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Abstract: Characterizing zone fragility is a significant challenge when managing protected natural areas, but it must be prioritized in conservation efforts. The most commonly employed methodology is to rely on criteria established by experts, which can introduce subjectivity. However, more objective approaches should be used when developing conservation plans. This study proposes one methodology for classifying zone vulnerability within a protected natural area, taking as a study case a temporal pond network located in SW Spain; threatened species of aquatic plants were used as a bioindicators. Spatial data were analysed using geographic information systems (GIS), and potentially vulnerable zones were identified using multicriteria decision analysis and, more specifically, the weighted overlay method. Criteria weights were determined using species distribution models, via the maximum entropy algorithm (MaxEnt). The purpose was to avoid artificial bias in decision-making. The analysis indicated that 42.04% of the study area was highly vulnerable. In contrast, only the 14.34% of the study area was at very low risk, meaning it can help maintain pond network biodiversity. These results indicate that potentially vulnerable and crucial zones can be identified using GIS, facilitating the establishment of conservation priorities in a complex system. This methodology could be useful for prioritizing and implementing management and conservation efforts focused on unique species and habitats in protected natural areas.

Combining multicriteria decision analysis and GIS to assess vulnerability within a protected area: an objective methodology for managing complex and fragile systems

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HIGHLIGHTS

-We assessed zone vulnerability within a protected area by combining multicriteria decision analysis and spatial analysis methods.

-The methodology is illustrated with reference to one of the most important Mediterranean temporary pond networks present in Europe.

-Integration of different spatial approaches offers reliable indicators for protected areas monitoring.

-MaxEnt modeling provided criteria's weight in an objective context and without expert choice bias.

-The produced vulnerability map can be useful for establishing management and conservation priorities in complex systems for future spatial planning.

Combining multicriteria decision analysis and GIS to assess vulnerability within a protected area: an objective methodology for managing complex and fragile systems

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Abstract

Characterizing zone fragility is a significant challenge when managing protected natural areas, but it must be prioritized in conservation efforts. The most commonly employed methodology is to rely on criteria established by experts, which can introduce subjectivity. However, more objective approaches should be used when developing conservation plans. This study proposes one methodology for classifying zone vulnerability within a protected natural area, taking as a study case a temporal pond network located in SW Spain; threatened species of aquatic plants were used as a bioindicators. Spatial data were analysed using geographic information systems (GIS), and potentially vulnerable zones were identified using multicriteria decision analysis and, more specifically, the weighted overlay method. Criteria weights were determined using species distribution models, via the maximum entropy algorithm (MaxEnt). The purpose was to avoid artificial bias in decision-making. The analysis indicated that 42.04% of the study area was highly vulnerable. In contrast, only the 14.34% of the study area was at very low risk, meaning it can help maintain pond network biodiversity. These results indicate that potentially vulnerable and crucial zones can be identified using GIS, facilitating the establishment of conservation priorities in a complex system. This methodology could be useful for prioritizing and implementing management and conservation efforts focused on unique species and habitats in protected natural areas.

Keywords: Aquatic plants, Conservation planning, MaxEnt, Protected areas management, Spatial analysis, Weighted overlay analysis

1. Introduction

Significant work is required to characterize the risks faced by protected natural areas, but this knowledge is necessary to establish conservation priorities (Margules and Pressey, 2000; Young, 2000). From an ecological point of view, ecosystem fragility is defined as how well a system can buffer damage caused by intrinsic or extrinsic forces precipitating environmental change (Nilsson and Grelsson, 1995). Although quantifying the fragility of different zones is a key part of conservation efforts (Gauthier et al., 2013), this task can be challenging because diverse factors are involved, and any decision must be based on multiple criteria (Noss et al., 2002). These criteria may relate to habitat vulnerability (Rouget, 2003), the presence of threatened species (Pressey and Taffs, 2001), or habitat connectivity (Spring et al., 2010). For this reason, it is important to develop simple and objective methodologies that can quantify the fragility of protected natural areas, which will facilitate conservation decisions and management strategies (Gauthier et al., 2013, 2010; Schatz et al., 2014). Indeed, it is now common to use multicriteria decision analysis (MCDA hereafter) to identify conservation priorities and threats (Forio et al., 2017; Nouri et al., 2017; Sarkar et al., 2016). Furthermore, MCDA can be combined with geographic information systems (GIS), allowing multiple criteria to be considered in tandem with spatial information (Malczewski and Rinner, 2015).

Although different methodologies exist for carrying out MCDA, the most common approach is to estimate the weight of each selected criterion using the opinions of experts (Malczewski, 2006). A pairwise comparison matrix is employed—each criterion is evaluated on a ratio scale by examining all possible pairings with other criteria and its relative importance emerges as a result; this approach is commonly known as the analytic hierarchy process (AHP) (Saaty, 1990). Consequently, experts' opinions and the literature have a major influence on the results (Krois and Schulte, 2014), and the weights that go into the MCDA could be biased (Sarkar et al., 2016). To deal with this concern, some authors have proposed combining GIS tools with machine learning techniques to estimate the weight of each used criterion, which would be more objective (Lu et al., 2012; Zhou et al., 2016). Indeed, the maximum entropy (MaxEnt) approach to modeling is one of the most effective algorithms for presence-only data, and it has been shown to work better than other methods, even when sample size is low and there are moderate georeferencing errors (Elith et al., 2006; Hernandez et al., 2006; Mateo et al., 2013; Phillips et al., 2006; Wisz et al., 2008).

Wetlands are ecosystems of great interest because they harbor high levels of biodiversity (Dudgeon et al., 2006). However, they are very vulnerable to disturbances and, for this reason, they are considered to be one of the most threatened ecosystems in the world (Strayer and Dudgeon, 2010). Topographically, they end up acting as sinks for effluents, which means that they can indicate the quality of conditions in adjacent areas (Martínez-López et al., 2014). One of the main threats faced by wetlands is the expansion of urban areas and irrigated farmlands, which, in recent decades, has reduced the number and quality of freshwater ecosystems, especially in coastal areas (Bustamante et al., 2016; Martínez-López et al., 2014). Of particular concern are Mediterranean temporary ponds (MTPs): because of their cycles of flooding and desiccation, they are home to unique assemblages of species that cannot survive elsewhere (Bagella et al., 2010). MTPs are highly threatened by human activities (Zacharias et al., 2007; Zacharias and Zamparas, 2010), making them a perfect study system for evaluating the ability of MCDA to assess vulnerability in an objective way.

Freshwater systems are extremely complex and face myriad pressures, which means that monitoring efforts must use precise indicators of system vulnerability and effective early warning tools (Fancy et al., 2009). Sometimes, characterizing physicochemical indicators in wetlands requires intensive sampling but does not necessarily yield biologically relevant results (Gergel et al., 2002). In contrast, bioindicators may better reflect system conditions and vulnerability and can be easier to obtain (Niemi and McDonald, 2004). For example, aquatic plants are very sensitive to environmental changes (O'Hare et al., 2017), and the Water Framework Directive has proposed that they be used as bioindicators of water quality and the systems that inhabit (European Commission, 2003). Consequently, characterizing the distribution of aquatic plants should be an essential part of conservation strategies (Hattab et al., 2013). Furthermore, species distribution models (SDMs), which utilize distribution data, may be useful tools for identifying zones of conservation priority in protected natural areas, especially when information on actual distribution patterns is limited (Hespanhol et al., 2015).

The main goal of this study was to use MCDA to objectively identify vulnerable zones in a protected natural area, Doñana's aeolian sand dunes region (SW Spain), which hosts one of the most important MTP networks in western Europe (Díaz-Paniagua et al., 2010). We had three specific objectives: (1) to establish a GIS-based set of criteria for assessing vulnerability within the pond network; (2) to develop SDMs for aquatic plants to determine each criterion weight; and (3) to perform MCDA to reveal the zones of greatest vulnerability.

2. Materials and Methods

2.1. Study area

Our study took place in the Doñana's aeolian sand dunes. They comprise one of the most important protected natural areas in the European Union and shelter a singular and extensive MTP network. This area is located in southwestern Spain, between the mouths of the Guadalquivir River and the Tinto River (Fig. 1). The pond network is an extensive system of small, heterogeneous, and dynamic water bodies; it is fed mainly through rainfall, although its hydrology also directly depends on the groundwater table (Gómez-Rodríguez et al., 2010). It is considered to play a crucial role in the maintenance of many species of aquatic flora and fauna (Díaz-Paniagua et al., 2010). Although there are different levels of protection in place (Fig. 1), there is nonetheless strong negative pressure on the pond network, which is mainly due to groundwater extraction for agricultural and urban usage (Bustamante et al., 2016; Díaz-Paniagua and Aragonés, 2015; Dimitriou et al., 2017).

This study area was chosen because it has been used in many conservation studies. We were therefore able to compare our results with those of previous studies and, consequently, determine whether the methodology proposed here could be useful for prioritizing management strategies and conservation objectives in complex and fragile systems.

To achieve the objectives described above, three main tasks were carried out: (1) were processed the spatial data; (2) were developed SDMs to estimate the weight of each criterion; and (3) were performed a MCDA (Fig. 2).

2.2. Data type and processing

The pond network vector layer was taken from Bustamante et al. (2016), who used the methodology proposed by Díaz-Delgado et al. (2016). This method identifies seasonally flooded areas within the aeolian sand dunes using a series of Landsat TM and ETM+ images that have been radiometrically normalized (time period: 1985–2014) via a semi-automatic procedure.

A database of threatened aquatic plants was compiled, using species occurrence data obtained from the Natural Resources and Processes Monitoring Team at the Doñana Biological Station (RBD-ICTS, CSIC); FAME, a conservation programme put in place by the Environmental Ministry of the Andalusian Regional Government, which supports the monitoring, localization, and integration of information on threatened flora; and Anthos (Anthos, 2017), a webpage that is associated with the Flora Iberica project and that provides information about plant biodiversity in Spain. R software (R Core Development Team, 2014) was used to filter the data, eliminate duplicate entries, and remove erroneous occurrences in the geographical data. In the vector layer, the occurrence data were associated with cells measuring 30x30 m, a methodological choice that limits the effects of spatial autocorrelation, an issue that can arise when modeling potential species distributions (García- Roselló et al., 2015). A bias layer was created to limit the possible bias associated with species data sampling, due to the survey effort when species occurrences data were used in the SDMs (Fernández et al., 2015); the ArcGIS Kernel density analysis tool was used to calculate the density of presences in the study area (ESRI, 2016).

The criteria used were associated with variables thought to influence the distribution of aquatic vegetation in the study area. Table 1 shows the criteria employed in the SDMs, which were subsequently included in the MCDA. These criteria were classified as intrinsic (i.e., natural variables that are part of the immediate habitat) or extrinsic (i.e., exterior natural or anthropogenic variables that provoke system or species stress). In the intrinsic category were pond density, the distance between ponds, and hydroperiod, which all contribute to species occurrence (Díaz-Paniagua et al., 2010; Fernández-Zamudio et al., 2016). In the extrinsic category were the distance to urban areas and farmlands (concretely irrigated lands); the distance to highways, paths, and cattle trails; the distance to streams and the coast; and the distance to neighbouring habitats, such as the marshes and the *La Vera* ecotone. This latter is a zone comprising highly heterogeneous habitats that result from the presence of small intermittent streams—they discharge into the marshes and less permeable substrate, resulting in the formation of ephemeral water bodies (Florencio et al., 2014).

Each criterion was processed to obtain a distance or density map. All analyses were performed using ArcGIS (ESRI, 2016). The Euclidean distance tool was used to determine distances, and the Kernel density analysis tool was used to calculate densities (Antognelli and Vizzari, 2017). All the data were used to create a raster with a pixel resolution of 30; they were then georeferenced and projected into ETRS 1989 UTM Zone 30N.

Criteria must be standardized before they can be used in MCDA (Lu et al., 2012). Here, standardization was carried out using fuzzy linear functions, which yielded values between zero and one (Nouri et al., 2017). These functions can take several forms; for example, they can be monotonically increasing or decreasing (lowest to highest on the measurement scale, respectively; Fuller et al., 2010). In this study, monotonically increasing functions were used for all the criteria, with the exception of the distance between water bodies and the distance to the *La Vera* ecotone. For these latter two, monotonically decreasing functions were used because shorter distances mean greater water availability and more available niches for various organisms (Díaz-Paniagua et al., 2010; Fernández-Zamudio et al., 2016; Florencio et al., 2014). This standardization approach was used because fuzzy linear functions can standardize variables even when no prior knowledge is available, but they can also retain the information present in the original data (Lu et al., 2012).

Criteria	**Format**	**Analysis**	**Source**
Pond density	Vector	Kernel density	Bustamante et al., 2016
Distance between ponds	Vector	Euclidean distance	Bustamante et al., 2016
Hydroperiod	Raster		Bustamante et al., 2016
Distance to farmlands	Vector	Euclidean distance	REDIEAM[1]
Distance to urban areas	Vector	Euclidean distance	REDIEAM[1]
Distance to the coast	Vector	Euclidean distance	REDIEAM[1]
Distance to marshes	Vector	Euclidean distance	MAPAMA[2]
Distance to the *La Vera*	Vector	Euclidean distance	MAPAMA[2]
Distance to streams	Vector	Euclidean distance	IECA[3]
Distance to highways	Vector	Euclidean distance	IECA[3]
Distance to paths	Vector	Euclidean distance	IECA[3]
Distance to cattle trails	Vector	Euclidean distance	IECA[3]

Table 1. GIS data layers used as criteria in the vulnerability assessment: 1. Andalusian Environmental Information Network (REDIAM, http://www.juntadeandalucia.es/medioambiente/site/rediam); 2. Ministry of Agriculture, Fisheries, and Environment (MAPAMA, http://www.mapama.gob.es/es/); and 3.

Institute of Statistics and Cartography of Andalusia (IECA, https://www.juntadeandalucia.es/institutodeestadisticaycartografia).

2.3. Estimating weights

MaxEnt´s default parameters defined the models' parameters (Elith et al., 2011; Phillips et al., 2006; Phillips and Dudík, 2008). To reduce the likelihood of overfitting the model, the value of the multiple regularization parameter (default = 1) was changed to 2.5 (Elith et al., 2010; Rodríguez-Merino et al., 2018, 2017). A bias layer was included in models to control the effects of sampling bias (Fernández et al., 2015). The models were calibrated using 80% of the occurrence data; the other 20% were used to test the models obtained. In addition, for each model, a 10-fold cross-validation procedure was used to estimate error (Elith et al., 2011). What the models yielded was a probability of presence for each species, whose value lay between zero and one (Phillips and Dudík, 2008). Model accuracy was calculated by determining the area under the curve (AUC), which is one of the most common methods for testing the performance of presence-only models (Merow et al., 2013). The average percentage contributions of the model variables were used as weights in the subsequent MCDA (Lu et al., 2012).

2.4. Multicriteria decision analysis

Once the criteria weights were established, a MCDA was performed using the multicriteria weighted overlay method. This method is one of the most common GIS approaches for carrying out MCDAs (Nzeyimana et al., 2014). It involves superposing multiple raster layers based on their relative importance (Singh and Katpatal, 2017). In this study, the raster associated with each criterion was multiplied by its weight, which was obtained using the SDMs. The product was a map of the vulnerability of different areas within the pond network. This output was reclassified using the Jenks method (natural breaks) in ArcGIS, which identifies small breaks in data sets by grouping similar values (Slocum et al., 2008). The final classes for area vulnerability were: very high, high, moderate, low, and very low.

3. Results

3.1. Data type and processing

SDMs were created for a total of 24 species: 5 were hygrophytes, 5 were helophytes, and 14 were hydrophytes (Table S1, Supplementary Material). All 24 species are included in national or regional lists of threatened flora belonging to different IUCN categories (Table S1). Overall, 478 records were used to generate the SDMs; the largest number of records was 86 for *Eryngium corniculatum*. At least five records were needed to create a model; for this reason, other threatened aquatic plants present in the study area were excluded from the analysis due to the low number of records to perform adequate SDMs, and species with fewer than five occurrences were removed. The spatial distribution of the sampling points used and the bias layer are depicted in Fig. S1A and Fig. S1B (Supplementary Material). Following standardization, criteria values ranged from zero to one, where a value of zero meant that a criterion's utility was very low to null and a value of one meant that a criterion was highly useful in helping to establish a species' potential distribution (Fig. S2, Supplementary Material).

3.2. Model accuracy

Based on the AUC values, accuracy was good for all the SDMs (mean ± SD: 0.874 ± 0.086; min: 0.657; max: 0.992; Table S2, Supplementary Material). This indicates that all models are adequate, since they are above what is expected by chance (AUC: 0.5).

3.3. Estimating weights

Among the various criteria, the distance to the *La Vera* ecotone (25.92%) and the distance between ponds (20.88%) contributed the most to the SDMs predictions, followed by the distance to the coast (11.83%) and pond density (8.09%) (Table 2).

Criteria	**Weights (Contribution percentage)**
Pond density	8.09
Distance between ponds	20.88
Hydroperiod	3.87
Distance to farmlands	3.70
Distance to urban areas	4.17
Distance to the coast	11.83
Distance to marshes	3.45
Distance to the *La Vera*	25.92
Distance to streams	5.76
Distance to highways	2.62
Distance to paths	3.80

Distance to cattle trails	5.91

Table 2. Weight of each criterion based on percent contribution obtained by MaxEnt algorithm.

3.4. Multicriteria decision analysis

The MCDA indicated that 42.04% of the study area was potentially highly vulnerable and, more specifically, that 20.59% of the study area was very highly vulnerable (Table 3). These zones were located in the northern part of the study area, as well as toward its southern edge (Fig. 3). There are a total of 755 ponds in these zones, of which 350 are very highly vulnerable based on various criteria (Table 4). In contrast, the level of vulnerability was low for 36.02% of the study area and, more specifically, very low for 14.34% of the study area (Table 3). These zones were mainly located in the southern part of the study area, as well as in the center, which is the part of the network that benefits from the greatest level of protection (National Park; Fig. 3). Pond density was highest in zones of low vulnerability (60.3% of ponds were found in these zones; Table 4).

	National park		Natural park		Biosphere reserve		Unprotected		Total area	
Vulnerability risk	**Km^2**	**%**	**Km^2**	**%**	**Km^2**	**%**	**Km^2**	**%**	**Km^2**	**%**
Very high	0.01	0	39.2	15.27	59.29	18.68	91.53	84.8	190.03	20.59
High	8.87	3.68	33.74	13.14	139	43.8	16.41	15.2	198.02	21.45
Moderate	38.37	15.92	56.83	22.14	107.4	33.84	0	0	202.59	21.95
Low	79.34	32.91	109.32	42.58	11.46	3.61	0	0	200.12	21.68
Very low	114.49	47.49	17.64	6.87	0.22	0.07	0	0	132.34	14.34
Total area (Km^2)	241.07		256.74		317.36		107.94		923.11	

Table 3. Total area and percent representation associated with the different vulnerability classes in the study area.

	National park		Natural park		Biosphere reserve		Unprotected		Total ponds	
Vulnerability risk	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
Very high	0	0	37	3.43	1	0.17	312	7.77	350	9.53
High	34	2.16	80	7.42	188	31.18	103	2.57	405	11.03
Moderate	181	11.48	165	15.31	357	59.2	0	0	703	19.14
Low	331	21	474	43.97	52	8.62	0	0	857	23.34
Very low	1030	65.36	322	29.87	5	0.83	0	0	1357	36.96
Total ponds	1576		1078		603		415		3672	

Table 4. Number and percentage of ponds found in zones belonging to different vulnerability classes in the study area.

4. Discussion

The benefits of combining MCDA and GIS have been widely discussed in the literature (Malczewski, 2006). Integrating freely available spatial information into studies that help inform decision-making has become an important part of conservation efforts (Harris et al., 2005): the ability to assess and manage habitats and species has grown considerably, notably in situations where data are incomplete (Rubino and Hess, 2003).

Fuzzy logic tools are also useful in this type of work because they allow criteria to be standardized on a scale between 0 and 1, even when imprecision exists, which means more information can be integrated into the final model. This situation contrasts with that seen in more traditional standardization methods, where each element must have a binary value (zero or one) (Malczewski and Rinner, 2015). Fuzzy logic was employed in this way in our study—to standardize different criteria. Indeed, the relative impact of different criteria was related to the degree of information available; sometimes nothing was known, or the data could not be used in spatial analyses. An example of this issue can be seen in the contact zone between the marshes and the aeolian sand dunes, where limitations associated with high and low values of salinity are unclear. Here, the use of fuzzy logic makes it possible to create a geographical pattern with a gradual scale, where zones with values of one or close to one will be highly saline and thus place limits on distributions within the marshes as compared to zones with salinity values of zero or close to zero. This geographical pattern helps clarify the different effects of each criterion on potential species distributions (greater or lesser habitat suitability) and, consequently, the varying vulnerability of different zones within the pond network.

Here, aquatic plants were chosen to serve as bioindicators of vulnerability because they are very sensitive to environmental changes (O'Hare et al., 2017). Furthermore, they have been well researched within the study area (Díaz-Paniagua et al., 2010; Garcia Murillo et al., 2006), as compared to other groups of organisms for which there are no precise data to perform SDMs (e.g. charophytes). In addition, the study area is considered one of the richest regions of aquatic plants in the Iberian Peninsula and one of the most threatened areas by the anthropogenic effect (Rodríguez-Merino et al., unpublished data). The low number of records of some of the studied species is presented as a challenge for the development of

SDMs. However, this study employed a maximum entropy approach, which is considered one of the best ways to generate reliable SDMs when few data are available (Hernandez et al., 2006; Wisz et al., 2008).

Machine learning methods provide an objective means for determining criteria weights, which can then be incorporated into models that can assess vulnerability based solely on the data, avoiding the bias introduced by the use of expert-established criteria (Lu et al., 2012). That said, certain criteria were weighted more heavily than others, which may be due to the identity of the study species, which were mainly found within the peridune area, located in the center of the study area (Florencio et al., 2014). This information is nonetheless key to understanding vulnerability within the pond network because it is in this area that aquifer discharge occurs: certain water bodies are present almost the entire year (e.g. Dulce, Santa Olalla or Sopetón ponds), and there are a large number of ponds located very close together (Díaz-Paniagua et al., 2010). This high pond density combined with the proximity of the *La Vera* ecotone make this zone one of the richest and most diverse in the entire study area for all the species studied (Fig. S1C, Supplementary Material). The Doñana pond network provides habitat for species such as *Caropsis verticillato-inundata*, which only occurs in the study area and is one of the most threatened aquatic plant species in Europe (Fig. 4A). Furthermore, it harbors one of the southernmost European populations of *Potamogeton natans*, which is separated by hundreds of kilometers from its more northern relatives and is a species that needs long-hydroperiod ponds to complete its life cycle (Fig. 4B) (Florencio et al., 2014). It is also equally important for multicriteria analyses to include criteria with less weight, such as the distance to urban areas and to farmlands. Here, their low relative contribution was likely mainly attributable to the fact that urban areas and farmlands are located to the north of the study area, where both species number and pond number are lower. In this study as well as in other studies, these distances are key indicators of intense groundwater removal, which produces desiccation in certain parts of the study area (Bustamante et al., 2016; Dimitriou et al., 2017). This phenomenon can be witnessed to the north of the study area, in an unprotected region where there are a large number of fields dedicated to berry cultivation (Bea Martínez et al., 2014). Our results also indicate that there is an area between the National Park and Natural Park, where the vulnerability increase dramatically, in agreement with previous studies (Fig. 3; see Díaz-Paniagua and Aragonés [2015]). This area coincides with *Matalascañas* and its surroundings, a large resort town which demands a large quantity of water, allowing the conflicts between the wetlands conservation and the groundwater abstractions. Some examples of this are the presence of dry ponds closest to *Matalascañas* (Brezo and Charco del Toro ponds) and others that already show signs of desiccation, such as the case of the Zahillo pond (Díaz-Paniagua and Aragonés, 2015).

The results of this study show that more protected zones are less vulnerable, as previously suggested by others (Bustamante et al., 2016). In contrast, unprotected zones are very highly vulnerable because they are more seriously impacted by anthropogenic activities. Yet, they remain important because they contain the sole populations of important species such as *Peucedanum lancifolium* and *Isoetes setaceum* (Fig. 4C, 4D). Another important variable to consider is the presence of streams, especially in the north, because streams transport nutrients that contribute to eutrophication (Serrano et al., 2006). This phenomenon affects species such as *Rhynchospora modesti-lucennoi* (Fig. 4E), which occurs near these streams and is already facing pressure from the declining level of the groundwater table and modifications in watercourses (Daoud-Bouattour et al., 2010). It is also important to manage very highly vulnerable zones because of the presence of floating aquatic plants. Compared to the rest of the Iberian Peninsula, native species of floating plants are exceptionally diverse in Doñana region. Both *Lemna trisulca,* found to the south, and *Wolffia arrhiza* , found to both the north and the south (Fig. 4F, 4G), generally occur in permanent artificial ponds, which were created for watering cattle and now act as biodiversity reservoirs (Fernández-Zamudio et al., 2016; Kloskowski et al., 2009).

There are ways in which our work could be improved. For example, it is worth highlighting that there is a paucity of GIS layers that can be used for developing more objective MCDAs. In our case, we could have benefitted from knowing the distribution of illegal wells, since such wells cause significant environmental stress in our study area (Dimitriou et al., 2017). It would have been important to characterize their effects on potential species distributions and pond network vulnerability. However, at present, we lack enough information to do so.

It could also have been useful to have a longer list of species for creating SDMs. However, when the focus is on rare and threatened species, which are of obvious importance from a conservation perspective, one of the risks is that the number of records available will be too low to carry out a SDMs. At the same time, the occurrence of threatened species is very well described within the study area, which means better-quality information with a higher spatial resolution is available. Better data lead to more reliable SDMs. Our results strongly support the use of aquatic plants as bioindicators. This group helps structure freshwater systems, and its members supply habitat and shelter for a multitude of organisms (Burks et al., 2006; Wang et al., 2015). The number of records required to carry out SDMs is also an important constraint, since the use of too few records could lead to unrealistic results. Here, we established a minimum threshold of five records; with five records, it is possible to obtain well-performing models with the techniques employed here (Hernandez et al., 2006).

These concerns aside, we feel that combining MCDA and GIS can significantly improve the way in which conservation priorities are established when managing complex systems. Indeed, this objective approach can reduce costs and time investment in a field where resources are frequently limited.

5. Conclusions

In management and conservation, an important part of prioritizing efforts involves identifying those areas that are the most vulnerable. Here, we describe a combination of methodological approach with which we expect to contribute to the improvement of management and monitoring actions in protected areas in a more objective context. However, it is only a first step, and more detailed field work must now take place to move forward. Our results highlight the utility of employing aquatic plants as bioindicators for evaluating the vulnerability of the Doñana pond network, which contains a combination of different habitats and whose management and protection can provide refuge for many species that cannot survive elsewhere. In view of our results, we consider that geography and geographic information science are fundamental in the study of zone vulnerability. In addition, the advancement of GIS and the availability of accurate spatial data are fostering our ability to establish priorities in the conservation and management of singular species and habitats. Finally, we believe that the methodology proposed here can easily be adapted to other complex and fragile systems and could serve as a powerful tool in the conservation and management of natural systems.

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References

Anthos, 2017. Sistema de información sobre las plantas de la Península Ibérica y Baleares. Available at: http://www.anthos.es (last accessed March 2017).

Antognelli, S., Vizzari, M., 2017. Landscape liveability spatial assessment integrating ecosystem and urban services with their perceived importance by stakeholders. Ecological Indicators 72, 703–725. https://doi.org/10.1016/j.ecolind.2016.08.015

Bagella, S., Gascón, S., Caria, M.C., Sala, J., Mariani, M.A., Boix, D., 2010. Identifying key environmental factors related to plant and crustacean assemblages in Mediterranean temporary ponds. Biodivers Conserv 19, 1749–1768. https://doi.org/10.1007/s10531-010-9801-5

Bea Martínez, M., López-Gunn, E., Vay del Caño, L., 2014. Forensic water governance? Analyzing land and water use changes in North-Western Doñana (Spain). International Journal of Water Governance 2, 133–152.

Burks, R.L., Mulderij, G., Gross, E., Jones, I., Jacobsen, L., Jeppesen, E., Donk, E.V., 2006. Center stage: the crucial role of macrophytes in regulating trophic interactions in shallow lake wetlands, in: Wetlands: Functioning, Biodiversity Conservation, and Restoration, Ecological Studies. Springer, Berlin, Heidelberg, pp. 37–59. https://doi.org/10.1007/978-3-540-33189-6_3

Bustamante, J., Aragonés, D., Afán, I., 2016. Effect of Protection Level in the Hydroperiod of Water Bodies on Doñana's Aeolian Sands. Remote Sensing 8, 867. https://doi.org/10.3390/rs8100867

Daoud-Bouattour, A., Gammar-Ghrabi, Z., Liman-Ben, S., Muller, S.D., 2010. Rhynchospora modesti-lucennoi. The IUCN Red List of Threatened Species 2010.

Díaz-Delgado, R., Aragonés, D., Afán, I., Bustamante, J., 2016. Long-Term Monitoring of the Flooding Regime and Hydroperiod of Doñana Marshes with Landsat Time Series (1974–2014). Remote Sensing 8, 775. https://doi.org/10.3390/rs8090775

Díaz-Paniagua, C., Aragonés, D., 2015. Permanent and temporary pond in Doñana National Park (SW Spain) are threatened by desiccation. Limnetica 34, 407–424.

Díaz-Paniagua, C., Fernández-Zamudio, R., Florencio, M., García-Murillo, P., Gómez-Rodríguez, C., Portheault, A., Serrano, L., Siljeström, P., 2010. Temporary ponds from Doñana National Park: a system of natural habitats for the preservation of aquatic flora and fauna. Limnetica 29, 41–58.

Dimitriou, E., Moussoulis, E., Díaz-Paniagua, C., Serrano, L., 2017. Hydrodynamic numerical modelling of the water level decline in four temporary ponds of the Doñana National Park (SW Spain). Journal of Arid Environments 147, 90–102. https://doi.org/10.1016/j.jaridenv.2017.09.004

Dudgeon, D., Arthington, A.H., Gessner, M.O., Kawabata, Z.-I., Knowler, D.J., Lévêque, C., Naiman, R.J., Prieur-Richard, A.-H., Soto, D., Stiassny, M.L.J., Sullivan, C.A., 2006. Freshwater biodiversity: importance, threats, status and conservation challenges. Biol Rev Camb Philos Soc 81, 163–182. https://doi.org/10.1017/S1464793105006950

Elith, J., Graham, C.H., Anderson, R.P., Dudík, M., Ferrier, S., Guisan, A., Hijmans, R.J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L.G., Loiselle, B.A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, M.M.J., Townsend, P.A., Phillips, S.J., Richardson, K., Scachetti-Pereira, R., Schapire, R.E., Soberón, J., Williams, S., Wisz, M.S., Zimmermann, N.E., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29, 129–151. https://doi.org/10.1111/j.2006.0906-7590.04596.x

Elith, J., Kearney, M., Phillips, S., 2010. The art of modelling range-shifting species. Methods in Ecology and Evolution 1, 330–342. https://doi.org/doi:10.1111/j.2041-210X.2010.00036.x

Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E., Yates, C.J., 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions 17, 43–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x

ESRI, 2016. ArcGIS Desktop: Release 10.4 Redlands, CA: Environmental Systems Research Institute.

European Commission, 2003. Horizontal guidance document on the role of wetlands in the Water Framework Directive. Common Implementation Strategy for the Water Framework Directive (2000/60/EC).

Fancy, S.G., Gross, J.E., Carter, S.L., 2009. Monitoring the condition of natural resources in US national parks. Environ Monit Assess 151, 161–174. https://doi.org/10.1007/s10661-008-0257-y

Fernández, P., Jordano, D., Haeger, J.F., 2015. Living on the edge in species distribution models: The unexpected presence of three species of butterflies in a protected area in southern Spain. Ecological Modelling 312, 335–346. https://doi.org/10.1016/j.ecolmodel.2015.05.032

Fernández-Zamudio, R., García-Murillo, P., Díaz-Paniagua, C., 2016. Aquatic plant distribution is driven by physical and chemical variables and hydroperiod in a mediterranean temporary pond network. Hydrobiologia 774, 123–135. https://doi.org/10.1007/s10750-016-2701-2

Florencio, M., Serrano, L., Siljeström, P., Fernández-Zamudio, R., García-Murillo, P., Díaz-Paniagua, C., 2014. The influence of geomorphology on the composition of aquatic flora and fauna within a temporary pond network. Limnetica 33, 327–340.

Forio, M.A.E., Mouton, A., Lock, K., Boets, P., Nguyen, T.H.T., Damanik Ambarita, M.N., Musonge, P.L.S., Dominguez-Granda, L., Goethals, P.L.M., 2017. Fuzzy modelling to identify key drivers of ecological water quality to support decision and policy making. Environmental Science & Policy 68, 58–68. https://doi.org/10.1016/j.envsci.2016.12.004

Fuller, D.O., Meijaard, E.M., Christy, L., Jessup, T.C., 2010. Spatial assessment of threats to biodiversity within East Kalimantan, Indonesia. Applied Geography 30, 416–425. https://doi.org/10.1016/j.apgeog.2009.11.004

Garcia Murillo, P., Fernández-Zamudio, R., Sousa, A., Cirujano, S., 2006. Aquatic macrophytes in Doñana protected area (SW Spain): An overview. Limnetica 25, 71–80.

García-Roselló, E., Guisande, C., Manjarrés-Hernández, A., González-Dacosta, J., Heine, J., Pelayo-Villamil, P., González-Vilas, L., Vari, R.P., Vaamonde, A., Granado-Lorencio, C., Lobo, J.M., 2015. Can we derive macroecological patterns from primary Global Biodiversity Information Facility data? Global Ecology and Biogeography 3, 335–347. https://doi.org/10.1111/geb.12260

Gauthier, P., Debussche, M., Thompson, J.D., 2010. Regional priority setting for rare species based on a method combining three criteria. Biological Conservation 143, 1501–1509. https://doi.org/10.1016/j.biocon.2010.03.032

Gauthier, P., Foulon, Y., Jupille, O., Thompson, J.D., 2013. Quantifying habitat vulnerability to assess species priorities for conservation management. Biological Conservation 158, 321–325. https://doi.org/10.1016/j.biocon.2012.08.012

Gergel, S.E., Turner, M.G., Miller, J.R., Melack, J.M., Stanley, E.H., 2002. Landscape indicators of human impacts to riverine systems. Aquat. Sci. 64, 118–128. https://doi.org/10.1007/s00027-002-8060-2

Gómez-Rodríguez, C., Bustamante, J., Díaz-Paniagua, C., 2010. Evidence of Hydroperiod Shortening in a Preserved System of Temporary Ponds. Remote Sensing 2, 1439–1462. https://doi.org/10.3390/rs2061439

Harris, G.M., Jenkins, C.N., Pimm, S.L., 2005. Refining Biodiversity Conservation Priorities. Conservation Biology 19, 1957–1968. https://doi.org/10.1111/j.1523-1739.2005.00307.x

Hattab, T., Lasram, F.B.R., Albouy, C., Sammari, C., Romdhane, M.S., Cury, P., Leprieur, F., Loc'h, F.L., 2013. The Use of a Predictive Habitat Model and a Fuzzy Logic Approach for Marine Management and Planning. PLOS ONE 8, e76430. https://doi.org/10.1371/journal.pone.0076430

Hernandez, P.A., Graham, C.H., Master, L.L., Albert, D.L., 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography 29, 773–785. https://doi.org/10.1111/j.0906-7590.2006.04700.x

Hespanhol, H., Cezón, K., Felicísimo, Á.M., Muñoz, J., Mateo, R.G., 2015. How to describe species richness patterns for bryophyte conservation? Ecol Evol 5, 5443–5455. https://doi.org/10.1002/ece3.1796

Kloskowski, J., Green, A.J., Polak, M., Bustamante, J., Krogulec, J., 2009. Complementary use of natural and artificial wetlands by waterbirds wintering in Doñana, south-west Spain. Aquatic Conservation: Marine and Freshwater Ecosystems 19, 815–826. https://doi.org/10.1002/aqc.1027

Krois, J., Schulte, A., 2014. GIS-based multi-criteria evaluation to identify potential sites for soil and water conservation techniques in the Ronquillo watershed, northern Peru. Applied Geography 51, 131–142. https://doi.org/10.1016/j.apgeog.2014.04.006

Lu, C.Y., Gu, W., Dai, A.H., Wei, H.Y., 2012. Assessing habitat suitability based on geographic information system (GIS) and fuzzy: A case study of Schisandra sphenanthera Rehd. et Wils. in Qinling Mountains, China. Ecological Modelling 242, 105–115. https://doi.org/10.1016/j.ecolmodel.2012.06.002

Malczewski, J., 2006. GIS-based multicriteria decision analysis: a survey of the literature. International Journal of Geographical Information Science 20, 703–726. https://doi.org/10.1080/13658810600661508

Malczewski, J., Rinner, C., 2015. Multicriteria Decision Analysis in Geographic Information Science, Advances in Geographic Information Science. Springer-Verlag, Berlin Heidelberg.

Margules, C.R., Pressey, R.L., 2000. Systematic conservation planning [WWW Document]. Nature. https://doi.org/10.1038/35012251

Martínez-López, J., Carreño, M.F., Martínez-Fernández, J., Esteve, M.A., 2014. Wetland and landscape indices for assessing the condition of semiarid Mediterranean saline wetlands under agricultural hydrological pressures. Ecological Indicators 36, 400–408. https://doi.org/10.1016/j.ecolind.2013.08.007

Mateo, R.G., de la Estrella, M., Felicísimo, Á.M., Muñoz, J., Guisan, A., 2013. A new spin on a compositionalist predictive modelling framework for conservation planning: A tropical case study in Ecuador. Biological Conservation 160, 150–161. https://doi.org/10.1016/j.biocon.2013.01.014

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36, 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x
Niemi, G.J., McDonald, M.E., 2004. Application of Ecological Indicators. Annu. Rev. Ecol. Evol. Syst. 35, 89–111. https://doi.org/10.1146/annurev.ecolsys.35.112202.130132
Nilsson, C., Grelsson, G., 1995. The Fragility of Ecosystems: A Review. Journal of Applied Ecology 32, 677–692. https://doi.org/10.2307/2404808
Noss, R.F., Carroll, C., Vance-Borland, K., Wuerthner, G., 2002. A Multicriteria Assessment of the Irreplaceability and Vulnerability of Sites in the Greater Yellowstone Ecosystem. Conservation Biology 16, 895–908. https://doi.org/10.1046/j.1523-1739.2002.01405.x
Nouri, H., Mason, R.J., Moradi, N., 2017. Land suitability evaluation for changing spatial organization in Urmia County towards conservation of Urmia Lake. Applied Geography 81, 1–12. https://doi.org/10.1016/j.apgeog.2017.02.006
Nzeyimana, I., Hartemink, A.E., Geissen, V., 2014. GIS-Based Multi-Criteria Analysis for Arabica Coffee Expansion in Rwanda. PLOS ONE 9, e107449. https://doi.org/10.1371/journal.pone.0107449
O'Hare, M.T., Aguiar, F.C., Asaeda, T., Bakker, E.S., Chambers, P.A., Clayton, J.S., Elger, A., Ferreira, T.M., Gross, E.M., Gunn, I.D.M., Gurnell, A.M., Hellsten, S., Hofstra, D.E., Li, W., Mohr, S., Puijalon, S., Szoszkiewicz, K., Willby, N.J., Wood, K.A., 2017. Plants in aquatic ecosystems: current trends and future directions. Hydrobiologia 1–11. https://doi.org/10.1007/s10750-017-3190-7
Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026
Phillips, S.J., Dudík, M., 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31, 161–175. https://doi.org/10.1111/j.0906-7590.2008.5203.x
Pressey, R.L., Taffs, K.H., 2001. Scheduling conservation action in production landscapes: priority areas in western New South Wales defined by irreplaceability and vulnerability to vegetation loss. Biological Conservation 100, 355–376. https://doi.org/10.1016/S0006-3207(01)00039-8
R Core Development Team, 2014. R: A language and environment for statistical computing. R Foundation for statistical computing, Viena, Austria. Available at: http://www.R-project.org.
Rodríguez-Merino, A., Fernández-Zamudio, R., García-Murillo, P., 2017. An invasion risk map for non-native aquatic macrophytes of the Iberian Peninsula. Anales del Jardín Botánico de Madrid 74, 055. http://dx.doi.org/10.3989/ajbm.2452
Rodríguez-Merino, A., García-Murillo, P., Cirujano, S., Fernández-Zamudio, R., 2018. Predicting the risk of aquatic plant invasions in Europe: How climatic factors and anthropogenic activity influence potential species distributions. Journal for Nature Conservation 45, 58–71. https://doi.org/10.1016/j.jnc.2018.08.007
Rouget, M., 2003. Measuring conservation value at fine and broad scales: implications for a diverse and fragmented region, the Agulhas Plain. Biological Conservation, Conservation Planning in the Cape Floristic Region 112, 217–232. https://doi.org/10.1016/S0006-3207(02)00415-9
Rubino, M.J., Hess, G.R., 2003. Planning open spaces for wildlife 2: modeling and verifying focal species habitat. Landscape and Urban Planning 64, 89–104. https://doi.org/10.1016/S0169-2046(02)00203-7

Saaty, T.L., 1990. How to make a decision: The analytic hierarchy process. European Journal of Operational Research, Desicion making by the analytic hierarchy process: Theory and applications 48, 9–26. https://doi.org/10.1016/0377-2217(90)90057-I
Sarkar, S., Parihar, S.M., Dutta, A., 2016. Fuzzy risk assessment modelling of East Kolkata Wetland Area: A remote sensing and GIS based approach. Environmental Modelling & Software 75, 105–118. https://doi.org/10.1016/j.envsoft.2015.10.003
Schatz, B., Gauthier, P., Debussche, M., Thompson, J.D., 2014. A decision tool for listing species for protection on different geographic scales and administrative levels. Journal for Nature Conservation 22, 75–83. https://doi.org/10.1016/j.jnc.2013.09.003
Serrano, L., Reina, M., Martín, G., Reyes, I., Arechederra, A., León, D., Toja, J., 2006. The aquatic systems of Doñana (SW Spain): watersheds and frontiers. Limnetica 25, 11–32.
Singh, C.K., Katpatal, Y.B., 2017. A GIS Based Design of Groundwater Level Monitoring Network Using Multi-Criteria Analysis and Geostatistical Method. Water Resour Manage 31, 4149–4163. https://doi.org/10.1007/s11269-017-1737-z
Slocum, T.A., McMaster, R.B., Kessler, F.C., Howard, H.H., 2008. Thematic cartography and geographic visualization, 3rd ed. Prentice Hall, Upper Saddle River, New Jersey.
Spring, D., Baum, J., Nally, R.M., Mackenzie, M., Sanchez-Azofeifa, A., Thomson, J.R., 2010. Building a Regionally Connected Reserve Network in a Changing and Uncertain World. Conservation Biology 24, 691–700. https://doi.org/10.1111/j.1523-1739.2009.01419.x
Strayer, D.L., Dudgeon, D., 2010. Freshwater biodiversity conservation: recent progress and future challenges. Journal of the North American Benthological Society 29, 344–358. https://doi.org/10.1899/08-171.1
Wang, C., Zheng, S., Wang, P., Hou, J., 2015. Interactions between vegetation, water flow and sediment transport: A review. Journal of Hydrodynamics, Ser. B 27, 24–37. https://doi.org/10.1016/S1001-6058(15)60453-X
Wisz, M.S., Hijmans, R.J., Li, J., Peterson, A.T., Graham, C.H., Guisan, A., NCEAS Predicting Species Distributions Working Group, 2008. Effects of sample size on the performance of species distribution models. Diversity and Distributions 14, 763–773. https://doi.org/10.1111/j.1472-4642.2008.00482.x
Young, T.P., 2000. Restoration ecology and conservation biology. Biological Conservation 92, 73–83. https://doi.org/10.1016/S0006-3207(99)00057-9
Zacharias, I., Dimitriou, E., Dekker, A., Dorsman, E., 2007. Overview of temporary ponds in the Mediterranean region: threats, management and conservation issues. J Environ Biol 28, 1–9.
Zacharias, I., Zamparas, M., 2010. Mediterranean temporary ponds. A disappearing ecosystem. Biodivers Conserv 19, 3827–3834. https://doi.org/10.1007/s10531-010-9933-7
Zhou, X., Zhao, M., Zhou, L., Yang, G., Huang, L., Yan, C., Huang, Q., Ye, L., Zhang, X., Guo, L., Ke, X., Guo, J., 2016. Regionalization of Habitat Suitability of Masson's Pine based on geographic information system and Fuzzy Matter-Element Model. Scientific Reports 6, 34716.

Figure Legends

Figure 1. Location of the study area (Doñana's aeolian sand dunes, SW Spain), including the pond network described in Bustamante et al. (2016). The different levels of protection within the study area are also indicated.

Figure 2. Flowchart for assessing vulnerability via multicriteria decision analysis.

Figure 3. Map of vulnerability classes.

Figure 4. Map of species distribution obtained by applying the 10th percentile training threshold to the MaxEnt output. The points represent the locations of certain species: A. *Caropsis verticillato-inundata*, B. *Potamogeton natans*, C. *Peucedanum lancifolium*, D. *Isoetes setaceum*, E. *Rhynchospora modesti-lucennoi*, F. *Lemna trisulca*, and G. *Wolffia arrhiza*.

Figure 1
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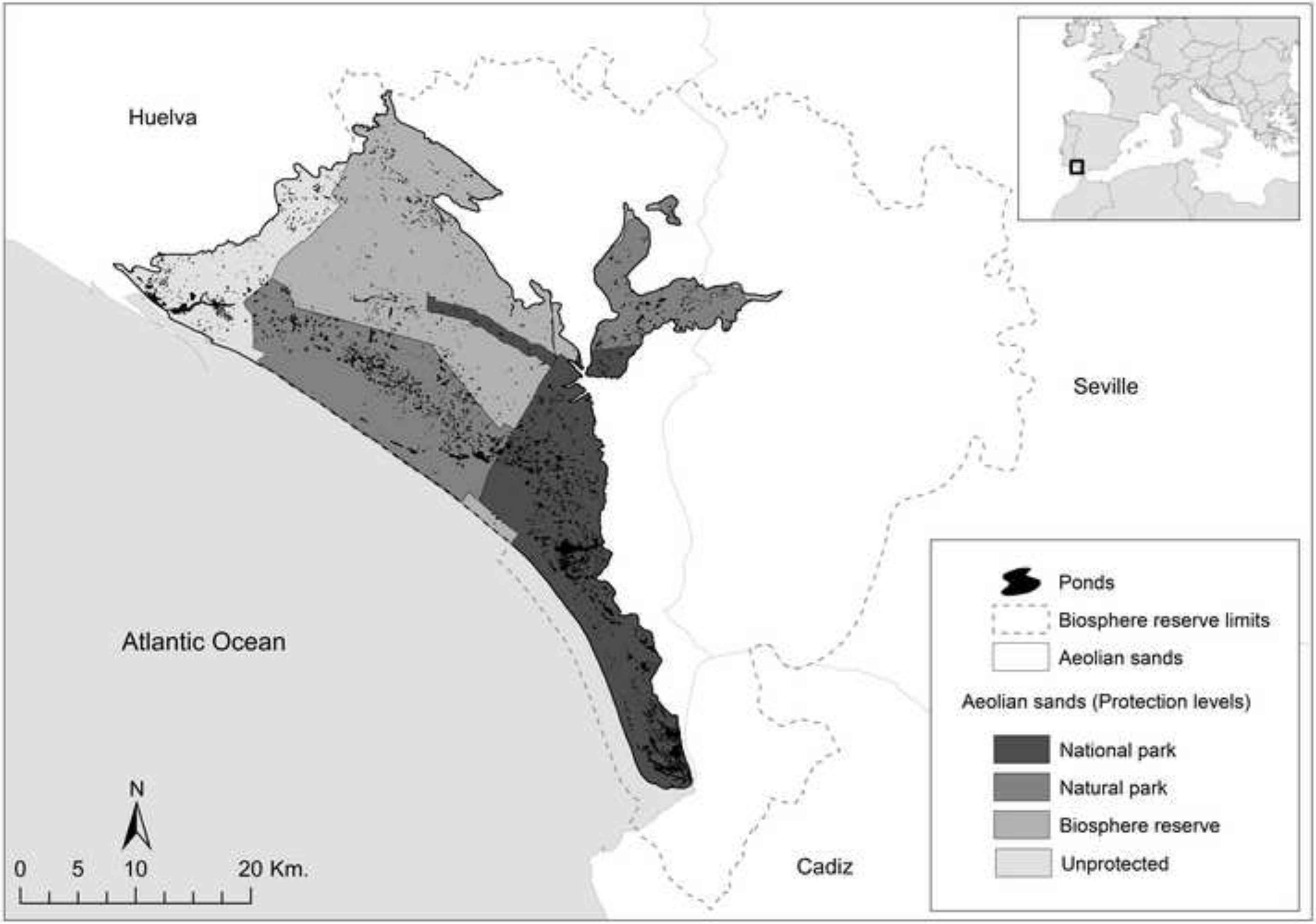
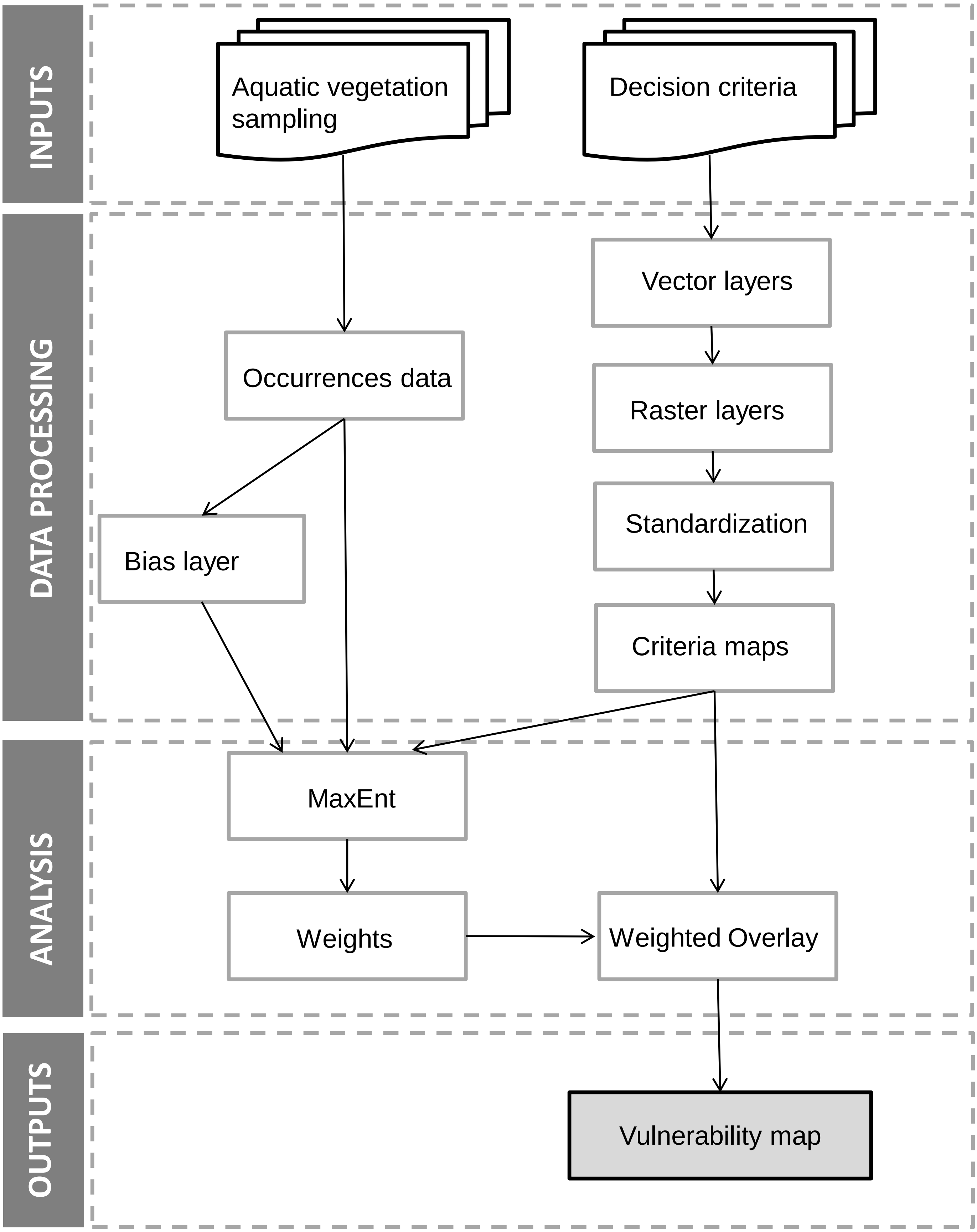


Figure 2


INPUTS
DATA PROCESSING
ANALYSIS
OUTPUTS
Aquatic vegetation sampling
Decision criteria
Vector layers
Occurrences data
Raster layers
Standardization
Bias layer
Criteria maps
MaxEnt
Weights
Weighted Overlay
Vulnerability map

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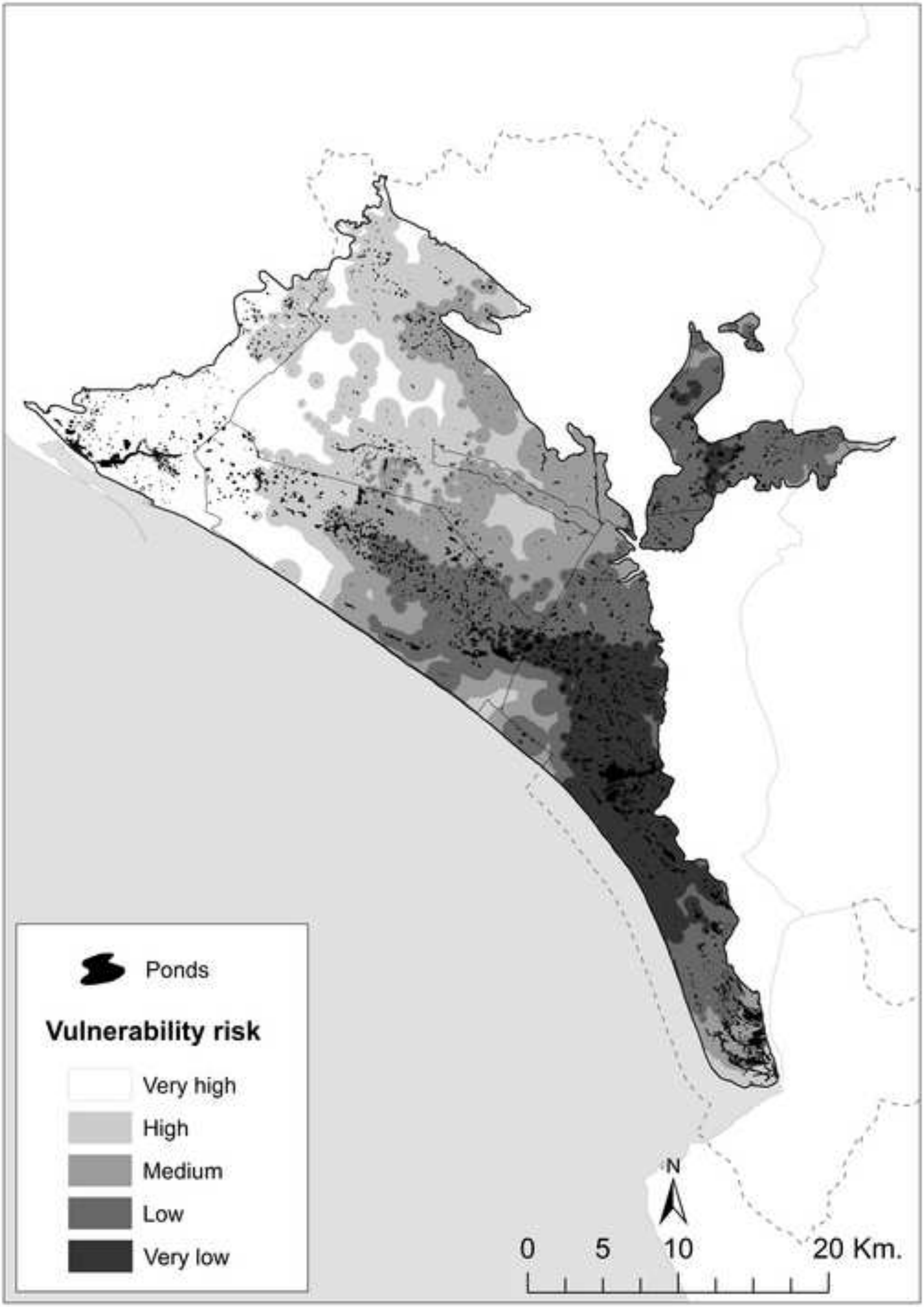

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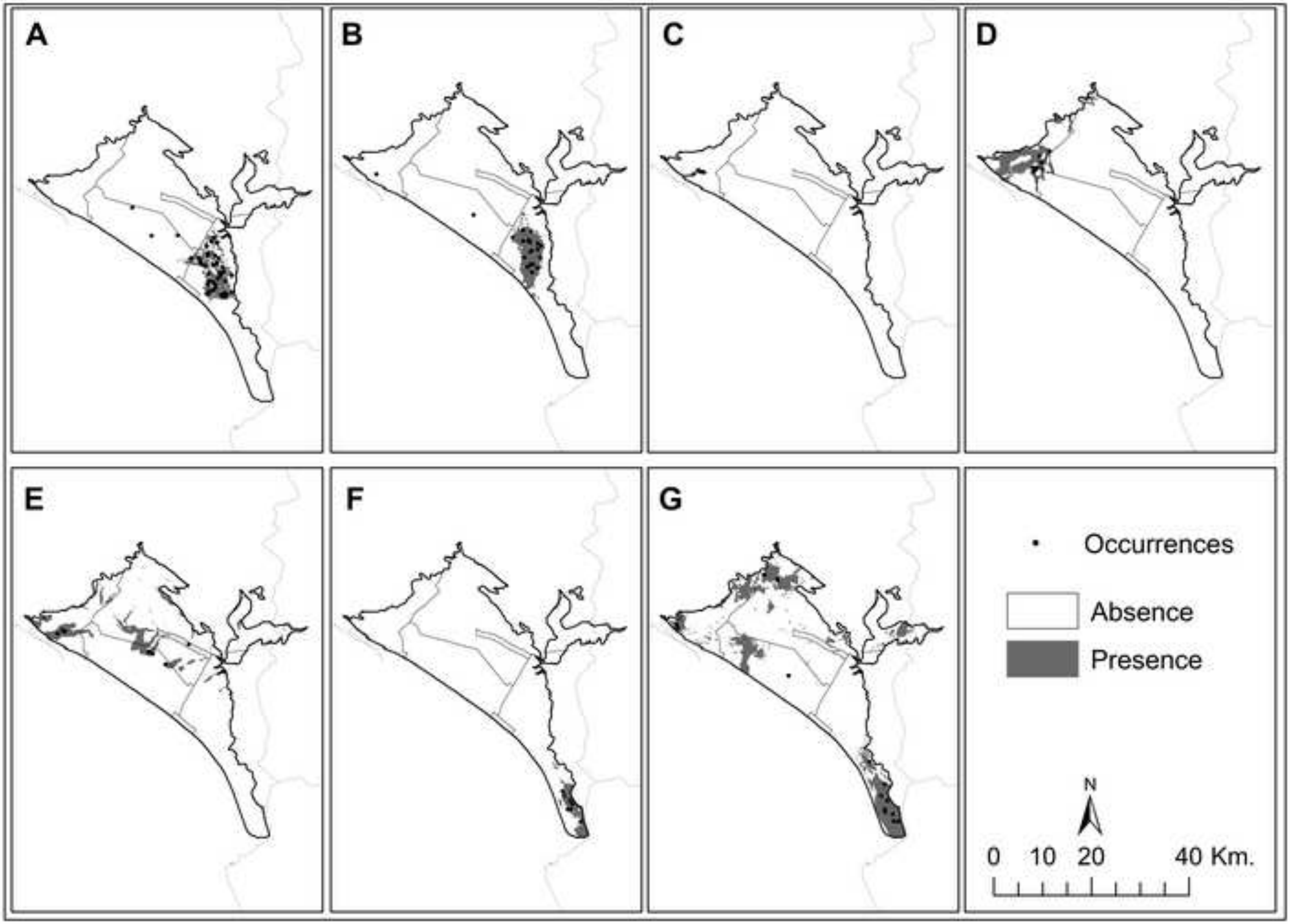

Supp. Figures- captions

Figure S1. A. Spatial distribution of sampling points. B. Bias layer used in the species distribution models, created using kernel density analysis. C. Map of potential species richness obtained by summing up the potential distribution of each species using MaxEnt algorithm.

Figure S2. Standardized criteria as determined by fuzzy logic. Values ranged from zero (least suitable) to one (most suitable). The black points, lines, and polygons are the original spatial information used to develop the criteria: A. Pond density, B. Distance between ponds, C. Hydroperiod, D. Distance to farmlands, E. Distance to urban areas, F. Distance to the coast, G. Distance to marshes, H. Distance to the *La Vera* ecotone, I. Distance to streams, J. Distance to highways, K. Distance to paths, and L. Distance to cattle trails.

Figure Supplementary 1

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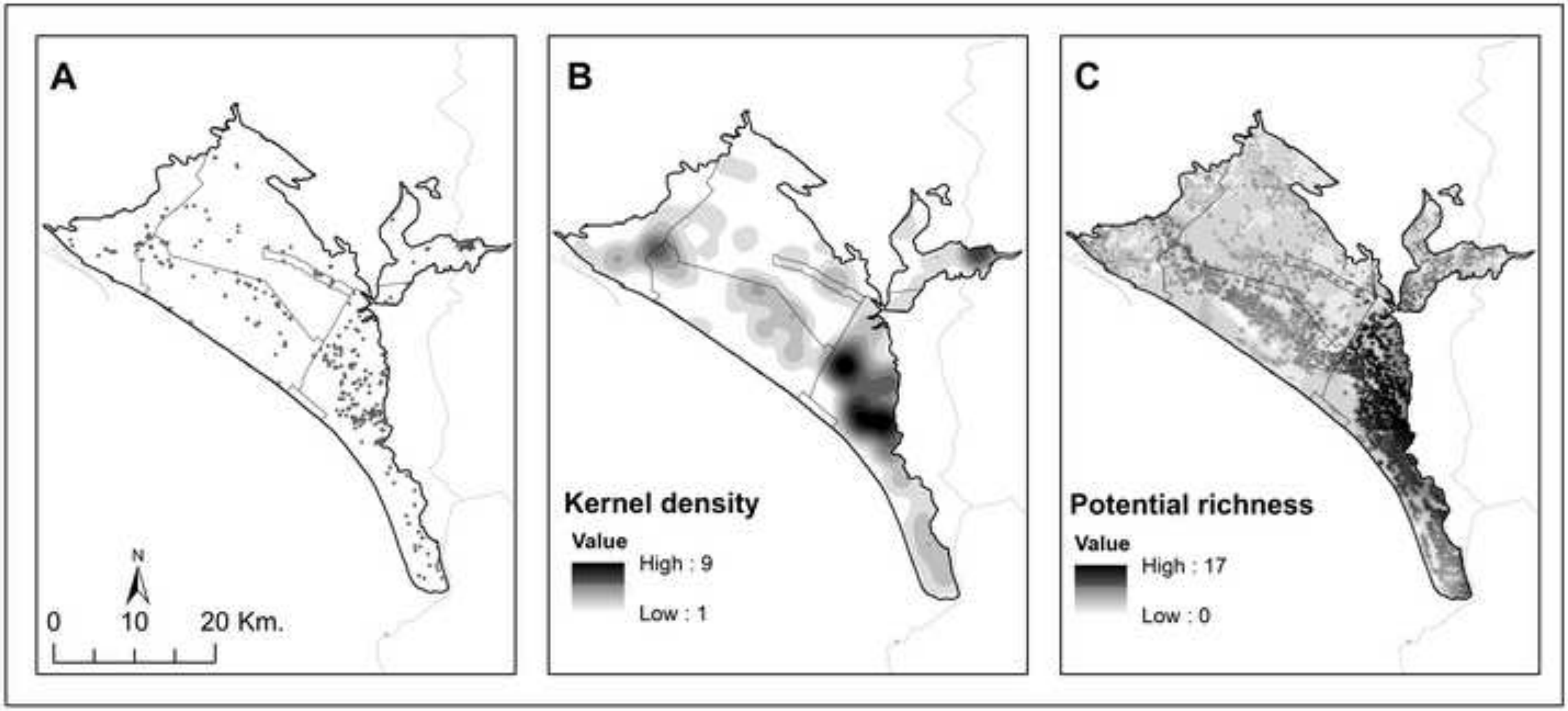

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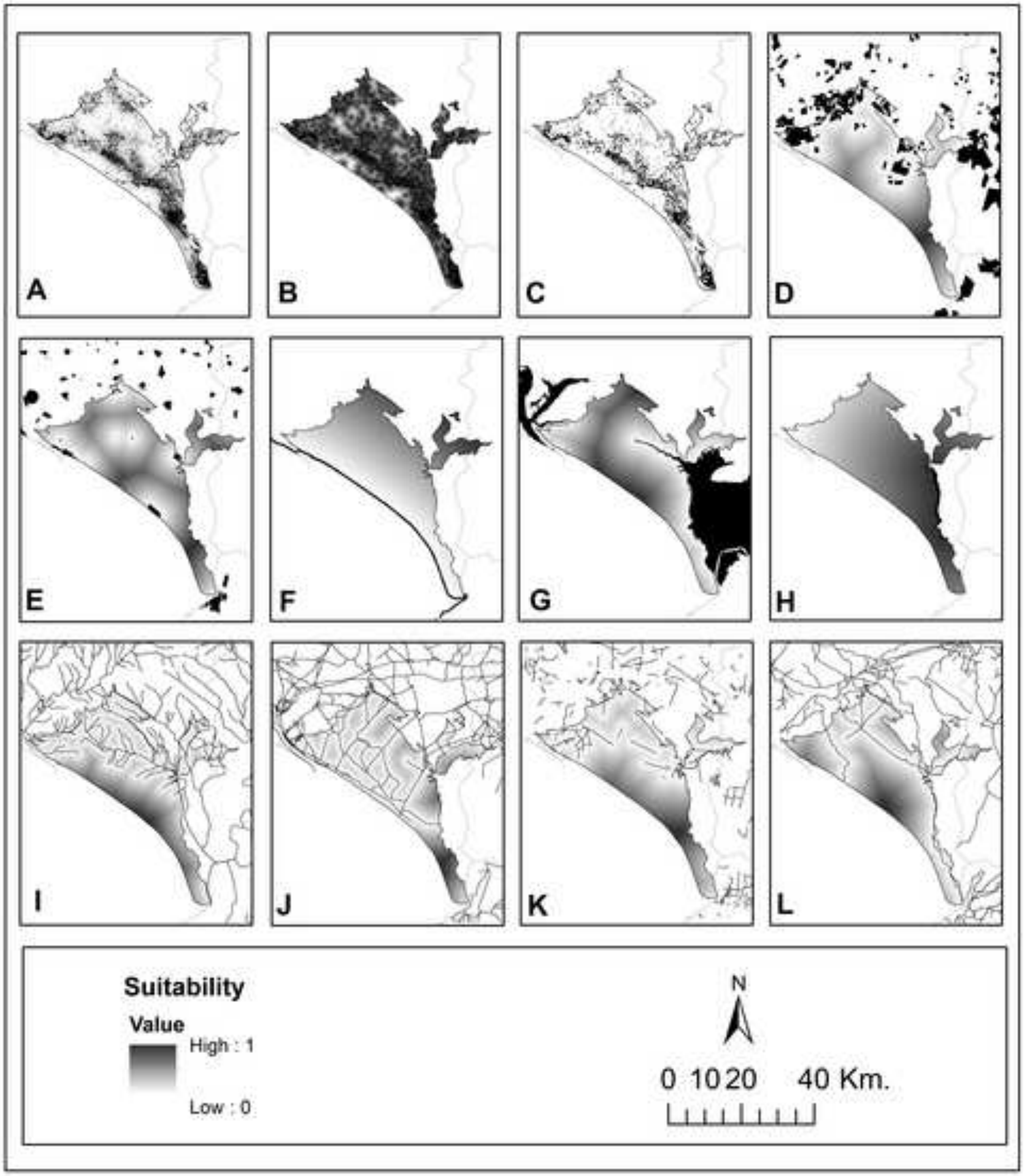

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