with more similar results between AHP+CLP and AHP+VIKOR and some divergences compared to AHP+TOPSIS.

The results are directly related to the alternatives chosen due to the aggregation and normalization method, which are based on the amplitude of the values of the alternatives.

4 Conclusion

The methodology plays an important role as the first step in locating places to plants of CSP. The results showed that large regions in Brazil are viable to CSP plants. Still, more than 50% of the country's territories are not viable due to DNI indices below the experts suggested efficiency threshold of 1785 kWh/m²/year or because of environmental restrictions.

The workflow presented made clear how to apply the methodology. In AHP, the use of online questionnaires enabled the collaboration of experts from different regions of Brazil via internet. Yet, the high number of subcriteria in last questionnaire (seven) increased the accuracy needed in questionnaires consistency check, from 34 questionnaires applied, less than 20 accorded to the minimal consistency required. So, we advise sending questionnaires to twice as many as suggested by Saaty equation, or reducing the number of subcriteria in the same criteria hierarchy. Meanwhile, WLC method needs a well-defined workflow to standardize the data and reduce inconsistencies. Setting a threshold in amplitude of continuous data is necessary to avoid involuntary weights when normalizing multiple criteria. In addition, an expert opinion is crucial to set accurate threshold values.

Table 4 AHP consistency ratio of the questionnaires.

Matrices	Consistency ratio
1	0.01
2	0.08
3	0.07
4	0.1

Table 5 Compared data sets.

Project criteria data set	External data set
Direct normal irradiance (DNI)	Solar irradiation data (LABREN 2017)
Proximity to electricity infrastructure	Transmission lines and substations (SIGEL 2019)
Proximity to transport infrastructure	Open Street Map 2019
Land use	Bing satellite Images 2019
Environmental and traditional communities restrictions	Conservation units (IBGE 2019) and Bing satellite images 2019

Table 6 Indices and ranking results by WLC, VIKOR and TOPSIS.

Point	Index of			Ranking of		
	AHP+WLC	AHP+VIKOR	AHP+TOPSIS	AHP+WLC	AHP+VIKOR	AHP+TOPSIS
1	0.06	0.97	0.15	10	10	10
2	0.45	0.30	0.35	6	6	9
3	0.66	0.00	0.65	1	1	2
4	0.55	0.12	0.39	4	4	8
5	0.61	0.06	0.68	2	3	1
6	0.28	0.68	0.59	7	7	4
7	0.61	0.08	0.62	3	2	3
8	0.52	0.13	0.57	5	5	5
9	0.27	0.75	0.55	8	8	6
10	0.16	0.91	0.47	9	9	7

The consistency of the final model was validated with AHP consistency accuracy of 90%. Besides that, the comparative analysis with 2 different MCDM not GIS based (TOPSIS and VIKOR) showed a good stability to the methodology with similar results and trend as the model values. AHP+TOPSIS got different values comparing to AHP+WLC and AHP+VIKOR, probably due to their normalize function differences, respectively vector and linear normalization.

Another important point was the application of the methodology with free and open source software QGIS, increasing accessibility and community discussion.

Therefore, as proposed, the methodology applied in free and open source software is an efficient method of decision-making to locate viable sites to construct and operate CSP plants and to help turning technologies from alternatives into plausible choices.

5 Acknowledgments

This research was supported by LACTEC – Instituto de tecnologia para o desenvolvimento, in collaboration with CESP – Companhia Energética de São Paulo, as a stage of the Strategic Research and Development project n° 019/2015 (PD-00061-0050/2016) of ANEEL – Agência Nacional de Energia Elétrica.

6 References

ANA – Agência Nacional de Águas e Saneamento Básico 2013, *Disponibilidade hídrica superficial*, Catálogo de Metadados da ANA, viewed 20 May 2018, <http://metadados.ana.gov.br/geonetwork/srv/en/resources.get?id=307&fname=SNIRH_DisponibilidadeSuperficial.zip&access=private>.

ANEEL – Agência Nacional de Energia Elétrica 2019, *Boletim de informações gerenciais*, Ministério de Minas e Energia, viewed

2 January 2020, <<http://www.aneel.gov.br/informacoes-gerenciais>>.

Azevêdo, V.W.B., Candeias, A.L.B. & Tiba, C. 2017, 'Location study of solar thermal power plant in the state of Pernambuco using geoprocessing technologies and multiple-criteria analysis', *Energies*, vol. 10, no. 7, 1042, DOI:10.3390/en10071042.

Broesamle, H., Mannstein, H., Schillings, C. & Trieb, F. 2001, 'Assessment of solar electricity potentials in North Africa based on satellite data and a geographic information system', *Solar Energy*, vol. 70, no. 1, pp. 1–12, DOI:10.1016/S0038-092X(00)00126-2.

CGIAR 2020, *Shuttle Radar Topography Mission (SRTM) - version 4*, SRTM Data, viewed 20 May 2018, <<http://srtm.csi.cgiar.org/srtmdata/>>.

Clifton, J. & Boruff, B.J. 2010, 'Assessing the potential for concentrated solar power development in rural Australia', *Energy Policy*, vol. 38, no. 9, p. 5272–80, DOI:10.1016/j.enpol.2010.05.036.

DNIT – Departamento Nacional de Infraestrutura de Transportes 2019, *SNV – Rodovias*, DNIT Cloud, viewed 20 May 2020, <<https://servicos.dnit.gov.br/dnitcloud/index.php/s/oTpPRmYs5AAiNr>>.

Effat, H. 2016, 'Mapping solar energy potential zones, using SRTM and spatial analysis, application in Lake Nasser Region, Egypt', *International Journal of Sustainable Land Use and Urban Planning*, vol. 3, no. 1, pp. 1–14, DOI:10.24102/ijslup.v3i1.551.

EPE – Empresa de Pesquisa Energética 2019, *Geoportal - Linhas de transmissão e subestações*, Webmap EPE, viewed 19 March 2019, <<https://gisepeprd.epe.gov.br/webmapepe/>>.

Fluri, T.P. 2009, 'The potential of concentrating solar power in South Africa', *Energy Policy*, vol. 37, no. 12, pp. 5075–80, DOI:10.1016/j.enpol.2009.07.017.

FUNAI – Fundação Nacional do Índio 2016, *Reservas indígenas*, Ministério da Justiça e Segurança Pública, viewed 19 March 2019, <<http://www.funai.gov.br/index.php/shape>>.

Greene, R., Devillers, R., Luther, J.E. & Eddy, B.G. 2011, 'GIS-based multiple-criteria decision analysis', *Geography*

- Compass*, vol. 5, no. 6, pp. 412–32, DOI:10.1111/j.1749-8198.2011.00431.x.
- IBGE – Instituto Brasileiro de Geografia e Estatística 2017, *Manual técnico de Geociências: avaliação da qualidade dos dados geoespaciais*, IBGE, Rio de Janeiro, viewed 4 November 2019, <<https://biblioteca.ibge.gov.br/visualizacao/livros/liv101152.pdf>>.
- IBGE – Instituto Brasileiro de Geografia e Estatística 2018, *Monitoramento do uso e cobertura da terra*, IBGE, viewed 25 November 2019, <<https://www.ibge.gov.br/geociencias/informacoes-ambientais/15831-cobertura-e-uso-da-terra-do-brasil.html?=&t=downloads>>.
- IBGE – Instituto Brasileiro de Geografia e Estatística 2019, *Portal de geoserviços – unidades de conservação, tribos indígenas, quilombolas, assentamentos rurais*, IBGE, viewed 20 September 2019, <<http://www.geoservicos.ibge.gov.br:80/geoserver/ows?SERVICE=WMS&>>.
- INCRA – Instituto Nacional de Colonização e Reforma Agrária 2018, *Quilombolas e assentamentos rurais*, INCRA, viewed 25 November 2018, <<http://acervofundiario.incra.gov.br/i3geo/geodownload/geodados.php>>.
- INFRAERO – Empresa Brasileira de Infra-Estrutura Aeroportuária 2010, *Terminal de carga*, INFRAERO, viewed 19 November 2018, <<http://www.infraero.gov.br/infraerocargo/>>.
- Küster, K.K., Penteado Neto, R.A., Oening, A.P.O. & Paschoalotto, L.A.C. 2021, *Combustível solar: conceitos de geração termosolar e experiência de planta piloto no complexo de fontes renováveis da UHE Porto Primavera*, 1st edn, Grafo Estúdio, Curitiba.
- LABREN – Laboratório de Modelagem e Estudos de Recursos Renováveis de Energia 2017, *Dados do Atlas Solarimétrico de irradiação solar*, LABREN, viewed 20 November 2017, <http://labren.ccst.inpe.br/atlas_2017.html#>>.
- Malczewski, J. 2000, 'On the use of weighted linear combination method in GIS: common and best practice approaches', *Transactions in GIS*, vol. 4, no. 1, pp. 5–22, DOI:10.1111/1467-9671.00035.
- Malczewski, J. 2006, 'GIS-based multicriteria decision analysis: A survey of the literature', *International Journal of Geographical Information Science*, vol. 20, no. 7, pp. 703–26, DOI:10.1080/13658810600661508.
- MI – Ministério de Infraestrutura 2017, *Ferrovias e Hidrovias*, MI, viewed 19 November 2018, <<https://antigo.infraestrutura.gov.br/bit.html/>>.
- MMA 2012, *Unidades de conservação*, MMA, viewed 25 November 2018, <<http://mapas.mma.gov.br/i3geo/datadownload.htm#>>>.
- Mokarram, M., Mokarram, M.J., Gitizadeh, M., Niknam, T. & Aghaei, J. 2020, 'A novel optimal placing of solar farms utilizing multi-criteria decision-making (MCDA) and feature selection', *Journal of Cleaner Production*, vol. 261, 121098, DOI:10.1016/j.jclepro.2020.121098.
- Opricovic, S. & Tzeng, G.-H. 2004, 'The compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS', *European Journal of Operational Research*, vol. 156, no. 2, pp. 445–55, DOI:10.1016/S0377-2217(03)00020-1.
- Pereira, E.M.D., Charbel, A., Aroreir, I. & Mesquita, L.C.S. 2014, *Mapeamento básico das condições gerais para tecnologias heliotérmicas no Brasil*, Energia Heliotérmica, viewed 4 October 2019, <<http://energiaheliotermica.gov.br/pt-br/especialistas/brasil-desafio-infraestrutura/precondicoes-para-tecnologia-heliotermica-no-brasil>>.
- Saaty, T.L. 2004, 'Decision making – the Analytic Hierarchy and Network Processes (AHP/ANP)', *Journal of Systems Science and Systems Engineering*, vol. 13, no. 1, pp. 1-35, DOI:10.1007/s11518-006-0151-5.
- SIGEL – Sistema de Informações Geográficas do Setor Elétrico 2019, *Portal de Geoprocessamento da ANEEL*, SIGEL, viewed 20 September 2019, <<https://sigel.aneel.gov.br/arcgis/services/PORTAL/Transmissao/MapServer/WMSer>>.
- Solargis 2019, *The World Bank Group - Global Solar Atlas 2.0*, Global Solar Atlas, viewed 25 November 2018, <<https://globalsolaratlas.info/download/brazil>>.
- Souza, L.E.V. & Cavalcante, A.M.G. 2017, 'Concentrated solar power deployment in emerging economies: the cases of China and Brazil', *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 1094-103, DOI:10.1016/j.rser.2016.10.027.

Author contributions

Eduardo Chiarani: conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – original draft; writing – review and editing. **Alzir Felipe Buffara Antunes:** conceptualization; supervision. **Danielle Drago:** conceptualization; data curation; resources; supervision. **Ana Paula Oening:** project administration. **Luís Alexandre Catussi Paschoalotto:** project administration.

Conflict of interest

The authors declare no potential conflict of interest.

How to cite:

Chiarani, E., Antunes, A.F.B., Drago, D., Oening, A.P. & Paschoalotto, L.A.C. 2022, 'Optimal Site Selection using Geographical Information System (GIS) Based Multicriteria Decision Analysis (MCDA): A case study to Concentrated Solar Power Plants (CSP) in Brazil', *Anuário do Instituto de Geociências*, 46:48188. https://doi.org/10.11137/1982-3908_2023_46_48188

Data availability statement

All data included in this study are publicly available in the literature and cited in references. The resulting model, scripts and code are available on request.

Funding information

Not applicable.

Editor-in-chief

Dr. Claudine Dereczynski

Associate Editor

Dr. Martim Moulton