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A GIS-MCDA Approach Addressing Economic-Social-Environmental Concerns for Selecting the Most Suitable Compressed Air Energy Storage Reservoirs

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Abstract: This article presents an assessment of the most suitable compressed air energy storage (CAES) reservoirs and facilities to better integrate renewable energy into the electricity grid. The novelty of this study resides in selecting the best CAES reservoir sites through the application of a multi-criteria decision aid (MCDA) tool, specifically the simple additive weighting (SAW) method. Besides using geographic information systems (GIS) spatial representation of potential reservoir areas, for the MCDA method, several spatial criteria, environmental and social constraints, and positive incentives (e.g., the proximity to existing power generation facilities of renewable energy sources) were contemplated. As a result, sixty-two alternatives or potential reservoir sites were identified, and thirteen criteria (seven constraints and six incentives) were considered. The final stage of this study consisted of conducting a sensitivity analysis to determine the robustness of the solutions obtained and giving insights regarding each criterion's influence on the reservoir sites selected. The three best suitable reservoir sites obtained were the Monte Real salt dome, Sines Massif, and the Campina de Cima—Loulé salt mine. The results show that this GIS-MCDA methodological framework, integrating spatial and non-spatial information, proved to provide a multidimensional view of the potential reservoir CAES systems incorporating both constraints and incentives.

Keywords: compressed air energy storage; potential underground reservoirs; economic-social-environmental concerns; multi-criteria decision analysis; simple additive weighting; sensibility analysis

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1. Introduction

Portugal has one of the highest shares of renewable energy production within the European Union (EU), with more than half of the electricity consumed in 2019 coming from renewable energy sources (RES). RES was responsible for the production of 27.3 TWh, contributing to 56.10% of the electricity mix [1]. With the increasing use of intermittent RES and their integration into the national electricity system, challenges are being constantly brought into the grid, and solutions must mitigate intermittency and load variation. Energy storage (ES) is one of the most interesting options since it increases the flexibility of generating, delivering, and consuming electricity. In addition, ES provides the ability to balance power supply and demand, making power networks more resilient, efficient, and cleaner than before [2]. Portugal has pumped hydro energy storage (PHES) systems, but a large-scale ES system not dependent on weather conditions could add flexibility to the grid in dry years. Compressed air energy storage (CAES) is an alternative not dependent on weather or topography, having a relatively lower environmental impact than PHES [3]. CAES is a bulk storage technology with the ability to store tens to hundreds of MW of power capacity for long-term and utility-scale applications in underground caverns in the form of pressurized air. Apart from PHES, CAES is also one of the lowest-cost utility-scale storage technologies currently available [3,4].

This study was based on the potential geological sites for large-scale CAES in mainland Portugal obtained from the Energy Storage Mapping and Planning (ESTMAP) studies—an EU Horizon 2020 project—described in [5]. While this latter project focuses on the several possible underground ES technologies available for Europe, the present study explicitly addressed CAES in Portugal, including potential reservoirs not previously considered [5]. Moreover, the novelties of this study are threefold: it suggests the use of a multi-criteria decision aid (MCDA) method to select the best specific CAES sites available in Portugal; it establishes suitable case studies; and it carries out sensitivity analyses (SA) to evaluate the robustness of solutions selected as the best reservoir sites, also giving insights regarding the impacts of each criterion on the final decision reached.

According to Belton & Stewart [6], MCDA can be viewed as "formal approaches which seek to take explicit account of multiple criteria in helping individuals and groups explore decisions that matter." MCDA methods have been applied across a broad spectrum of disciplines [7] and are often used to deal with the difficulties that decision-makers (DMs) face when they have to handle large amounts of complex information [6,8]. These methods have been used to tackle geographic problems involving many alternatives and often conflicting evaluation criteria [9,10]. Combining a GIS and MCDA method produces excellent analysis tools, creating extensive spatial and non-spatial databases, which can simplify and solve problems while promoting the use of multiple criteria [11]. GIS and MCDA methods have been widely employed in the selection of the most suitable locations for RES facilities [8,10] [12–17]. Several studies [18–20] used SAW in a web-based GIS environment to identify preferable locations for wind farms and solar power plants. Silva et al. [21] coupled GIS and MCDA methods to select biomass plants in a Portuguese region. In a similar vein, Perpiña et al. [22] used an MCDA method to identify suitable areas for locating biomass plants. Marques-Perez et al. [16] used a GIS-based approach combined with a multi-criteria evaluation methodology for the territorial planning of photovoltaic power plants. In contrast, Mokarram et al. [17] defined a novel optimal placing of solar farms utilizing MDCA and GIS. Sánchez-Lozano et al. [23] used MCDA techniques to evaluate GIS-based photovoltaic solar farms' site selection. Finally, Rediske et al. [20] utilized GIS-MCDA tools for the decision location of photovoltaic power plants' installation in Brazil. In the context of location problems, several spatial variables are usually involved, such as environmental protection areas, proximity to rivers, roads, populations, and spatial characteristics of the region, like geology or even slope issues [21,24].

The present study applied MCDA in a GIS environment to select the most suitable CAES reservoir sites using the simple additive weighting (SAW) MCDA method. The SAW method was chosen because it has been largely employed in management and engineering problems, such as facility location problems [25,26], especially for RES site selection [10] and also for ES purposes [27]. Finally, a robust assessment of the results found was conducted through a sensibility analysis (SA).

2. Compressed Air Energy Storage Reservoirs and GIS

In a large-scale CAES plant, the off-peak power from the grid or the electricity generated from RES is used to compress ambient air stored under pressure in an underground geological reservoir. Later, when power demand requirements are high, the pressurized air is released back up to the surface, where it is heated and expanded, rushing through a turbine and driving a generator to produce electricity [2,4,28,29].

The suitable geological reservoirs for CAES technologies are (a) host rocks (engineered caverns and abandoned mines), (b) caverns in salt formations (salt domes or bedded salt), and (c) porous rocks (saline aquifers or depleted hydrocarbon reservoirs) [30]. CAES usage in salt caverns is demonstrated at the industrial scale in two large-scale facilities: Huntorf (Germany) and McIntosh (USA) [30,31]. Porous rocks appear to be the lowest cost option, but these have not been studied at an industrial scale. Cavities in host rocks are a more expensive alternative due to the cost of mining a new reservoir unless abandoned mines are possible [30,31].

This study mainly addressed CAES underground reservoirs in Portugal, and, besides considering the potential geological formations suitable for these reservoirs identified in ESTMAP [5], it also considered deep mines. Hence, these reservoirs were obtained through the inspection of public access data collected from geological surveys, geological maps, scientific publications, drilling records, and borehole logs, as well as data collected from companies and governmental and regulatory authorities, such as the Directorate-General for Energy and Geology (DGEG), the National Laboratory of Energy and Geology (LNEG), the Nacional Entity for the Energy Sector (ENMC), the Mining Development Company (EDM), National Energy Networks (REN), CUF Industrial Chemicals SA, and Solvay Portugal. The potential reservoirs considered were igneous host rocks, deep mines, salt formations, and saline aquifers. However, since there are no depleted hydrocarbon fields in Portugal, these reservoirs were not considered. Instead, a spatial database was compiled with the publicly available information for each reservoir type in a GIS environment (ArcGIS software, Évora, Portugal). Then, it was cross-checked with the pre-selected criteria for CAES potential reservoirs (available in [32]) and spatial, environmental, and social constraints and positive incentives.

GIS technologies are widely used to collect, store, manage, calculate, analyze, display, and describe geo-referenced data. Thus, they are valuable tools for assisting planning and decision-making in multiple contexts in which geo-referenced information plays a relevant role [10]. Subsequently, GIS data can generate inputs to spatial decision-making analysis [9], utilizing functions of overlay analysis [10].

The identified potential reservoirs are represented in the GIS environment by an ArcGIS attribute map (Figure 1), showing a total of six-ty-two potential sites with geological characteristics suitable for CAES, namely twenty, host rocks, nine deep mines, eighteen salt formations, nine salt caverns, and six saline aquifers.

Then, the selection of the most suitable reservoirs for CAES was obtained by applying the SAW methodology to these sixty-two potential geological sites (Figure 1).

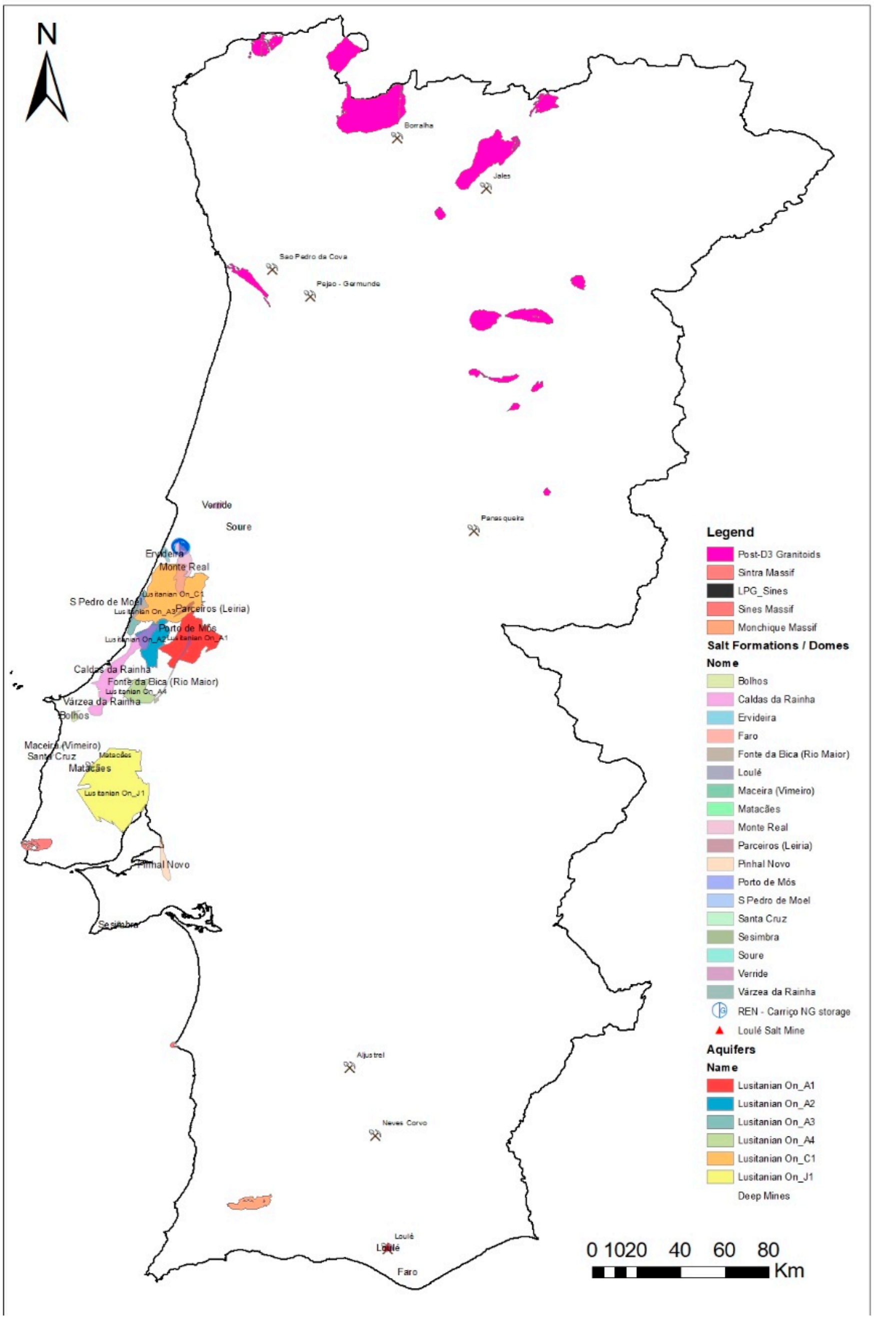

Figure 1. Potential CAES reservoirs in mainland Portugal are represented in an ArcGIS map.

3. Methodology

The SAW method, also called the weighted linear combination (WLC) method, is a widely known and often used MCDA technique [25,27,33], integrating criteria values and weights into a single framework [34] due to its reliability and proven results. The SAW method is based on a weighted average, calculating a score for each alternative by multiplying the scaled value given to the alternative of that attribute by the weights of relative importance directly assigned by the decision-makers [25].

This method was chosen because it is reliable and has the advantage of allowing a proportional linear transformation of raw data, meaning that the relative order of magnitude of standardized scores remains equal [25]. The chosen method is based on the MCDA method selection tool [35] developed by Wątróbski et al. [7].

Figure 2 illustrates the different phases of this MCDA method.

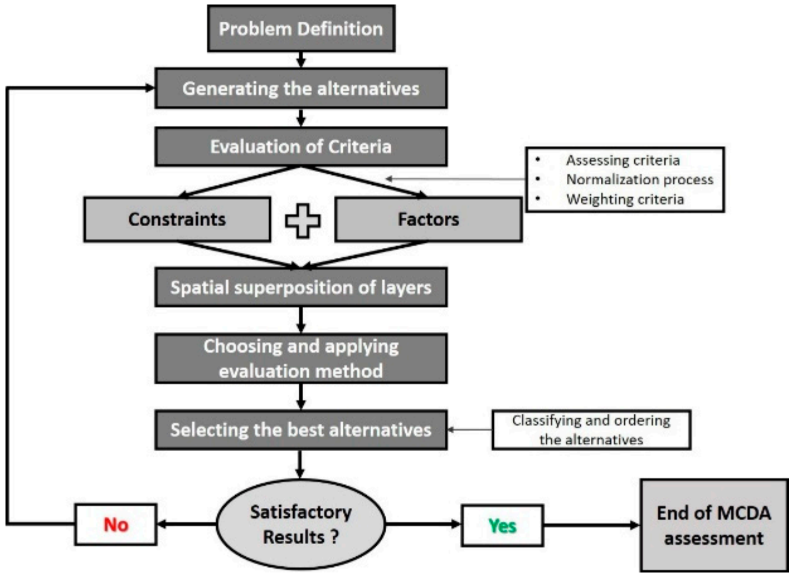

Figure 2. Schematic representation of the MCDA-GIS process for site selection of CAES reservoirs.

3.1. Problem Definition and Alternatives

The approach followed herein aimed to identify the best and most suitable potential reservoir sites for the possible installation of a CAES facility to better integrate RES into the Portuguese electricity grid. In this case, the generated alternatives are the sixty-two potential geological reservoirs depicted in Figure 1, according to CAES suitability analysis for Portugal based on the criteria established by [32]. These alternatives are listed in Tables in Appendix A, namely: twenty igneous host rocks (Table A1), nine deep mines (Table A2), eighteen salt formations and nine salt caverns (Table A3), and six saline aquifers (Table A4).

3.2. Criteria Definition: Constraints and Factors

The second SAW phase selects and evaluates the criteria that directly influence the CAES facility site choice. In this study, thirteen criteria were adopted and subdivided into constraints and incentives. All the presented criteria are based on measures and legislation used for Portugal's natural gas (NG) storage safety [36]. Although compressed air does not have the same explosive potential as NG, assuming a conservative stance, it was decided to adopt the same criteria regarding distances to infrastructures since there is still subsidence risk due to potential underground caverns.

Constraints stand for the criteria that can limit or restrict the placement of a CAES reservoir at a particular location. For this study, seven constraints were identified (Table 1), overlaid individually with the identified reservoirs, and cross-checked with the defined criteria, resorting to basic GIS operations such as buffering and overlapping.

Incentives are the criteria that may be beneficial to the implementation of a CAES reservoir and facility. In this research, six incentives were identified (Table 2) and overlaid with the sixty-two reservoirs.

Table 1. Description of the constraints defined as criteria for the suitable CAES reservoirs analysis.

Constraints	Description
Sensitive areas	Environmental sensitive areas, including Natura 2000 areas, sites of community importance, and special protection areas.
Groundwater	Groundwater protection zones.
Populated Areas	Distance to populated areas of less than 200 m.
Roads	Distance to roadways or highways of less than 100 m.
Land Slope	Terrain slope of above 12%.
Neotectonics	Known active faults.
Seismic risk	High seismic risk.

Table 2. Description of the incentives defined as criteria for the suitability CAES reservoirs analysis.

Incentives	Description
Renewable energy sources (RES)	Proximity to existing RES (wind, solar, hydro) power generation facilities
High-voltage (HV) network	Proximity to high-voltage electricity lines
Natural gas (NG) network	Proximity to natural gas pipelines (only for diabatic CAES technologies)
Deep geological data	Availability of deep geological data
Technology maturity	Maturity of the technology according to the type of reservoir
Existence of proven caverns	Existence of already proved caverns as a storage mean

The thirteen criteria were divided by decision-makers into three classes (Table 3): (a) environmental, (b) social, and (c) economic.

Table 3. Scheme of the classification of each criterion (constraints and incentives) and their objectives.

Type	Criteria	Name	Objective
Environmental	Sensitive areas	J1	Minimize
	Groundwater	J2	Minimize
	Neotectonics	J3	Minimize
	Seismic risk	J4	Minimize
Social	Populated areas	J5	Minimize
Economic	Land slope	J6	Minimize
	Roads	J7	Minimize
	Renewable energy sources (RES)	J8	Maximize
	High voltage (HV) network	J9	Maximize
	Natural gas (NG) network	J10	Maximize
	Deep geo data	J11	Maximize
	Maturity of the technology	J12	Maximize
	Existence of proven caverns	J13	Maximize

Constraints are non-beneficial criteria to be minimized, while incentives are beneficial criteria to be maximized, as depicted in Table 4. Although SAW may be used if all the criteria are being maximized [34], there are ways of converting minimizing into maximizing criteria, just by using a simple inversion of the scale for the minimizing criteria, as explained in the following sub-section.

Table 4. Maturity of the CAES technology according to the type of geological reservoir (based on [32]).

STORAGES	Reservoirs	CAES
Salt formations	Salt caverns	Mature technology, widely implemented
Host rocks	Engineered cavities	Prospective technology, pre-commercial pilots, and conceptual designs
	Abandoned mines	Prospective technology, pre-commercial pilots, and conceptual designs
Porous Media	Aquifers and traps	Prospective technology, pre-commercial pilots, and conceptual designs
	Depleted hydrocarbons reservoirs	Prospective technology, pre-commercial pilots, and conceptual designs

On the one hand, a CAES facility should be as far away as possible from sensitive areas, such as ecological and agricultural value, like special protection areas, Natura 2000 areas, and sites of community importance, to protect the environment and reduce any risk. On the other hand, proximity to energy sources (RES, HV networks, or even NG networks), proximity to roads, and land slope are important factors when considering the economic feasibility of any candidate site. Last but not least, social factors such as distance to populated areas should also be considered since a CAES plant can impact the population living within proximity to the chosen site due to noise, safety, or even a decrease in property value.

Some incentives are related to the proximity to energy sources. RES are used to store energy provided by renewable sources; transmission grid high-voltage (HV) networks are used for transmission and distribution purposes; and NG networks are used since natural gas is usually the fossil fuel used in the diabatic CAES expansion phase [30]. Other incentives are the availability of deep geological data, proven caverns for storage, and the technology's maturity depending on the type of geological reservoir. Table 4 depicts this last incentive showing that salt caverns are the most mature and implemented type of reservoirs. They are implemented in two diabatic CAES plants (Huntorf and McIntosh) and are widely implemented for NG storage and hydrogen worldwide [32].

3.3. Normalization Process

The next step is the normalization process since some criteria are qualitative, and others are quantitative. Normalization in MCDA is a transformation process to obtain numerical and comparable input data using a common scale [37]. Normalization (or transformation) of the initial data is generally used so that the best criterion value (the largest one for a maximizing criterion and the smallest one for a minimizing criterion) would obtain the largest value equal to unity [34]. There are several normalization methods, but given the subjectivity of the qualitative criteria, a simplification was done by the experts using a rating scale and attributing values. The chosen rating scale is comparable for all criteria and sets in the interval (0, 1) with intervals of 0.25, and a linear normalization method was used, where:

(a) For non-beneficial criteria or constraints

$$\overline{X}ij = 1 - \frac{Xij}{XjMax} \quad (1)$$

(b) For beneficial criteria or incentives

$$\overline{X}ij = \frac{Xij}{XjMax} \quad (2)$$

Constraints were normalized and transformed into maximizing criteria by inverting their scale through Equation (1). Hence, constraints were rated from 0 to 1 with intervals of 0.25, where 0 means the most favorable situation, and 1 depicts the most unfavorable situation. However, the rating scale was inverted, and 0 became the most unfavorable situation and 1 the most favorable (Table 5). Incentives (already maximizing criteria) were also rated from 0 to 1 (with intervals of 0.25) and normalized according to Equation (2), where 0 means the most unfavorable situation, and 1 represents the most favorable situation (Table 5).

Table 5. Normalized rating scale (0,1) attributed to all the criteria (constraints and incentives).

Criteria	Rating Scale—Normalized				
	1	0.75	0.5	0.25	0
J1	Absence of constraint	Presence of constraint not limiting more than 25% area.	Presence of constraint not limiting more than 50% area.	Presence of constraint not limiting more than 75% area.	Presence of constraint limiting the area.
J2	Absence of constraint	Presence of constraint not limiting more than 25% area.	Presence of constraint not limiting more than 50% area.	Presence of constraint not limiting more than 75% area.	Presence of constraint limiting the area.
J3	Absence of constraint	Presence of constraint not limiting more than 25% area.	Presence of constraint not limiting more than 50% area.	Presence of constraint not limiting more than 75% area.	Presence of constraint limiting the area.
J4	IV ≤ Seismic risk ≤ VII	VII < Seismic risk ≤ VIII	VIII < Seismic risk ≤ IX	IX < Seismic risk ≤ X	Seismic risk > X
J5	Absence of constraint	Presence of constraint not limiting more than 25% area.	Presence of constraint not limiting more than 50% area.	Presence of constraint not limiting more than 75% area.	Presence of constraint limiting the area.
J6	Land slope < 12%	n.a.	Land slope ≥12% not limiting all the area.	n.a.	Land slope ≥12% limiting the area
J7	Roads not present	Roads not crossing more than 25% of the area.	Roads not crossing more than 50% of the area.	Roads not crossing more than 50% of the area.	Roads crossing and limiting the use of the area.
J8	Presence of RES	Proximity of RES of less than 5 km.	Proximity of RES of approximately 5 km.	Proximity of RES of more than 5 km.	Absence of RES.
J9	Presence of HV network	Proximity of HV network of less than 5 km.	Proximity of HV network of approximately 5 km.	Proximity of HV network of more than 5 km.	Absence of HV network.
J10	Presence of HG network	Proximity of NG network of less than 5 km.	Proximity of NG network of approximately 5 km.	Proximity of NG network of more than 5 km.	Absence of NG network.
J11	Availability of deep geological data	Availability of 75% deep geological data but without enough data.	Availability of 50% deep geological data but without enough data.	Availability of 25% of deep geological data but without enough data.	Absence of deep geological data.
J12	Mature technology	Proven technology without installed facilities.	Proven technology.	Prospective technology with proven research.	Prospective technology.
J13	Existence of proven caverns for storage	Presence of caverns with bad conditions for storage.	Presence of caverns.	Projected caverns.	Absence of proven caverns.

Despite the equal rating scale, there is always some arbitrariness in this conversion and normalization process. It depends on the analysis of the overlaying layers of reservoirs; each of the criteria; and the scale that GIS maps are analyzed with.

3.4. Assigning Weights to the Criteria

An essential step of the methodology is the assignment of weights to the criteria. A weight can be defined as a value assigned to an evaluation criterion that indicates its importance relative to other criteria under consideration [8]. Such assigned weights are based on experts' judgments and should provide a general priority set to evaluate and compare the alternatives.

Two research team members, experts on underground energy storage, were responsible for this decision-making process. First, the experts (i.e., decision-makers) individually assigned the weights according to their experience to identify Portugal's most suitable CAES sites. This methodology considered all the environmental, social, and economic criteria (Table 3) and weighted together all the constraints and incentives. Then, the two experts were engaged in a discussion to reach a consensus and assign the weights in Table 6.

Table 6. Weights assigned to the criteria (constraints and incentives) for CAES potential reservoirs.

Criteria	Constraints & Incentives	Weights (%)
J1	Sensitive areas	10%
J2	Groundwater	10%
J3	Neotectonics	5%
J4	Seismic risk	7.5%
J5	Populated areas	5%
J6	Land slope	7.5%
J7	Roads	5%
J8	Renewable energy sources (RES)	12.5%
J9	High-voltage (HV) network	12.5%
J10	Natural gas (NG) network	5%
J11	Deep geological data	7.5%
J12	Maturity of technology	7.5%
J13	Existence of proven caverns	5%
Total		**100%**

The weights of constraints and incentives (Table 6) were attributed according to the level of importance, limitation, or motivation for the CAES purposes that each criterion can impose on an area.

Environmental criteria such as sensitive areas and groundwater constraints have higher weights since they can completely limit a potential site if they are overlapped with the potential reservoir. Sensitive areas are fundamental constraints in respecting environmental, conservative, and protectionist policies (flora, fauna, heritage, and natural reserves). Groundwater resources are also a significant constraint since underground reservoirs should be placed in areas with the minimum risk of contamination for groundwater, including natural springs and geothermal resources.

The land slope is important because slopes greater than 12% can increase the instability for surface CAES facilities, and their correction can also increase the project's capital costs. So, areas with slopes from 0% to 12% are the most suitable for a CAES plant due to lower economic costs and minimum morphological problems.

Portugal is a country with significant seismic risk due to its location near the boundaries of the European and African tectonic plates. Thus, the seismic risk may be an essential constraint for selecting CAES potential reservoirs where the risk is lower in the north of the country and higher in the south (according to Portugal's seismic risk map).

Lastly, constraints such as neotectonic structures, populated areas, and roads should also be considered. However, their attributed weights are lower since they are not disabling factors.

According to Costa [36], for safety reasons (mainly subsidence risk), the distance between populated areas and CAES facilities should be at least 200 m, and the distance between roads or highways should be at least 100 m. So, a buffer was used in ArcGIS to determine the safety area around these constraints and visualize the site free of constraint.

RES and HV have higher weights because they are the most important energy sources for a large-scale CAES facility. However, HV networks have a slightly bigger weight than RES because HV lines can work as sources supplying energy from the grid to feed the CAES plant in periods of electricity shortage from RES or high energy demand.

NG has a lower weight than the previous two since NG pipelines proximity only matters for diabatic CAES facilities, which need fossil fuels for the expansion phase. Although the only two CAES facilities in the world are diabatic systems (Huntorf—Germany, and McIntosh—USA) [4,6], this criterion is not disabling because it is possible to build a more efficient system with Adiabatic CAES technology.

Deep geological data and technology maturity have similar weights to those assigned to NG networks. They are important factors to consider since they both can increase the capital costs of a CAES project. Deep geological data are scarce in Portugal, and acquiring such information is extremely expensive, meaning that potential areas with deep data are favored. CAES technology maturity depends on the type of geological reservoir. For instance, salt is the lithology where CAES technology is already proven and mature.

Lastly, proven caverns for storage have the lowest weight of all the incentives, demonstrating the area can support that type of underground caverns and decreasing the initial cost of a project if those caverns could be reused.

3.5. Obtaining SAW Results

SAW results were obtained by analyzing local conditions of the different criteria at the alternative locations in the GIS database and applying Equation (3) to each alternative and each criterion (constraints and incentives individually):

$$S(a_i) = \sum_{j=1}^{n} w_j \cdot v_j(a_i) \tag{3}$$

where a_i is the alternative, $S(a_i)$ is the suitability level of alternative i or the result of the weighted sum for alternative a_i, w_j is the weight of criterion j, and v_j is the value of alternative a_i in criterion j.

Therefore, the last steps of this MCDA methodology consist of sorting and applying the evaluation method and selecting the best alternatives after classifying and ordering them. Thus, Equation (3) was applied directly to all of the criteria. Therefore, the higher the total score, the better the alternative for CAES purposes, meaning the highest results obtained indicate the best alternatives and chose the best potential CAES reservoir sites in mainland Portugal.

3.6. Sensibility Analysis

Saltelli et al. [38,39] state that sensibility analysis aims to ascertain how much the uncertainty in input factors influences the uncertainty in a model's output. So, MCDA methods usually resort to sensibility analysis as the last step of evaluation in all decision problems [22] because the majority of data in MCDA problems are unstable and changeable [40], and model outcomes are open to multiple types of uncertainty [41]. That is why doing a sensibility analysis after problem-solving can effectively contribute to make robust decisions [42]. A "what if" sensibility analysis is recommended to check the stability of results against the subjectivity of the experts [11], explaining how much the decision-makers judgements bias the assessment of an MCDA study [43]. The sensibility analysis helps in the validation of results and enables assessing its robustness [44]. The aim is to ensure that results are more reliable and to identify the criteria that can significantly influence them [22].

The most common sensibility analysis method for MDCA is to modify the weighting obtained from the experts' judgment [11,27,42]. Thus, in this study, sensibility analysis was done using an approach based on Memariani et al. [42], where the effect of change in the weight of one attribute or criteria on the weight of other criteria was evaluated and the change in the final score of alternatives when a change occurred in the weight of criteria was calculated.

Within the scope of this work, two different sensibility analyses were developed to ensure that the results of the SAW method were robust. The first was based on the variation of the weights of two defined main clusters of criteria: constraints and incentives. The second one was developed with four new criteria sub-clusters. Then, the results obtained in both sensibility analyses were evaluated and compared with the original SAW results.

The first step of sensibility analysis is to determine the assumptions for the changes in criteria weights. After that, the computation must be executed, and the results are checked and compared.

For the first sensibility analysis, a uniform distribution of weights was used with variations of 5%. Since thirteen criteria were distributed in two main clusters (constraints and incentives), the variation of weights was done by cluster. It starts and ends with extreme cases, such as 100% weight for constraints and 0% weight for incentives, applying variations of 5% until the opposite percentage of 0% weight for constraints and 100% weight for incentives were reached (Table A5, in Appendix A). The criteria variations' computation was executed in Excel for each of the percentages, evaluating the change in the final score of alternatives (in light of criteria weight changes) and observing the influence of the weights' variation on the results.

For this step, the weighted linear summation represented by Equation (3) was used.

As a matter of sensibility analysis comparison, the previous clusters were subdivided into sub-clusters. Constraints were divided into (a) surface and (b) sub-surface constraints. Incentives were divided into (c) energy sources and (d) technology/reservoirs maturity and data. Then, a new sensibility analysis was executed with weight variations of 0%, 25%, 50%, 75%, and 100% distributed by the new sub-clusters, according to the assumptions depicted in Table A3 (Tables A6 and A7, in Appendix A).

All the sensibility analyses results were cross-checked with the obtained SAW results, and the changes in the final score of alternatives were observed.

4. Results and Discussion

4.1. Results of the MCDA

In this MCDA-SAW method, the results obtained did not rely only on selecting one alternative, usually classified as the best. However, since choosing the best case studies for CAES was desired, it was decided to select several best alternatives.

The ranking of the best ten results is depicted in Table 7. The complete final results are represented in Table A8 (Appendix A) with a color gradation from green to red (from the best to the less good).

Table 7. MCDA-SAW final results, ranking the best ten alternatives and identifying them by their reservoir name, set, and type of reservoirs. The columns "score" and "ranking have a greenish color gradation from darkest greens to lighter tones representing the decreasing gradation of the alternatives scores and ranking. The blue colors in the column "set of reservoirs" represent the gradation of each set of reservoirs according to their ranking since several alternatives can correspond to the same set of reservoirs.

Ranking of the Best Ten Alternatives					
Score	**Ranking**	**Alternative**	**Reservoir**	**Set of Reservoirs**	**Type of Reservoirs**
0.844	1	*a34*	Carriço—1S		
0.844	1	*a35*	Carriço—2		
0.844	1	*a36*	Carriço—3		
0.844	1	*a37*	Carriço—4		

Table 7. *Cont.*

Ranking of the Best Ten Alternatives					
Score	**Ranking**	**Alternative**	**Reservoir**	**Set of Reservoirs**	**Type of Reservoirs**
0.844	1	*a38*	Carriço—5	1	Salt Rocks
0.844	1	*a39*	Carriço—6		
0.806	2	*a40*	Carriço—7		
0.806	2	*a41*	Carriço—8		
0.806	2	*a42*	Carriço—9		
0.800	3	*a29*	Loulé—Campina de Cima	2	
0.744	4	*a19*	LPG_Sines	3	Host Rock
0.731	5	*a33*	Monte Real salt dome	1	
0.731	5	*a52*	Matacães salt dome	4	
0.694	6	*a26*	Matacães Mine		
0.663	7	*a55*	Loulé salt dome	2	Salt Rocks
0.631	8	*a53*	Pinhal Novo salt dome	5	
0.625	9	*a30*	Verride salt dome	6	
0.625	9	*a49*	Bolhos salt dome	7	
0.613	10	*a47*	Caldas da Rainha diapir	8	

The chosen final results are the three best sets of potential reservoirs for CAES in Portugal (Table 7), depicted in Figure 1, and also in a higher detail, from north to south in Figures 3–5. They are:

(a) Alternatives 34 to 42 are Carriço NG storage caverns belonging to Monte Real salt dome (alternative 33). Together they are the Monte Real salt dome set (Figure 3);
(b) Alternative 19 corresponds to the Sines liquid petroleum gas (LPG) reservoir located in Sines host rock massif (Figure 4).
(c) Alternative 29 corresponds to the Campina de Cima salt mine located in the Loulé salt dome (Figure 5).

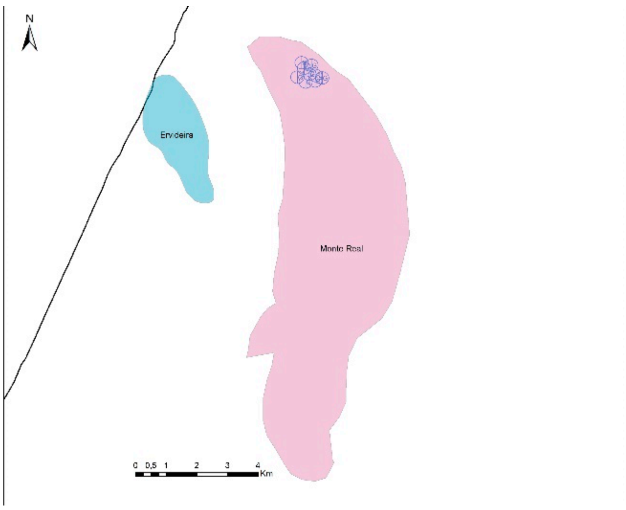

Figure 3. ArcGIS representation of the first best potential reservoir site, Monte Real salt dome colored in violet, and Carriço salt caverns represented in blue circles inside the violet salt dome.

Other alternatives or potential CAES reservoirs with good SAW scores and a high potential for CAES could be considered: the Matacães salt mine and salt dome, or the Pinhal Novo, Loulé, and Bolhos salt domes. However, the Matacães salt mine is abandoned and has severe stability issues (according to Solvay Portugal), and the other mentioned salt domes lack deep geological data that are very sparse or inexistent.

The chosen alternatives for CAES potential reservoirs are generally located in the western and southern part of the country (Figures 3–5), having the most favorable locations with fewer constraints and more incentives.

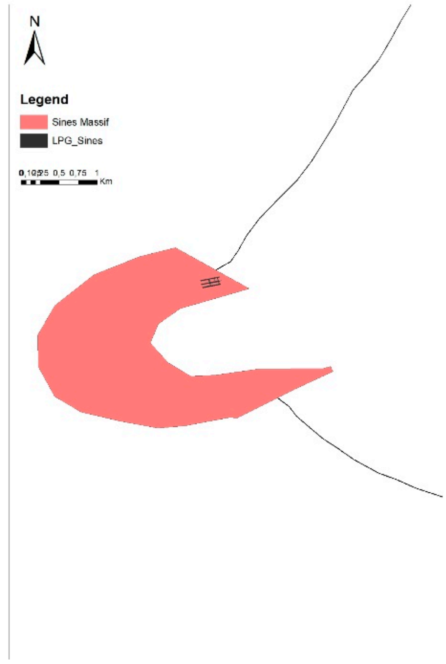

Figure 4. ArcGIS representation of the best potential host rock reservoir, the Sines LPG storage depicted in black inside the Sines sub-volcanic massif represented in light red.

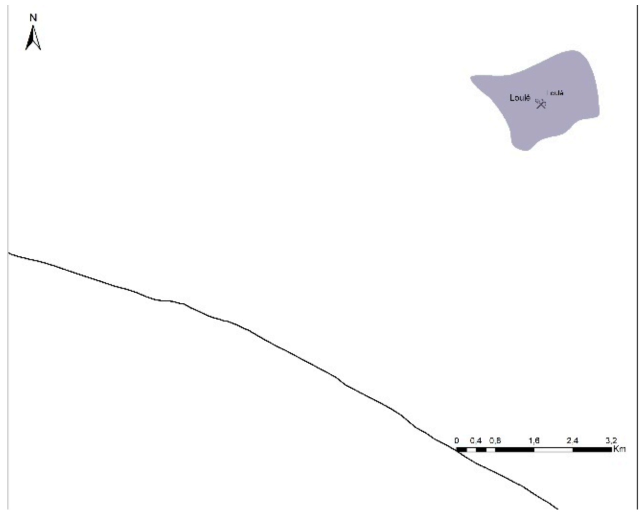

Figure 5. ArcGIS representation of the best potential reservoir Campina de Cima salt mine inside the Loulé salt dome depicted in grey.

Alternative 33 corresponds to the Monte Real salt dome, and alternatives 34 to 42 are six dissolution salt caverns and three other planned ones (Figure 3), held by REN Armazenagem in Carriço (Pombal). On the one hand, these salt caverns are being used to store NG in that geological formation, meaning that the Monte Real salt dome has already proved its suitability for storing energy underground. On the other hand, REN storage facilities have infrastructure like HV lines and NG networks available on-site, decreasing the costs of a possible CAES project. Thus, joining the absence of limiting constraints, deep geological data availability, and the proximity to the sea, Monte Real/Carriço would be a great suitable location for settling new salt caverns to a CAES system in Portugal.

Alternative 19 corresponds to the Sines LPG reservoir, an engineered cavern to store LPG built in Sines' sub-volcanic massif (Figure 4). This potential underground reservoir has deep geological data and a proven storage capacity, both a plus when considering a CAES geological reservoir. It is located in the coastal line and has special wind conditions for installing wind parks. Sines is one of the most important Portuguese seaports and is the country's principal port of energy supply (oil and by-products, coal, and natural gas) [45]. So, it already has energy surface infrastructures such as HV lines and gas pipelines (necessary in case of potential diabatic CAES facilities), and it still has the potential to grow.

Alternative 29 corresponds to the Campina de Cima—Loulé salt mine (Figure 5). This mine is settled in Loulé diapir and has several salt excavated galleries, which could host CAES underground reservoirs, decreasing the initial costs of a possible CAES project.

4.2. Results of the Sensitivity Analysis

The sensibility analysis provides information about the influence that criteria and clusters may have on the final score of alternatives and how the variation in weights of criteria may change the final results in terms of the chosen reservoirs for CAES purposes, contributing to accurate decisions.

The first sensibility analysis was done considering cluster weights with variations of 5%, analyzing twenty-one scenarios. The summary depicting only the main results (with intervals of 25%) is shown in Table A9 (Appendix A).

The results comparison did not show significant differences between scenarios, even in the extreme and improbable ones where 100% of the weight was attributed to one cluster. Thus, the possible reservoirs with the best scores remain the same throughout the various analyses: (a) the Monte Real/Carriço NG storages and salt dome, (b) the LPG Sines in the Sines Sub-Volcanic Complex, and (c) the Campina de Cima—Loulé salt mine.

The second sensibility analysis dividing each main cluster into sub-clusters evaluated seven scenarios (even the most extreme and improbable ones) to determine which sub-cluster had the most influence on the results. Those results are shown in Table A10 (in Appendix A). The results of scenarios one to three did not significantly change the previous GIS-SAW results. Thus, the case studies selected for CAES purposes were the same as before. However, this selection varied when extreme cases were contemplated. The best results for scenario four (placing 100% of the weight on the sub-cluster of surface constraints) were Sines LPG, Ervideira, the Loulé salt mine, the Carriço salt caverns, and the S. Pedro de Moel and Várzea da Rainha salt domes. Scenario five's (with 100% of the weight on the sub-cluster of subsurface constraints) best results were four host rocks (Vila Verde de Raia, Vila Nova de Covelo, Celorico da Beira, and Capinha) and five deep mines (Jales, Borralha, Pejão-Germunde, S. Pedro da Cova, and Panasqueira) followed by Soure, Ervideira, the S. Pedro de Moel saline domes, the Carriço salt caverns, and also the Lusitanian On_A3 aquifer. Scenario six's (with 100% of the weight in the sub-cluster of energy sources) best results were the Lusitanian On_J1 and Lusitanian On_A1 saline aquifers. Finally, scenario seven's (placing 100% of the weight in the sub-cluster of technology/reservoir maturity and data) best results were the Carriço salt caverns, the Monte Real and Matacães salt domes, and the Loulé salt mine.

Both sensibility analyses were done with different weights for clusters, sub-clusters, and criteria. In the first SA, there were minor variations in potential reservoirs with better scores. Still, there were no significant changes in the results with the highest scores, which gives robustness to the initial combination of GIS and SAW results and suggests they are correct. It also indicates that weight variation influence was not significant and did not drastically alter the outcome of the chosen case studies. Despite the first three scenarios maintaining the same highest score reservoirs in the second sensibility analysis, the last four scenarios changed the highest-score potential reservoirs. However, those four scenarios were based on extreme, unlikely, and unreal assumptions, where the entire weight of the criteria was placed only in one cluster or sub-cluster. They serve to understand the types of criteria that value certain reservoirs at the expense of others and the possible influence that each sub-cluster may have on the final decision of case studies for CAES.

Therefore, according to the analysis carried out through GIS-MDCA and corroborated by the sensibility analysis, the criteria that seem to have greater weight and influence in the three chosen case studies were:

(a) For Monte Real/Carriço, the maturity and data availability on the reservoirs were predominant factors, but other criteria such as a lower absence of constraints and proximity of energy sources were also important;
(b) For LPG—Sines, the lower absence of surface constraints;
(c) For Campina de Cima-Loulé, the less lower of constraints and the reservoir's maturity and data availability.

However, it is mandatory to mention that these choices result from evaluating all the criteria, clusters, and sub-clusters together since, in reality, they are essential and take a significant part in the final decision.

5. Conclusions

The grouping of GIS-MCDA and sensibility analysis methods is a powerful tool for selecting sites for different installations, representing a promising research line in large-scale ES, especially for selecting the best location of facilities.

This study is not comparable to others since the combined techniques of GIS and MCDA were never used, as far as we know, to select the most suitable CAES potential reservoirs in Portugal. Thus, it represents an innovation since, apart from the ESTMAP European project (which had a different scope), no exclusively CAES studies in Portugal could select and determine the three best reservoir case studies to store the excess RES.

Some uncertainties can be held since this method yields a certain degree of arbitrariness, where the most significant one is the decision-makers' subjective choices. Specifically, the criteria evaluation, the process of normalization, or attributing weights to the criteria are subjective, having a considerable effect on the entire evaluation process. However, most of the selection processes commonly used in the literature also present arbitrariness and are mainly dependent on the decision-makers' choices, turning them subjective. Thus, this well-known MCDA-SAW method was chosen since it can be straightforward and efficient to serve the defined purpose and provide the expected results.

In total, for sixty-two potential reservoirs for CAES represented in a GIS environment, thirteen criteria (seven constraints and six incentives) were identified. First, criteria and potential reservoir sites (the alternatives) were cross-checked using GIS techniques and the MCDA-SAW method, and the best results were chosen. Then, two sensibility analyses were conducted to check the robustness of previous results.

The most suitable reservoir sites for a possible CAES facility were Monte Real-Carriço Sines LPG and Campina de Cima-Loulé. The Monte Real salt dome holds NG reserves for the country in REN Armazenagem salt caverns, and Sines has an LPG engineered cavern. So, these two suitable sites have the advantage of being already proven capacity. Furthermore, Campina de Cima in Loulé salt dome is an out-of-labor salt mine with several salt galleries that could be reused for storage. Thus, these three sites have the highest potential and best location for a CAES system regarding lower constraints and proximity/overlapping positive incentives.

These results are important for the Portuguese electricity grid because they show the best potential CAES sites for large-scale ES of RES, adding flexibility to the grid and an alternative to the country's weather and topography-dependent PHES.

The results also show that this GIS-based and MCDA-SAW method integrating spatial and non-spatial information provided a multidimensional view of the potential reservoir CAES systems.

Techno-economic studies need to be done for further work, including more detailed studies about these three selected reservoirs.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Alternatives represented by the igneous host rocks' potential reservoirs.

Alternative (a)	Reservoir's Name	Reservoir's Type
1	Monção	
2	Peneda	
3	Gerês	
4	Vila Verde da Raia	
5	Vila Pouca de Aguiar	
6	Vila Real—Alvão	
7	Vila Nova de Gaia	
8	Fiães	
9	Vila Nova de Foz Côa	Host rocks
10	Penedono	
11	Moimenta da Beira	
12	Esmolfe	
13	Vila Nova de Covelo	
14	Celorico da Beira	
15	Linhares	
16	Capinha	
17	Sintra	
18	Sines	
19	LPG_Sines	
20	Monchique	

Table A2. Alternatives represented by deep mines' potential reservoirs, including salt mines.

Alternative (a)	Reservoir's Name	Reservoir's Type
21	Jales	
22	Borralha	
23	Pejão-Germunde	
24	S. Pedro da Cova	
25	Panasqueira	Deep mines
26	Matacães	
27	Aljustrel	
28	Neves-Corvo	
29	Loulé—Campina de Cima	

Table A3. Alternatives represented by salt formations and salt domes potential reservoirs, including salt caverns.

Alternative (a)	Reservoir's Name	Reservoir's Type
30	Verride salt dome	Salt formations
31	Soure salt dome	
32	Ervideira salt dome	
33	Monte Real salt dome	
34	Carriço—1S	
35	Carriço—2	
36	Carriço—3	
37	Carriço—4	
38	Carriço—5	
39	Carriço—6	
40	Carriço—7	
41	Carriço—8	
42	Carriço—9	
43	S. Pedro de Moel salt dome	
44	Parceiros (Leiria) salt dome	
45	Porto de Mós salt dome	
46	Fonte da Bica (Rio Maior) salt dome	
47	Caldas da Rainha diapir	
48	Várzea da Rainha salt dome	
49	Bolhos salt dome	
50	Maceira (Vimeiro) salt dome	
51	Santa Cruz salt dome	
52	Matacães salt dome	
53	Pinhal Novo salt dome	
54	Sesimbra salt dome	
55	Loulé salt dome	
56	Faro salt dome	

Table A4. Alternatives represented by saline aquifers' potential reservoirs.

Alternative (a)	Reservoir's Name	Reservoir's Type
57	Lusitanian On_A1	Saline aquifers
58	Lusitanian On_A2	
59	Lusitanian On_A3	
60	Lusitanian On_A4	
61	Lusitanian On_C1	
62	Lusitanian On_J1	

Table A5. Assumptions table for the first sensitivity analysis with variation in criteria weights for the ratio of clusters constraints/incentives with intervals of 5%, from 100% to 0% (in constraints weights and 0% to 100% in incentives weights).

					Ratio of Weights of Criteria: Constraints/Incentives (%)																				
	Criteria	Classification	Original G. W.	SAW IW.	(100/0)	(95/5)	(90/10)	(85/15)	(80/20)	(75/25)	(70/30)	(65/35)	(60/40)	55/45)	(50/50)	(45/55)	(40/60)	(35/65)	(30/70)	(25/75)	(20/80)	(15/85)	(10/90)	(5/95)	(0/100)
J1	Sensitive areas			10%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J2	Groundwater			10%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J3	Neotectonics			5%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J4	Seismic risk	Constraints	50	7.5%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J5	Populated areas			5%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J6	Land Slope			7.5%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J7	Roads			5%	14.29	13.57	12.86	12.14	11.43	10.71	10	9.29	8.57	7.86	7.14	6.429	5.71	5.00	4.29	3.57	2.86	2.14	1.43	0.71	0.00
J8	Renewable Energy Sources (RES)			12.5%	0	0.83	1.67	2.5	3.33	4.17	5	5.83	6.67	7.5	8.33	9.167	10	10.83	11.67	12.50	13.33	14.17	15.00	15.83	16.67
J9	High-voltage (HV) network			12.5%	0	0.83	1.67	2.5	3.33	4.17	5	5.83	6.67	7.5	8.33	9.167	10	10.83	11.67	12.50	13.33	14.17	15.00	15.83	16.67
J10	Natural gas (NG) network			5%	0	0.83	1.67	2.5	3.33	4.17	5	5.83	6.67	7.5	8.33	9.167	10	10.83	11.67	12.50	13.33	14.17	15.00	15.83	16.67
J11	Deep geological data	Incentives	50	7.5%	0	0.83	1.67	2.5	3.33	4.17	5	5.83	6.67	7.5	8.33	9.167	10	10.83	11.67	12.50	13.33	14.17	15.00	15.83	16.67
J12	Maturity of technology			7.5%	0	0.83	1.67	2.5	3.33	4.17	5	5.83	6.67	7.5	8.33	9.167	10	10.83	11.67	12.50	13.33	14.17	15.00	15.83	16.67
J13	Existence of proven caverns			5%	0	0.83	1.67	2.5	3.33	4.17	5	5.83	6.67	7.5	8.33	9.167	10	10.83	11.67	12.50	13.33	14.17	15.00	15.83	16.67
Total			100	100%	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Where:
G.W. means group weight
I. W. means individual weights

Table A6. Assumptions table for the second sensitivity analysis with variation in criteria weights for the ratio of the four sub-clusters: (A) surface constraints; (B) sub-surface constraints; (C) Energy sources; and (D) maturity and data of the technology/reservoirs.

			Assumptions													
Sub-Clusters	**Original**	**Original**	**1**		**2**		**3**		**4**		**5**		**6**		**7**	
	Weights	**Weights**	**G. W.**	**Clusters**	**G. W.**	**Clusters**	**G. W.**	**Clusters**	**G. W.**	**Clusters**	**G. W.**	**Clusters**	**G. W.**	**Clusters**	**G. W.**	**Clusters**
A—Surface constraints	50%	27.5%	50	25	75	37.5	25	12.5	100	100	100	0	0	0	0	0
B—Sub-surface constraints		22.5%		25		37.5		12.5		0		100		0		0
C—Energy sources	50%	30%	50	25	25	12.5	75	12.5	0	0	0	0	100	100	100	0
D—Maturity and data		20%		25		12.5		12.5		0		0		0		100
Total	**100%**	**100%**	100	100	100	100	100	50	100	100	100	100	100	100	100	100

Table A7. Assumptions table for the second sensitivity analysis with variation in individual criteria weights according to the variation of the sub-clusters' weights of Table A6.

						Assumptions			
Classification	**Clusters**	**Original SAW Weights**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
	A	10%	6.25%	9.38%	3.125%	25.00%	0.00%	0.00%	0.00%
	B	10%	8.33%	12.50%	4.167%	0.00%	33.33%	0.00%	0.00%
	B	5%	8.33%	12.50%	4.167%	0.00%	33.33%	0.00%	0.00%
Constraints	B	7.5%	8.33%	12.50%	4.167%	0.00%	33.33%	0.00%	0.00%
	A	5%	6.25%	9.38%	3.125%	25.00%	0.00%	0.00%	0.00%
	A	7.5%	6.25%	9.38%	3.125%	25.00%	0.00%	0.00%	0.00%
	A	5%	6.25%	9.38%	3.125%	25.00%	0.00%	0.00%	0.00%
	C	12.5%	8.33%	4.167%	4.167%	0.00%	0.00%	33.33%	0.00%
	C	12.5%	8.33%	4.167%	4.167%	0.00%	0.00%	33.33%	0.00%
	C	5%	8.33%	4.167%	4.167%	0.00%	0.00%	33.33%	0.00%
Incentives	D	7.5%	8.33%	4.167%	4.167%	0.00%	0.00%	0.00%	33.33%
	D	7.5%	8.33%	4.167%	4.167%	0.00%	0.00%	0.00%	33.33%
	D	5%	8.33%	4.167%	4.167%	0.00%	0.00%	0.00%	33.33%
		100%	100%	100%	100%	100%	100%	100%	100%

Table A8. Table presenting the results from the application of Equation (3) to constraints and incentives and the final score results with a color gradation (from green until red) and the chosen case studies highlighted in dark green.

Alternatives	Constraints								Incentives					Total Score
	J1	*J2*	*J3*	*J4*	*J5*	*J6*	*J7*	*J8*	*J9*	*J10*	*J11*	*J12*	*J13*	
a1	0.1	0.075	0.038	0.038	0.038	0.025	0.075	0.063	0.063	0.025	0	0	0	**0.538**
a2	0	0.1	0.05	0.05	0	0.038	0.075	0	0	0	0	0	0	**0.313**
a3	0	0.075	0.038	0.038	0	0.025	0.075	0.125	0.031	0	0	0	0	**0.406**
a4	0.1	0.1	0.038	0.038	0.038	0.05	0.075	0.063	0	0	0	0	0	**0.500**
a5	0.075	0	0.038	0.038	0	0	0.075	0.125	0.125	0	0	0	0	**0.475**
a6	0	0.1	0.05	0.038	0	0.038	0.075	0.063	0	0	0	0	0	**0.363**
a7	0.1	0.1	0	0.025	0.075	0.025	0.075	0	0.125	0.05	0	0	0	**0.575**
a8	0.1	0.1	0	0.025	0.075	0.025	0.075	0	0.125	0.05	0	0	0	**0.575**
a9	0.1	0.1	0.05	0.038	0	0.038	0.075	0	0.031	0	0	0	0	**0.431**
a10	0.1	0.1	0.025	0.038	0.038	0.038	0.075	0.063	0	0	0	0	0	**0.475**
a11	0.075	0.1	0.025	0.038	0.038	0.038	0.075	0.063	0	0	0	0	0	**0.450**
a12	0.1	0.075	0.025	0.05	0	0.05	0.075	0	0	0	0	0	0	**0.375**
a13	0.1	0.1	0.038	0.05	0	0.05	0.075	0	0	0	0	0	0	**0.413**
a14	0.1	0.1	0.013	0.025	0	0.05	0.075	0	0.063	0.025	0	0	0	**0.450**
a15	0.025	0	0.038	0.038	0	0.038	0.075	0	0.063	0.025	0	0	0	**0.300**
a16	0.1	0.1	0.05	0.038	0	0.05	0.075	0	0.063	0	0	0	0	**0.475**
a17	0	0.1	0.038	0.025	0	0.05	0.019	0	0	0	0	0	0	**0.231**
a18	0.1	0.1	0.025	0.038	0.075	0.05	0.019	0.063	0.063	0.025	0	0	0.05	**0.606**
a19	0.1	0.1	0.05	0.05	0.075	0.05	0.019	0.063	0.063	0.025	0.075	0	0.05	**0.719**
a20	0	0.05	0.025	0.038	0	0.038	0.019	0.125	0.125	0	0	0	0	**0.419**
a21	0.1	0.1	0.05	0.05	0.038	0.05	0.075	0.063	0.063	0	0	0	0	**0.588**
a22	0.1	0.1	0.038	0.05	0	0.05	0.075	0.063	0.063	0	0	0	0	**0.538**
a23	0.1	0.1	0.05	0.05	0	0.05	0.075	0	0.063	0	0	0	0	**0.488**
a24	0.1	0.1	0.025	0.05	0	0.05	0.075	0	0.063	0.025	0	0	0	**0.488**
a25	0.1	0.1	0.05	0.05	0	0.05	0.075	0.063	0.063	0	0	0	0	**0.550**
a26	0.1	0.1	0.05	0.019	0.038	0	0.038	0.063	0.063	0.013	0.075	0.075	0.025	**0.656**
a27	0.05	0.1	0.013	0.05	0.038	0.05	0.038	0	0.063	0	0	0	0	**0.400**
a28	0	0.1	0.05	0.05	0.075	0.05	0.038	0.063	0.063	0	0	0	0	**0.488**
a29	0.1	0.1	0.038	0.05	0.075	0.05	0.038	0.063	0.063	0	0.075	0.075	0.025	**0.750**
a30	0.1	0.1	0.038	0.05	0.075	0.038	0.056	0	0.031	0.013	0.038	0.075	0	**0.613**
a31	0.1	0.1	0.038	0.038	0.075	0.05	0.056	0	0	0.025	0.038	0.075	0	**0.594**
a32	0.1	0.1	0.05	0.05	0.075	0.05	0.056	0	0	0	0	0.075	0	**0.556**
a33	0.1	0.075	0.038	0.038	0.075	0.038	0.056	0	0.125	0.05	0.038	0.075	0.05	**0.756**
a34	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.05	**0.844**
a35	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.05	**0.844**
a36	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.05	**0.844**
a37	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.05	**0.844**
a38	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.05	**0.844**
a39	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.05	**0.844**
a40	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.013	**0.806**
a41	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.013	**0.806**
a42	0.1	0.1	0.038	0.05	0.075	0.05	0.056	0	0.125	0.05	0.075	0.075	0.013	**0.806**
a43	0.1	0.1	0.05	0.038	0.075	0.05	0.056	0	0	0	0.038	0.075	0	**0.581**
a44	0.1	0.05	0	0.025	0.038	0.05	0.056	0	0.125	0	0.038	0.075	0	**0.556**
a45	0.025	0.05	0.025	0.038	0	0	0.056	0.063	0.125	0	0.038	0.075	0	**0.494**
a46	0.025	0.05	0.038	0.05	0	0.013	0.038	0.063	0.125	0.025	0.038	0.075	0	**0.538**
a47	0.1	0.075	0.038	0.038	0.075	0.05	0.038	0.063	0	0.025	0.038	0.075	0	**0.613**
a48	0.1	0.1	0.038	0.05	0.075	0.05	0.038	0	0	0	0.038	0.075	0	**0.563**
a49	0.1	0.1	0.038	0.038	0.075	0.038	0.038	0.125	0	0	0	0.075	0	**0.625**
a50	0.1	0.05	0.038	0.05	0.038	0.05	0.038	0	0	0	0	0.075	0	**0.438**
a51	0.05	0.1	0	0.025	0.075	0.05	0.038	0	0	0	0	0.075	0	**0.413**
a52	0.1	0.1	0.05	0.019	0.038	0.038	0.038	0.063	0.063	0.013	0.075	0.075	0.025	**0.694**
a53	0.075	0.1	0.025	0.038	0.075	0.038	0.019	0	0.125	0.038	0.038	0.075	0	**0.644**
a54	0	0.1	0.025	0.038	0	0.038	0.019	0	0	0	0	0.075	0	**0.294**
a55	0.1	0.1	0.025	0.038	0.038	0.038	0.038	0.063	0.063	0	0.038	0.075	0.025	**0.638**
a56	0.1	0.1	0.025	0.038	0.075	0.038	0.019	0	0	0	0	0.15	0	**0.544**
a57	0.05	0.075	0.038	0.038	0	0.013	0.056	0.063	0.125	0.05	0.038	0	0	**0.544**
a58	0.1	0.075	0.025	0.038	0.038	0.038	0.056	0.031	0.031	0.05	0.038	0	0	**0.519**
a59	0.1	0.1	0.038	0.038	0.075	0.05	0.056	0.063	0	0	0.038	0	0	**0.556**
a60	0.1	0.1	0.038	0.038	0	0.05	0.038	0.031	0.094	0.05	0.038	0	0	**0.575**
a61	0.1	0.075	0.025	0.025	0.038	0.038	0.056	0	0.094	0.05	0.038	0	0	**0.538**
a62	0.1	0.075	0	0.025	0	0.038	0.038	0.125	0.125	0.05	0.038	0	0	**0.613**

Table A9. Summary of the first SA results with the variation of criteria weights by cluster or classification of types of criteria.

Reservoirs		Original SAW					
		Score	(100/0)	(75/25)	(50/50)	(25/75)	(0/100)
Reservoir Name	Alternatives						
Monção	*a1*	0.538	0.750	0.625	0.500	0.375	0.250
Peneda	*a2*	0.313	0.679	0.509	0.339	0.170	0.000
Gerês	*a3*	0.406	0.536	0.454	0.372	0.290	0.208
Vila Verde da Raia	*a4*	0.500	0.857	0.663	0.470	0.277	0.083
Vila Pouca de Aguiar	*a5*	0.475	0.464	0.431	0.399	0.366	0.333
Vila Real—Alvão	*a6*	0.363	0.643	0.503	0.363	0.223	0.083
Vila Nova de Gaia	*a7*	0.575	0.715	0.619	0.524	0.429	0.333
Fiães	*a8*	0.575	0.715	0.619	0.524	0.429	0.333
Vila Nova de Foz Côa	*a9*	0.431	0.786	0.599	0.414	0.228	0.042
Penedono	*a10*	0.475	0.786	0.610	0.435	0.259	0.083
Moimenta da Beira	*a11*	0.450	0.750	0.583	0.417	0.250	0.083
Esmolfe	*a12*	0.375	0.750	0.562	0.375	0.187	0.000
Vila Nova de Covelo	*a13*	0.413	0.822	0.616	0.411	0.205	0.000
Celorico da Beira	*a14*	0.450	0.679	0.550	0.423	0.295	0.167
Linhares	*a15*	0.300	0.500	0.417	0.333	0.250	0.167
Capinha	*a16*	0.475	0.822	0.637	0.452	0.268	0.083
Sintra	*a17*	0.231	0.500	0.375	0.250	0.125	0.000
Sines	*a18*	0.606	0.786	0.693	0.601	0.509	0.417
LPG_Sines	*a19*	0.719	0.893	0.815	0.738	0.661	0.583
Monchique	*a20*	0.419	0.393	0.378	0.363	0.348	0.333
Jales	*a21*	0.588	0.929	0.738	0.548	0.357	0.167
Borralha	*a22*	0.538	0.822	0.657	0.494	0.330	0.167
Pejão-Germunde	*a23*	0.488	0.857	0.663	0.470	0.277	0.083
S. Pedro da Cova	*a24*	0.488	0.786	0.631	0.476	0.321	0.167
Panasqueira	*a25*	0.550	0.857	0.684	0.512	0.339	0.167
Matacães	*a26*	0.656	0.679	0.665	0.652	0.638	0.625
Aljustrel	*a27*	0.400	0.679	0.530	0.381	0.232	0.083
Neves-Corvo	*a28*	0.488	0.786	0.631	0.476	0.321	0.167
Loulé—Campina de Cima	*a29*	0.750	0.893	0.815	0.738	0.661	0.583
Verride salt dome	*a30*	0.613	0.893	0.753	0.613	0.473	0.333
Soure salt dome	*a31*	0.594	0.893	0.753	0.613	0.473	0.333
Ervideira salt dome	*a32*	0.556	0.965	0.765	0.565	0.366	0.167
Monte Real salt dome	*a33*	0.756	0.822	0.803	0.786	0.768	0.750
Carriço—1S	*a34*	0.844	0.929	0.904	0.881	0.857	0.834
Carriço—2	*a35*	0.844	0.929	0.904	0.881	0.857	0.834
Carriço—3	*a36*	0.844	0.929	0.904	0.881	0.857	0.834
Carriço—4	*a37*	0.844	0.929	0.904	0.881	0.857	0.834
Carriço—5	*a38*	0.844	0.929	0.904	0.881	0.857	0.834
Carriço—6	*a39*	0.844	0.929	0.904	0.881	0.857	0.834
Carriço—7	*a40*	0.806	0.929	0.873	0.818	0.763	0.708
Carriço—8	*a41*	0.806	0.929	0.873	0.818	0.763	0.708
Carriço—9	*a42*	0.806	0.929	0.873	0.818	0.763	0.708
S. Pedro de Moel salt dome	*a43*	0.581	0.929	0.759	0.589	0.420	0.250
Parceiros (Leiria) salt dome	*a44*	0.556	0.607	0.559	0.512	0.464	0.417
Porto de Mós salt dome	*a45*	0.494	0.393	0.420	0.446	0.473	0.500
Fonte da Bica (Rio Maior) salt dome	*a46*	0.538	0.464	0.494	0.524	0.554	0.583
Caldas da Rainha diapir	*a47*	0.613	0.822	0.720	0.619	0.518	0.417
Várzea da Rainha salt dome	*a48*	0.563	0.893	0.732	0.571	0.411	0.250
Bolhos salt dome	*a49*	0.625	0.822	0.699	0.577	0.455	0.333
Maceira (Vimeiro) salt dome	*a50*	0.438	0.750	0.604	0.458	0.312	0.167
Santa Cruz salt dome	*a51*	0.413	0.643	0.524	0.405	0.286	0.167
Matacães salt dome	*a52*	0.694	0.750	0.719	0.688	0.656	0.625
Pinhal Novo salt dome	*a53*	0.644	0.715	0.671	0.628	0.585	0.542
Sesimbra salt dome	*a54*	0.294	0.464	0.390	0.315	0.241	0.167
Loulé salt dome	*a55*	0.638	0.715	0.660	0.607	0.554	0.500
Faro salt dome	*a56*	0.544	0.750	0.604	0.458	0.312	0.167
Lusitanian On_A1	*a57*	0.544	0.536	0.527	0.518	0.509	0.500
Lusitanian On_A2	*a58*	0.519	0.715	0.619	0.524	0.429	0.333
Lusitanian On_A3	*a59*	0.556	0.893	0.711	0.530	0.348	0.167
Lusitanian On_A4	*a60*	0.575	0.715	0.640	0.565	0.491	0.417
Lusitanian On_C1	*a61*	0.538	0.679	0.602	0.527	0.451	0.375
Lusitanian On_J1	*a62*	0.613	0.500	0.521	0.542	0.562	0.583

Table A10. Summary of the second sensibility analysis results with the variation of criteria weights by sub-cluster or classification of sub-types of criteria.

Reservoirs		Original SAW Score	Sensibility Analysis of Clusters						
Reservoir Name	Alternatives		1	2	3	4	5	6	7
Monção	*a1*	0.538	0.500	0.6252	0.3672	0.750	0.750	0.500	0.000
Peneda	*a2*	0.313	0.354	0.5314	0.2083	0.500	0.917	0.000	0.000
Gerês	*a3*	0.406	0.385	0.4740	0.3203	0.375	0.750	0.417	0.000
Vila Verde da Raia	*a4*	0.500	0.479	0.6772	0.2813	0.750	1.000	0.167	0.000
Vila Pouca de Aguiar	*a5*	0.475	0.391	0.4194	0.3385	0.563	0.333	0.667	0.000
Vila Real—Alvão	*a6*	0.363	0.380	0.5287	0.2630	0.438	0.917	0.167	0.000
Vila Nova de Gaia	*a7*	0.575	0.531	0.6303	0.4323	0.625	0.833	0.667	0.000
Fiães	*a8*	0.575	0.531	0.6303	0.4323	0.625	0.833	0.667	0.000
Vila Nova de Foz Côa	*a9*	0.431	0.422	0.6121	0.2318	0.688	0.917	0.083	0.000
Penedono	*a10*	0.475	0.443	0.6225	0.2630	0.688	0.917	0.167	0.000
Moimenta da Beira	*a11*	0.450	0.427	0.5991	0.2630	0.625	0.917	0.167	0.000
Esmolfe	*a12*	0.375	0.385	0.5783	0.1849	0.625	0.917	0.000	0.000
Vila Nova de Covelo	*a13*	0.413	0.422	0.6330	0.2109	0.688	1.000	0.000	0.000
Celorico da Beira	*a14*	0.450	0.443	0.5808	0.3047	0.438	1.000	0.333	0.000
Linhares	*a15*	0.300	0.339	0.4246	0.2448	0.438	0.583	0.333	0.000
Capinha	*a16*	0.475	0.464	0.6538	0.2734	0.688	1.000	0.167	0.000
Sintra	*a17*	0.231	0.266	0.3985	0.1641	0.313	0.750	0.000	0.000
Sines	*a18*	0.606	0.599	0.6903	0.5078	0.813	0.750	0.500	0.333
LPG_Sines	*a19*	0.719	0.729	0.8023	0.6563	1.000	0.750	0.500	0.667
Monchique	*a20*	0.419	0.370	0.3881	0.3672	0.313	0.500	0.667	0.000
Jales	*a21*	0.588	0.552	0.7450	0.3594	0.875	1.000	0.333	0.000
Borralha	*a22*	0.538	0.505	0.6746	0.3359	0.688	1.000	0.333	0.000
Pejão-Germunde	*a23*	0.488	0.479	0.6772	0.2813	0.750	1.000	0.167	0.000
S. Pedro da Cova	*a24*	0.488	0.490	0.6512	0.3281	0.625	1.000	0.333	0.000
Panasqueira	*a25*	0.550	0.521	0.6981	0.3438	0.750	1.000	0.333	0.000
Matacães	*a26*	0.656	0.656	0.6720	0.6406	0.625	0.750	0.417	0.833
Aljustrel	*a27*	0.400	0.391	0.5444	0.2526	0.563	0.833	0.167	0.000
Neves-Corvo	*a28*	0.488	0.479	0.6356	0.3542	0.750	0.833	0.333	0.000
Loulé—Campina de Cima	*a29*	0.750	0.734	0.8101	0.6589	0.938	0.833	0.333	0.833
Verride salt dome	*a30*	0.613	0.609	0.7476	0.4714	0.938	0.833	0.167	0.500
Soure salt dome	*a31*	0.594	0.615	0.7554	0.4740	0.875	0.917	0.167	0.500
Ervideira salt dome	*a32*	0.556	0.562	0.7606	0.3646	1.000	0.917	0.000	0.333
Monte Real salt dome	*a33*	0.756	0.781	0.7971	0.7578	0.875	0.750	0.667	0.833
Carriço—1S	*a34*	0.844	0.880	0.9039	0.8568	0.938	0.917	0.667	1.000
Carriço—2	*a35*	0.844	0.880	0.9039	0.8568	0.938	0.917	0.667	1.000
Carriço—3	*a36*	0.844	0.880	0.9039	0.8568	0.938	0.917	0.667	1.000
Carriço—4	*a37*	0.844	0.880	0.9039	0.8568	0.938	0.917	0.667	1.000
Carriço—5	*a38*	0.844	0.880	0.9039	0.8568	0.938	0.917	0.667	1.000
Carriço—6	*a39*	0.844	0.880	0.9039	0.8568	0.938	0.917	0.667	1.000
Carriço—7	*a40*	0.806	0.818	0.8726	0.7630	0.938	0.917	0.667	0.750
Carriço—8	*a41*	0.806	0.818	0.8726	0.7630	0.938	0.917	0.667	0.750
Carriço—9	*a42*	0.806	0.818	0.8726	0.7630	0.938	0.917	0.667	0.750
S. Pedro de Moel salt dome	*a43*	0.581	0.589	0.7580	0.4193	0.938	0.917	0.000	0.500
Parceiros (Leiria) salt dome	*a44*	0.556	0.521	0.5730	0.4531	0.500	0.750	0.333	0.500
Porto de Mós salt dome	*a45*	0.494	0.448	0.4220	0.4818	0.375	0.417	0.500	0.500
Fonte da Bica (Rio Maior) salt dome	*a46*	0.538	0.521	0.4897	0.5599	0.500	0.417	0.667	0.500
Caldas da Rainha diapir	*a47*	0.613	0.615	0.7137	0.5078	0.875	0.750	0.333	0.500
Várzea da Rainha salt dome	*a48*	0.563	0.568	0.7268	0.4089	0.938	0.833	0.000	0.500
Bolhos salt dome	*a49*	0.625	0.573	0.6929	0.4531	0.875	0.750	0.333	0.333
Maceira (Vimeiro) salt dome	*a50*	0.438	0.453	0.5965	0.2943	0.813	0.667	0.000	0.333
Santa Cruz salt dome	*a51*	0.413	0.417	0.5418	0.3073	0.500	0.833	0.000	0.333
Matacães salt dome	*a52*	0.694	0.687	0.7189	0.6563	0.750	0.750	0.417	0.833
Pinhal Novo salt dome	*a53*	0.644	0.625	0.6668	0.5912	0.750	0.667	0.583	0.500
Sesimbra salt dome	*a54*	0.294	0.328	0.4089	0.2787	0.313	0.667	0.000	0.333
Loulé salt dome	*a55*	0.638	0.609	0.6642	0.5547	0.688	0.750	0.333	0.667
Faro salt dome	*a56*	0.544	0.453	0.5965	0.3099	0.813	0.667	0.000	0.333
Lusitanian On_A1	*a57*	0.544	0.521	0.5314	0.5182	0.500	0.583	0.833	0.167
Lusitanian On_A2	*a58*	0.519	0.526	0.6225	0.4219	0.688	0.750	0.500	0.167
Lusitanian On_A3	*a59*	0.556	0.531	0.7137	0.3490	0.875	0.917	0.167	0.167
Lusitanian On_A4	*a60*	0.575	0.573	0.6512	0.4948	0.625	0.833	0.667	0.167
Lusitanian On_C1	*a61*	0.538	0.531	0.6095	0.4453	0.625	0.750	0.583	0.167
Lusitanian On_J1	*a62*	0.613	0.552	0.5365	0.5599	0.375	0.667	1.000	0.167

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