Atlantis Studies in Uncertainty Modelling, volume 3
Joint Proceedings of the 19th World Congress of the International Fuzzy Systems Association (IFSA), the 12th Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT), and the 11th International Summer School on Aggregation Operators (AGOP)

A Comparative Analysis Based on GIS and Fuzzy MCDM Approaches. Case Study: Offshore Wind Site Selection in the Gulf of Maine

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Abstract

The site selection process to optimize renewable facilities has become a relevant issue, mainly due to the variability of such resources. Among the different solutions, Geographic Information Systems in combination with fuzzy logic and Multi-Criteria Decision Making approaches provide a consistent tools to solve these complex decision problems. Moreover, the versatility of GIS software has led to the generation of spatial analysis extensions, such as the fuzzy membership tool transforming the input data into real numbers that belongs to the unit interval. In this work, a comparative study between fuzzy membership tool of ArcGIS software and a combination of the fuzzy MCDM methodologies (AHP-TOPSIS) is applied to optimize the offshore wind site selection. A case study based on the offshore wind resource in the Gulf of Maine is also included and discussed.

Keywords: Criteria, Alternatives, Fuzzy membership tool, Multi-Criteria Decision Making (MCDM), Renewable energy.

1 Introduction

In parallel to the emergence of fuzzy logic [24], new approaches have been designed during the last decades, such as intuitionistic fuzzy sets [3], neutrosophic sets [17], pythagorean fuzzy sets [23] and picture fuzzy sets [5]. Furthermore, their combination with Multi-Criteria Decision Making (MCDM) methodologies has allowed to solve numerous decision problems in a variety of fields: science, management and business, engineering, or technology [13].

The renewable energy sector has not been an exception. Indeed, it can be framed within the 17 Sustainable Development Goals, as for example the assurance of accessing to affordable, reliable, sustainable and modern energy for all [20] . Applications combining MCDM methodologies with fuzzy series have been carried out in the last decades [18]. Recent studies can be also found in the specific literature, such as the combination of Analytical Hierarchy Process (AHP) [15] with the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) [10], for evaluation of the energy alternatives in India based on their sustainability [16], or the application of fuzzy Analytical Network Process (ANP) and fuzzy TOPSIS for selection of wave power plants in Vietnam [21].

Furthermore, the search and evaluation of optimal sites to implant renewable energies facilities has brought about the emergence of tools. As an example, Geographic Information Systems (GIS) combined with fuzzy logic and MCDM approaches have allowed to solve complex decision problems, such as the wind-powered pumped storage power plant site selection [1], the offshore and onshore wind energy power plants site selection [19, 2] or even the solar installation site selection [25]. The versatility of GIS software has even led to the generation of spatial analysis extensions, such as the fuzzy membership tool of the ArcGIS software. This tool transforms the input data into real numbers that belongs to the interval [0,1] through fuzzy membership functions specified by the user [11]. However, not all membership functions can be useful for solving a given decision problem, since their effectiveness highly depends on the nature of the input data. Under this framework, this paper aims to carry out a comparative study between the fuzzy membership tool of ArcGIS and the application of a combination of MCDM methodologies (AHP-TOPSIS) through their fuzzy versions. Few studies can be found in the specific literature to integrate AHP-TOPSIS with different extensions of fuzzy sets [14], such as Interval type–2

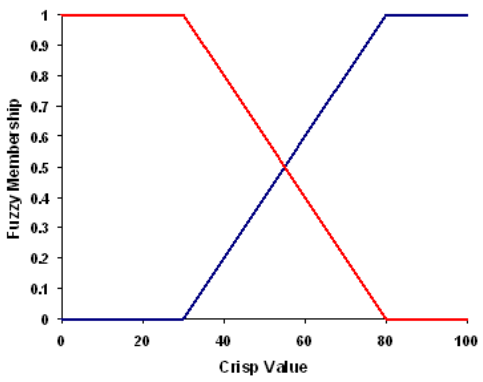

Figure 1: Linear fuzzy membership.

fuzzy set, interval-valued intuitionistic fuzzy set, hesitant fuzzy sets and neutrosophic sets. The authors select the ordinary fuzzy sets by considering numerous studies conducted on the extended TOPSIS methods within a fuzzy environment [4]. The proposed decision problem is assessed through the offshore wind energy power plant site selection in the Gulf of Maine, USA.

The rest of the paper is structured as follows: Section 2 describes the methodology used for the decision problem considered, i.e., the fuzzy membership tool of the ArcGIS software and the fuzzy versions of the AHP-TOPSIS combination; Section 3 presents and discusses the proposed decision problem (via the description of its study area, alternatives and criteria); and finally, Section 4 gives the main conclusions.

2 Methodology

2.1 Fuzzy membership tool

From a mathematical point of view, a membership function, $f_A : U \to [0,1]$, can be defined as a rule that ascribes each element $x \in U$ to the degree of membership of x to A, $f_A(x) \in [0,1]$. In fact, this type of functions can be considered, depending on the context in which was applied, as a membership function associated with fuzzy sets. In ArcGIS software, the different membership functions (f_A) associated with fuzzy sets includes fuzzy gaussian, fuzzy large or small, fuzzy near and fuzzy linear. The graphical representation of the fuzzy linear function is shown as an example in Figure 1. These fuzzy membership functions allow data to be reclassified and placed in the domain of the unit interval [0,1]. A further explanation about the mathematical expressions involved and how such fuzzy membership functions work can be seen in [11, 6].

2.2 Fuzzy Analytic Hierarchy Process (FAHP)

The AHP methodology was developed by T. Saaty in the 1980s [15]. This MCDM approach is based on three main characteristics:

1. Modeling the decision problem through a specific hierarchy: upper vertex the objective of the decision problem is located; the alternatives to be evaluated are positioned in the lowest level of the hierarchy.
2. Comparing by pairs of elements in each level of the hierarchy with respect to each element in the previous level.
3. Synthesizing the judgments vertically on different levels of the hierarchy.

The judgments provided by the decision maker on the criteria pairs (Ci, Cj) are represented in a nxn–matrix (C_{nxn}). The C_{12} value is then an approximation of the relative importance of C_1 to C_2, that is, $C_{12} \approx ({}^{w_1}/_{w_2})$:

1. $c_{ij} \approx ({}^{w_i}/_{w_j}) \quad i,j = 1,2,...,n$
2. $c_{ii} = 1 \quad i = 1,2,...,n$
3. If $c_{ij} = \alpha, \alpha \neq 0$, thus $a_{ji} = ({}^{1}/_{\alpha}) \quad i,j = 1,2,...,n$
4. If c_i is more important than c_j, thus $c_{ij} \approx ({}^{w_i}/_{w_j}) > 1$

These assertions imply that C must be positive and reciprocal with 1 on the main diagonal. The values assigned to c_{ij} according to the Saaty scale is located in the interval 1-9 or the corresponding inverses. Such scale is shown in Table 1, represented through triangular fuzzy numbers.

In AHP decision problems, where the values are fuzzy numbers, the normalized geometric mean is used as estimator of the weight in instead of λ.

$$w_i = \frac{\prod_{j=1}^{n}(a_{ij},b_{ij},c_{ij})^{(1/n)}}{\sum_{i=1}^{m}\prod_{j=1}^{n}(a_{ij},b_{ij},c_{ij})^{(1/n)}}$$

with (a_{ij}, b_{ij}, c_{ij}) being a fuzzy number

In this study, the AHP approach is applied to obtain the weights of the criteria.

2.3 Fuzzy Technique for Order Preference by Similarity to the Ideal Solution (FTOPSIS)

TOPSIS approach has become, together with the AHP methodology, the most widely used MCDM methodologies [12], mainly due to their rational and un-

Verbal judgments of preferences	Triangular fuzzy scale and reciprocals
C_i and C_j is equally important	(1,1,1)/(1,1,1)
C_i is moderately More/Less Important than C_j	(2,3,4)/(1/4,1/3,1/2)
C_i is More/Less Important than C_j	(4,5,6)/(1/6,1/5,1/4)
C_i is Much More/Less Important than C_j	(6,7,8)/(1/8,1/7,1/6)
C_i is Extremely More/Less Important than C_j	(8,9,9)/(1/9,1/9,1/8)

Table 1: Scale of valuation in the pair-wise comparison process.

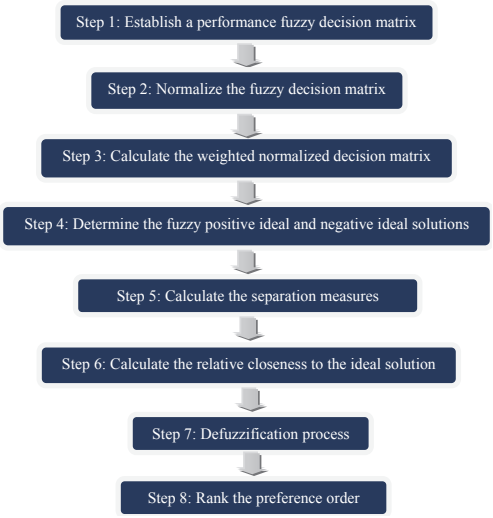

Figure 2: Fuzzy TOPSIS algorithm.

derstandable logic as well as other additional advantages [22]. More recently, fuzzy versions of these approaches are also available to be applied on a variety of sectors [13]. TOPSIS solution is based on the concept of the ideal alternative, providing a relationship of proximity to each alternative through the Euclidean distance. With this aim, two fictitious alternatives so-called Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are defined. This method calculates the distance to such fictitious solutions depending on whether the criteria that influence the evaluation are of benefit or cost. In this work, the Fuzzy TOPSIS method is used to evaluate the alternatives. The operations associated to triangular fuzzy numbers involved in the TOPSIS algorithm can be found in [8]. Figure 2 summarizes schematically the fuzzy TOPSIS algorithm.

3 A decision problem: Offshore wind farm site selection in the Gulf of Maine

The state of Maine is one of the 50 states that make up the United States of America. It is located in the northeast region of the country. Its southern zone borders

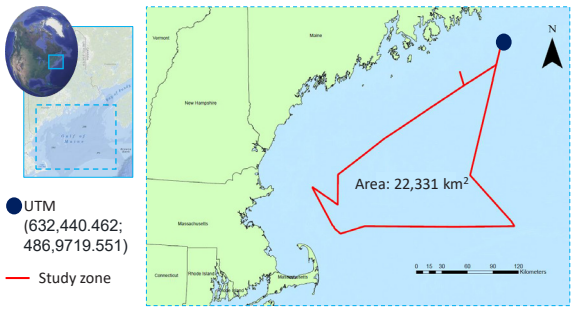

Figure 3: General view of the Gulf of Maine. Study area.

the Gulf of Maine, see Figure 3. It is a state of great offshore wind potential. Factors such as wind speed, bathymetry, distance from potential areas to coasts, etc. are signs of that. In fact, the average wind speed on its coasts at $150m$ height exceeds $9.5m/s$ per year. The offshore wind potential of the Maine coast is analyzed through the ArcGIS software. Both thematic layers of the restrictions and criteria are considered to evaluate potential sites (alternatives). Such analysis, derived from the study carried out by [9], also exclude such non-available areas based on technical and legal restrictions and define the criteria that influence the evaluation of said potential. From the study area and the orientation of a prototype wind farm, 56 alternatives are finally selected, see Figure 4. Each of them is capable of containing a wind power plant with 1 GW power installed capacity. Such alternatives constitute the potential locations, which are subsequently evaluated based on the 9 criteria previously depicted. Figure 5 to Figure 13 summarize the different criteria to be considered in this case study.

3.1 Determination of the weight of the criteria

To assess the potential offshore wind farm sites based on said criteria, a previous stage to estimate the weights of the criteria is performed. With this aim, a group of experts filled out a questionnaire based on the application of the AHP methodology. Due to the use of fuzzy numbers in the next stage, the correspond-

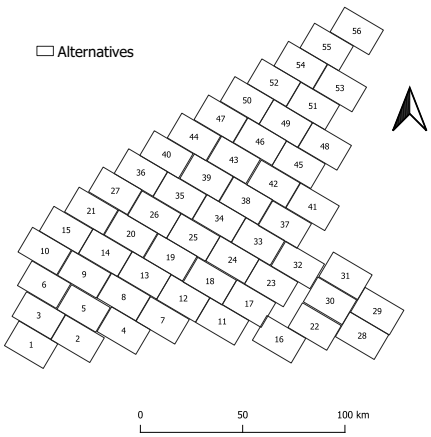

Figure 4: Summary of alternatives. Study area.

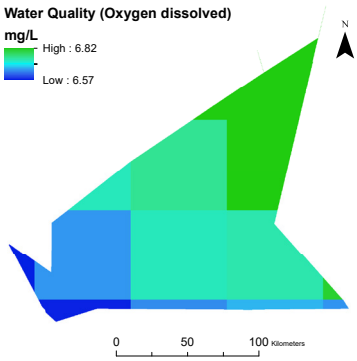

Figure 7: Criterion 3 - Water quality (oxygen concentration).

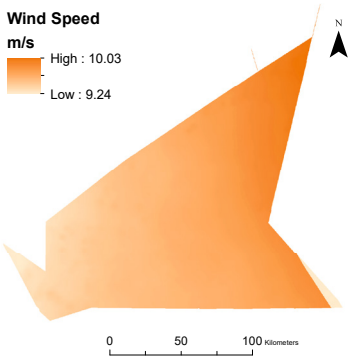

Figure 5: Criterion 1 - Average Wind Speed (m/s).

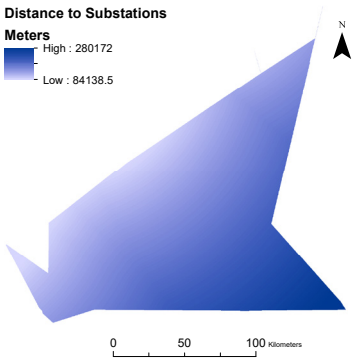

Figure 8: Criterion 4 - Distance to substations (m).

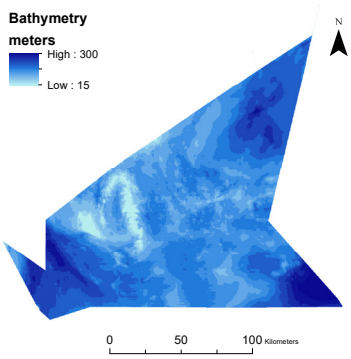

Figure 6: Criterion 2 - Bathymetry (m).

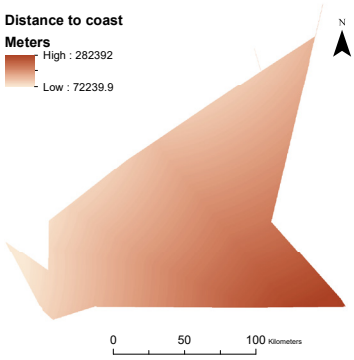

Figure 9: Criterion 5 - Distance to coast (m).

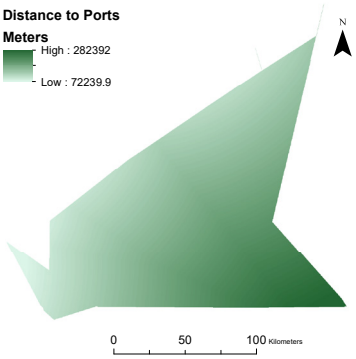

Figure 10: Criterion 6 - Distance to ports (m).

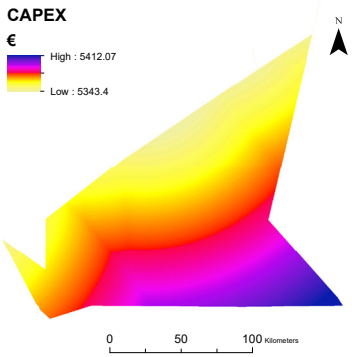

Figure 11: Criterion 7 - Investment costs (CAPEX).

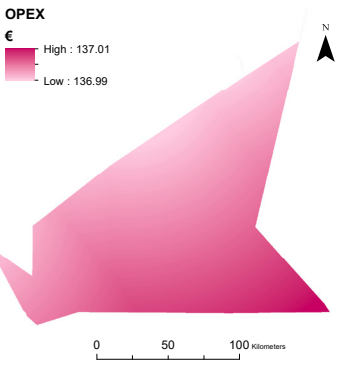

Figure 12: Criterion 8 - Operation and maintenance costs (OPEX).

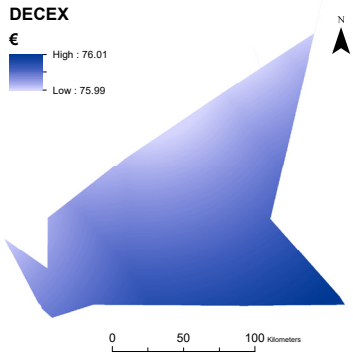

Figure 13: Criterion 9 - Dismantling cost (DECEX).

ing weights are then carried out taking into consideration the Saaty scale through triangular fuzzy numbers, see Table 1. Once the weights of the criteria for each expert are calculated, it is possible to obtain the global vector of the weights represented through triangular fuzzy numbers. A homogeneous aggregation by the arithmetic mean (considering that all experts are equally important in the decision problem) is summarized in Table 2. Through homogeneous aggregation it is observed that the most important criterion is C_1 (Wind speed), while the second most important is C_2 (Bathymetry). The least important criteria are C_3 and C_4 (Water quality and Distance to substations, respectively).

3.2 Assessment of the alternatives via ArcGIS

Once the set of criteria is selected, and the weight of the criteria obtained, the fuzzy membership tools of ArcGIS software can be applied [11]. These tools allow the thematic layers of criteria to be reclassified and placed in the domain of the unit interval [0,1]. In this way, it is possible to carry out superpositions of criteria with their associated weights and obtain a ranking of alternatives through the ArcGIS raster calculator tool. ArcGIS software uses the Weighted Sum Model (WSM) [7].

Performing the calculations with the fuzzy membership functions Large and Small, it can be noted that those criteria with a greater amplitude give greater fuzzified values and vice–versa. Therefore, the ranking of alternatives become distorted in the reclassification process. Similarly, the behavior of the Gaussian and Near fuzzy membership functions doesn't allow to use them in distance criteria, such as the criteria C_4 (Distance to substations), C_5 (Distance to coast) and C_6 (Distance to ports). In fact, the linear function is

	Experts' homogeneous aggregation (Triangular fuzzy numbers)	Weight (%)	Order of importance
C1.- Wind speed	(0.262, 0.371, 0.505)	37.07	1
C2.- Bathymetry	(0.157, 0.232, 0.339)	23.16	2
C3.- Water quality	(0.013, 0.019, 0.030)	1.85	9
C4.- Distance to substations	(0.018, 0.026, 0.042)	2.59	8
C5.- Distance to coast	(0.074, 0.116, 0.180)	11.61	3
C6.- Distance to ports	(0.041, 0.064, 0.103)	6.38	5
C7.- Investment costs (CAPEX)	(0.056, 0.089, 0.143)	8.91	4
C8.- Operation costs (OPEX)	(0.027, 0.041, 0.068)	4.10	7
C9.- Dismantling cost (DECEX)	(0.028, 0.043, 0.071)	4.33	6

Table 2: Weights of criteria through experts' homogeneous aggregation.

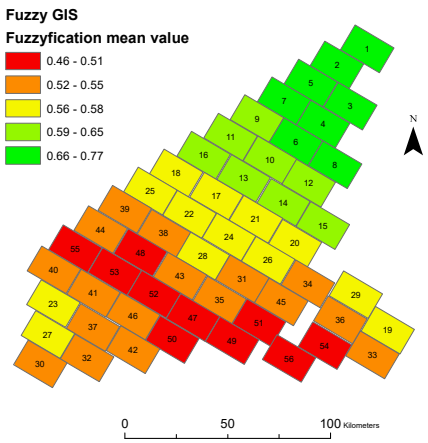

Figure 14: Ranking fuzzy GIS of the capacity to accommodate offshore wind farms in the Gulf of Maine.

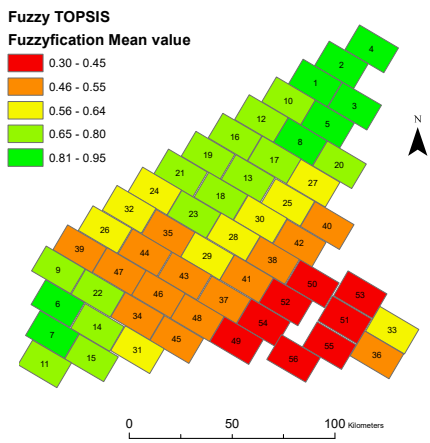

Figure 15: Ranking fuzzy AHP-TOPSIS of the capacity to accommodate offshore wind farms in the Gulf of Maine.

the most appropriate fuzzy membership function for the thematic layers of criteria. This function allows us to transform the values of each criteria into values located within the [0,1] interval, providing ranking of alternatives considering the weights of the criteria. Figure 14 depicts the ranking fuzzy GIS of the case study. From the results, it can be appreciated that the alternatives located to the northeast are those that obtain the best valuations. The explanation of that lies in the fact that this zone not only has the highest wind speed values (the most important criterion), but also the best bathymetry (second criterion in order of importance).

3.3 Assessment of the alternatives via Fuzzy TOPSIS

From the criteria weights, the alternatives for each criterion are evaluated through the combination of Fuzzy AHP-TOPSIS. Due to GIS software provides not only the mean value of each criterion for each alternative, but also their maximum and minimum values, the criteria can be then defined by triangular fuzzy numbers. Therefore, the decision matrix composed by 56 alternatives and 9 criteria, based on triangular fuzzy numbers, can be determined. Such matrix is the starting point of the application of Fuzzy TOPSIS methodology via defuzzification process [8]. As a result,the potential alternatives are ordered and ranked according to the relative closeness to the ideal solution. The decision maker has the possibility to analyze the positions of each of the alternatives i.e., sites to locate offshore wind power plants in the Gulf of Maine, see Figure 15.

3.4 Results and comparative study

In order to analyze the rankings obtained through the two afore-mentioned approaches (fuzzy membership tool vs. fuzzy AHP-TOPSIS), a comparison with the twenty top–ranked alternatives is given in Table 3.

By considering Table 3, Figure 14 and Figure 15, we affirm that the first five most appropriate alternatives are the same in both rankings. In fact, the order of such alternatives is practically similar, with only one position exchanged between them. Furthermore,

Alternative	Defuzzyfication process TOPSIS	Ranking Fuzzy TOPSIS	Ranking Fuzzy tool GIS
A54	0.954	1	5
A55	0.949	2	2
A53	0.919	3	3
A56	0.901	4	1
A51	0.880	5	4
A6	0.879	6	23
A3	0.861	7	27
A49	0.815	8	6
A10	0.799	9	40
A52	0.796	10	7
A1	0.771	11	30
A50	0.743	12	9
A43	0.736	13	13
A5	0.726	14	37
A2	0.720	15	32
A47	0.719	16	11
A46	0.713	17	10
A39	0.709	18	17
A44	0.708	19	16
A48	0.701	20	8

Table 3: Comparison of the twenty Top-ranked alternatives

among the twenty top–ranked alternatives provided by Fuzzy TOPSIS, fourteen alternatives are also in the top–twenty according to the Fuzzy GIS ranking. The justification for the differences observed in both rankings lies in the way of prioritizing such alternatives. Fuzzy GIS prioritizes the criterion with the greatest weight (C_1- Wind speed) above the rest. It applies the WSM approach in the reclassification process: the larger weight in this criterion is the key to order and prioritize. However, the Fuzzy TOPSIS methodology compensates values for said criterion (C_1) relatively far from the ideal solution with other favorable values in criteria that are also well weighted, such as the criteria C_2– Bathymetry and C_5– Distance to coast.

4 Conclusions

This paper compares and assesses fuzzy membership tools of GIS software and a combination of fuzzy-based MCDM methodologies to optimize offshore wind site selection. A case study focused on Gulf of Maine (USA) offshore wind resource is carried our and included in the work. It is worth mentioning that not all the fuzzy membership function tools of the GIS software can be used to solve the study problem, since these tools highly depend on the input data (thematic layers in this case). It should also be highlighted that although the first positions are the same in both methodologies, there are differences regarding the MCDM methodology that underlies the GIS software, WSM in this case. As a consequence of the compensatory nature of the TOPSIS methodology, appreciable differences are observed when the range of the best alternatives is extended.

Future study focused on analyzing the influence of the criteria weights will be carried out by the authors. Moreover, a detailed analysis of the GIS software fuzzy membership functions will allow us to study their suitability based on the input data.

Acknowledgement

This work is supported by grants TIN2017-86647-P and 19882-GERM-15 from the Spanish Ministry of Economy and Competitiveness (MINECO) and Fundación Séneca (Región de Murcia), respectively.

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