

RESEARCH ARTICLE

MODEL: a Multi-criteria OrDinal EvaLuation tool for GIS

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While the integration of Geographical Information Systems (GIS) and Multicriteria Decision Aiding (MCDA) has attracted increasing interest from researchers in recent years, due to the wide array of applications that can benefit from GIS as well as the different types of decision problems and various models that can be used through MCDA, plenty of opportunities of integrating GIS and MCDA remain. In this paper we present the result of such an opportunity in the form of a methodology and a software that is currently used by the Naval Hydrographic and Oceanographic Service in France. Furthermore, this tool may be used in conjunction with other GIS-MCDA applications with a single decision maker, multiple decision makers or even where the decision has a hierarchical structure.

Keywords: GIS; MCDA; applications; software, multiple decision makers

1. Introduction

Evaluating and comparing territorial zones according to multiple points of views (industrial activity, population, risk hazard, etc.) can be a time-consuming task and often requires the participation of several stakeholders. Rather than a direct evaluation of these zones, building a qualitative ordinal evaluation scale and using it in a formal procedure permits to automate the assessment and therefore to apply it in a repeated way in large-scale contexts, and, provided the chosen procedure and scale are accepted, to make it objective, in the eyes of the various stakeholders. However, one of the main difficulties of building such a formal evaluation procedure is to account for the multiple decision makers' preferences and the various, often conflicting, points of view which have to be considered. The field of multicriteria decision aiding provides techniques which allow to give answers to these challenges.

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We have applied the alphabetical ordering of the authors.

Multicriteria (MC) decision aiding is the activity which provides a decision maker (DM) with a prescription on a set of decision alternatives, when facing multiple, usually conflicting points of view or criteria. The DM, who is either a single person or a collegial body, takes the responsibility for the decision act and bears a value system or preferences related to the decision problem, which should be taken into account in the final prescription. The finite set X of decision alternatives represents the potential options on which the DM has to make a decision. The multiple criteria which have to be considered in the prescription are indexed by the set N .

Usually, three types of decision problems are put forward in this context (Roy 1996):

- the *choice problem*, which aims to recommend a subset of alternatives, as restricted as possible, containing the “satisfactory” ones;
- the *sorting problem*, whose goal is to assign each alternative into predefined categories;
- the *ranking problem*, which orders the alternatives by decreasing degree of preferences.

Various models have been proposed to support DMs facing a MC decision problem (Keeney and Raiffa 1976, Roy 1996) and to represent their preferences. Roughly speaking, they originate from two methodological schools. First, in the *outranking* methodologies, any two alternatives are compared pair-wisely on basis of their evaluations on the set of criteria, according to a majority rule. More precisely, a DM could consider that an alternative a *outranks* an alternative b when a *weighted majority* of criteria validates the fact that a is performing at least as good as b and there is no criterion where b seriously outperforms a . The majority-related condition is called concordance, whereas the second condition (veto) is called discordance. From a computational point of view, various implementations of these conditions, and their conjunction, have been proposed in the literature (see for example Roy and Bouyssou (1993)). Second, methods based on *multiattribute value theory* aim to construct a numerical representation of the DM's preference on the set of alternatives. The main differences between these two streams of thought lie in the way the alternatives are compared and in the type of information which is required from the decision maker to build the model. Outranking methods might be preferable if the evaluations of the alternatives on the criteria are qualitative and of very diverse nature and if the DM would like to include some impreciseness about his preferences in the model, whereas value-based methods can be favored if a compensatory behavior of the DM should be modeled. These methodologies are usually integrated in a more general decision aiding process, as described by Tsoukiàs (2007).

MC decision aiding has been coupled with Geographical Information Systems (GIS) since the early 1990s, a connection which has given birth to a lot of research opportunities, especially in recent years. The amount of papers focusing on the GIS-MCDA integration is mainly motivated by the inherent multi-criteria nature of GIS problems (Carver 1991, Chakhar and Martel 2003, Laaribi *et al.* 1993, Malczewski 1999). A thorough review of GIS-MCDA papers from before 2006 may be found in Malczewski (2006), where it is shown that the integration of MC decision aiding tools in GIS software is often quite limited, and generally very specific to one type of applications. Furthermore, in spatial decision problems, the DM is often confronted with points of view which are evaluated on qualitative ordinal scales. In such cases, it is generally advocated to use outranking-based preference models, as they tend to be more robust in their decision recommendations. However, as shown in Malczewski (2006) and Chakhar (2006), only very few MCDA tools implemented in GIS software are based on such outranking models. Besides, a further advantage of integrating MCDA techniques into GIS-based procedures is that the DMs are able to add value judgments (preferences) into spatial decision procedures. Last but

not least, as mentioned by [Chakhar and Mousseau \(2007\)](#), a large body of the past works cannot be effectively applied outside academic contexts. We therefore consider that further focus on elaborating effective tools for applying MC decision aiding within GIS is necessary. This motivates in part the contributions of this work.

In this paper, we present a general decision aiding methodology which can be used to support a quite large variety of decision problems related to territorial zones described by a variety of points of view, and where the opinion of multiple DMs has to be accounted for. We highlight how it integrates in the general decision aid process described by [Tsoukiàs \(2007\)](#), and we show that building a *qualitative ordinal evaluation scale* for territorial zones, amounts to building a *MC sorting model*. In other words, each zone being described by a vector of points of views involved in the problem, the task at hand consists in assigning these zones to a set of ordered categories, by taking into account the preferences of the DMs. In order to give operational arguments for this proposed methodology, we present how it can be supported by MODEL, a novel plugin for QGIS ([QGIS Development Team 2009](#)).

The present paper is also motivated by the need for integrating advanced MC decision aiding techniques in decision processes of the Service Hydrographique et Océanographique de la Marine (SHOM) in France. This prompted the creation of the MODEL decision aiding process and the corresponding plug-in, which can be used by the SHOM to help them to determine areas of interest for making surveys, by taking into account multiple points of view and DMs.

The rest of the article is structured as follows. In the next section we first present the general modelling framework and motivate the choices which have been made in the context of the SHOM's decision problem. Then, in [Section 3](#) we present an overview of the MODEL tool, before switching in [Section 4](#) to an illustrative example. Finally, in [Section 5](#) we discuss the novelty of the proposed approach and software, draw some conclusion and detail perspectives opened by this research.

2. The problem

As mentioned, the development of the MODEL plugin for QGIS was guided by motivations and constraints originating from the decision problem expressed by the SHOM.

2.1. General considerations

The SHOM is a French administrative public body administered by the Ministry of Defense and it incorporates three main missions ([Service Hydrographique et Océanographique de la Marine 2014](#)): supporting the maritime navigation, supporting the defense and supporting the government in relation to maritime and coastal policies. Data with respect to the marine environment is essential in fulfilling these missions, therefore the SHOM continuously takes the initiative to update and enrich the information they hold on it by performing regular surveys of the sea. However, due to the size of the jurisdiction of the SHOM, the multitude of areas of interest given the wide range of existing and potential beneficiaries of the data and the limited resources that are at SHOM's disposal, a significant percentage of areas are not sufficiently described by the data. Furthermore, the current process of deciding which areas to survey is lacking.

Starting from these observations, we propose in this article a formal decision aiding methodology, integrated in the general framework of [Tsoukiàs \(2007\)](#), which can be used by the SHOM to plan such surveys. The MODEL plugin for QGIS can then be used

to support this process in order to address the mentioned issues and provide decision support to the SHOM. The general decision aiding framework of Tsoukiàs, summarized in Fig. 1, consists of four steps. The methodology we propose mainly focuses on the second and third steps. Robustness and sensitivity issues (fourth step) are not addressed by this work.

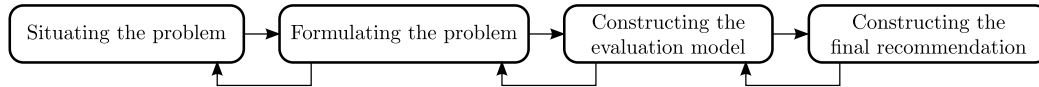


Figure 1. Decision aiding process;

We call in the rest of the paper a *decision-maker* (DM) any individual involved in the decision process whose angle on the problem we try to model. A *criterion* represents a perspective or point of view of the decision problem. It can be represented by a piece of data (which may be constructed using different rules and using different data sources) that reflects a characteristic of a territorial zone that is important to the DM when modeling a particular decision problem. It can be represented as a layer in the GIS, where each territorial zone is described by an evaluation on this criterion. In the context of the SHOM, such a criterion can be the quality of existing surveys, a distance to a specific type of area, information on the variability of the underwater soils, etc. An *alternative* represents any contiguous territorial zone that has a full set of evaluations on the criteria that are used to model the problem. All the alternatives (territorial zones) of the decision problem put together represent the *multi-criteria layer*. Consequently, an alternative corresponds to a feature in the multi-criteria layer. As shown on Fig. 2, the multi-criteria layer is obtained from the individual criteria layers by the geometrical operations of intersection and difference of the elementary territorial zones.

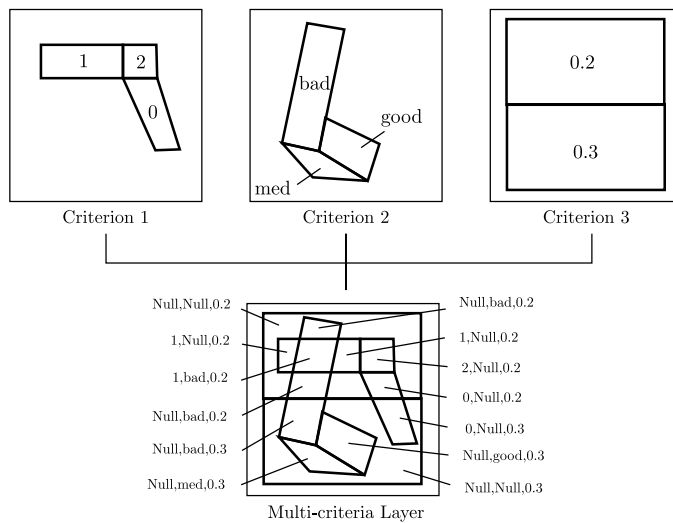


Figure 2. Construction of the multi-criteria layer;

The *decision map* is a layer containing the alternatives of a decision problem which have been evaluated by taking into account the DMs preferences and thus represents the output, the *decision recommendation*, of the proposed decision aiding methodology.

2.2. Motivation

The SHOM expressed several constraints with respect to their decision problem :

- the existence of multiple *disconnected* and *independent* DMs, not necessarily sharing the same goals;
- a *hierarchical* structure of the decision process;
- the necessity to obtain a highly *readable* decision aid model;
- the existence of very *heterogeneous* input data.

The first constraint corresponds to the need to accommodate multiple individuals within the decision process, although not necessarily all of them involved in every aspect of the decision, and not necessarily sharing the same objectives and preferences. This observation is not in accordance with the use of models which seek to search for a unified preference model for all the DMs (see for example [Damart *et al.* \(2007\)](#), [Cailloux *et al.* \(2012\)](#) for such models), and where the decision aiding process focuses on reaching a consensus on the final recommendation, while maintaining the individual preference models as unchanged as possible. In our case the different DMs may be considered as experts of one or several decision problems which are to be modeled and for which decision recommendations are to be provided without considering any other perspective.

The second constraint is linked to the first in that the multiple DMs may be part of a hierarchical structure. In such a structure, the recommendations produced for DMs at a given level of the hierarchy may be reused at higher levels by other DMs. The MODEL plugin that we present here implements a 3-level hierarchy, as seen in Fig. 3. As we show in Section 4, this structure is well suited for the decision problem of the SHOM. A more flexible structure is considered within future developments of the tool.

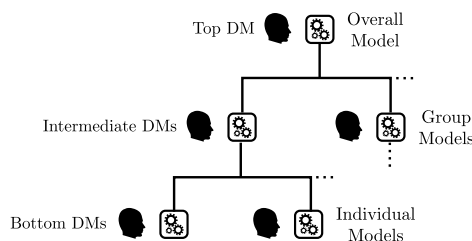


Figure 3. The hierarchical structure of the decision;

This hierarchical structure of the decision problem is represented in Fig. 3, where three types of models may be noticed. At the bottom of the hierarchy we have the individual models, which correspond to the basic decision problems that are to be modeled for the DMs within their field. These models have access to the different types of data that they require, which are specific to the individual problem that is considered. For instance, in the SHOM context, an individual model may reflect the quality of the survey data with respect to a certain activity, as for example fishing activities, mining sites, current military operations, or it may reflect the potential benefit of surveying areas based on prospective activities. Notice that at this stage the overall decision problem of the SHOM, the desirability to survey an area, does not need to be taken directly into account. The group models of the higher levels are used to unify the results of the individual decision models into recommendations that reflect the perspective of more general categories of activities. For example, in the SHOM context, such a model may be used to group together models that refer a certain type of activities, such a economical activities, military activities, etc. The model at the top is similar to the group models only that is used to unify the results of all the group models under a global perspective.

The third constraint is also linked to the previous two in that due to the heterogeneity of the DMs, the models need to be easy to interpret and understand by most of the people involved, especially those taking part in decision problems within the higher levels

of the hierarchy. We therefore advocate for an evaluation of the various territorial zones (alternatives) on a qualitative ordinal evaluation scale, where each of the levels has a clear meaning for the DMs involved in the determination of the areas to survey. Combined with the necessity to take into account multiple criteria, this constraint comes down to building a sorting preference model (Roy 1996), also known as ordinal classification model, in order to assign each alternative to one out of a set of ordered categories. In contrast to ranking the alternatives or simply providing scores for each of them, assigning them to one out of a few ordered categories simplifies the understanding of the results by non-experts on the decision problem. Furthermore, we have selected to use either decision rules or MC outranking models in order to evaluate the alternatives inside a decision model. The choice of using expert rules is straightforward. They are directly given by the concerned DM and originate from his expertise. Consequently, they are easily readable and understandable, and provide great transparency in the evaluation of the alternatives. This constraint is also an argument for our choice to use outranking models. As we will show in Section 2.3, outranking models in conjunction with ordinal classification generate very comprehensive recommendations. Additional arguments in favor of using outranking relations are found in (Chakhar and Mousseau 2008).

The fourth constraint is related to the information used by the SHOM in order to model this problem. It originates from different sources and may be numerical, categorical as well as potentially containing missing data. This additionally advocates for the use of decision rules given by the DMs and outranking models, which, by nature, are able to deal quite conveniently with very heterogeneous and missing data.

2.3. Implemented preference models

In each of the nodes of the hierarchy of Fig. 3, we propose to use either an MC sorting method to account for the preferences of the corresponding DM, or decision rules, based on his expertise.

The MC sorting method we advocate here is a simplified version of Electre Tri (Figueira *et al.* 2005, Mousseau *et al.* 2000, Roy 1991). The version considered here is very close to the version studied by Bouyssou and Marchant (2007a,b).

Electre Tri requires, as a definition of the preferences of a DM, criteria importance parameters and category limits separating the categories. The criteria importance parameters include a weight for each of the criteria and a majority threshold that defines when a coalition of criteria is good enough to be decisive. The category limits separate, for each criterion, two consecutive levels in the qualitative ordinal scale.

Consider a finite set of territorial zones A , a set of category limits $B = \{b_1, \dots, b_k\}$, and a finite set of criteria indexes J . A criterion g_j ($j \in J$) is a function from $A \cup B$ to \mathbb{R} where $g_j(a)$ denotes the performance of the zone $a \in A$ and $g_j(b_h)$ denotes the performance of the category limit $b_h \in B$, on the criterion g_j . The zones have to be sorted in k qualitative levels, c_1, \dots, c_k , ordered by their desirability. c_1 is the worst qualitative level, and c_k is the best one. Each level c_h is defined by the performances of its lower frontier, or category limit, b_{h-1} and its upper frontier b_h of B (except the worst level c_1 has no lower frontier). The performances are here supposed to be such that a higher value denotes a better performance and the performances on the frontiers are non-decreasing, i.e. $\forall j \in J, 2 \leq h \leq k : g_j(b_{h-1}) \leq g_j(b_h)$. In this work we will simultaneously consider several different models that may hold different values for k .

To sort the zones, Electre Tri uses the concept of outranking relation. The assignment rule used here, known as the pessimistic rule, assigns a zone a to the highest possible

risk level c_h such that the zone outranks the category's lower frontier b_{h-1} .

A zone a outranks a frontier b_{h-1} if and only if there is a sufficient coalition of weighted criteria supporting the assertion “ a is at least as good as b_{h-1} ”. To compute this, preferential parameters given by a DM are used.

The coalition of criteria in favor of the outranking, $\forall a \in A, 1 \leq h \leq k$, is defined as $\sum_{j \in J} w_j C_j(a, b_{h-1})$, where w_j is the weight of criterion g_j , and $C_j(a, b_{h-1}) \in \{0, 1\}$ measures if a is at least as good as b_{h-1} from the point of view of the criterion j or not: $C_j(a, b_{h-1}) = 1 \Leftrightarrow g_j(a) \geq g_j(b_{h-1})$, 0 otherwise. The weights are defined so that they sum to one ($\sum_{j \in J} w_j = 1$). The coalition is compared to a majority threshold $\lambda \in [0.5, 1]$ defined by the decision maker along with the weights. If $\sum_{j \in J} w_j C_j(a, b_{h-1}) < \lambda$, the coalition is not a sufficient coalition and the zone does not outrank the frontier b_{h-1} and will therefore be assigned in a risk level below c_h .

The weights and majority thresholds (defining the sufficient coalitions) and the category limits may be given directly by the DM, based on his expertise. However, this requires that the DM understands how these values will be used. It is moreover a difficult process to directly ask the DM for these parameters. The approach used here supposes that the DM provides assignment examples which are used to infer the preferential parameters.

Existing inference approaches suggest to find all of the Electre Tri preference model parameters (Mousseau and Slowinski 1998) from assignment examples, or only the importance coefficients (Mousseau *et al.* 2001) or the categories limits (Ngo The and Mousseau 2002), the other parameters being supposedly known. Robust approaches are suggested which compute for each alternative a range of possible categories to which alternatives can be assigned under incomplete determination of the parameters (Dias and Clmaco 1999, 2000, Dias *et al.* 2002). Some tools deal with the problem of non existing preference model solutions which may arise due to an inconsistent set of assignment examples (i.e. assignment examples that do not match Electre Tri) (Mousseau *et al.* 2003, 2006).

However, learning these parameters requires linear programming techniques which necessitate the use of binary variables. In our context, where large sets of alternatives are potentially involved, such an approach cannot be considered, as it requires large computing times. We therefore use a method based on a metaheuristic (Olteanu and Meyer 2014) to learn the parameters of the sorting model. It uses similar ideas as Sobrie *et al.* (2013) by dividing the problem in two, therefore iteratively running a sequence of two steps. The first step infers the criteria importance weights and majority threshold while keeping the category limits fixed, whereas the second step does the opposite. The first step uses a simple linear program, while the second step uses a simulated annealing algorithm which contains several parameters that allow it to better adapt to the problem.

3. The MODEL tool: An overview

The MODEL tool (Meyer and Olteanu 2014) allows us to model the previously mentioned class of problems. It is constructed as a plug-in for the QGIS software (QGIS Development Team 2009), sharing its user interface while keeping a separate data model. According to the classification of Spatial Decision Support Systems from Malczewski (2006) (presented in introduction), the tool may be considered as fully integrated within the GIS software. It may also be considered as dynamically integrated within it due to the fact that at any point changes to the maps are reflected into both the GIS software and the data model of the MODEL plug-in.

The MODEL tool allows a DM to define, structure and tune a decision problem con-

taining a hierarchical structure of the decision, with the final goal of outputting a decision map for each decision problem in this structure. Every decision map will contain a series of features of type area, each of them being assigned to one category out of a set of ordered categories (or levels of a qualitative ordinal scale) defined by the DM. These categories may, for instance, illustrate the degree of quality or the interest of an area with respect to the decision problem for which the map has been built.

The process of using the MODEL tool is presented in Fig. 4.

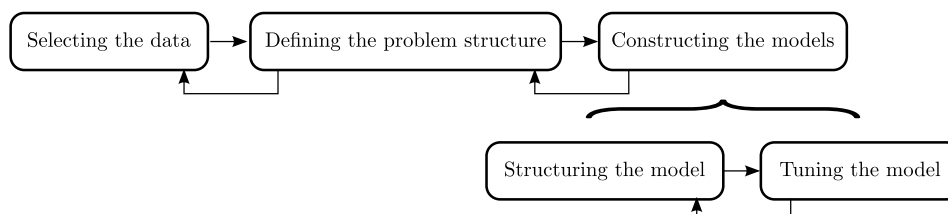


Figure 4. MODEL process;

This process has three steps: *selecting the input data*, *defining the decision problem structure* and *constructing the decision models*. These steps initially need to be tackled in a sequence, although they may be revisited until the DM is satisfied with the outcome.

The first step represents that of selecting and structuring the data that will be used in order to build the first series of decision models. Each piece of data corresponds to a set of features from a vector layer which are characterized by a single attribute. Naturally, several pieces of data may be defined using the same vector layer and the same features as long as they are described inside that vector layer by more than one attribute.

The second step consists in building the hierarchical structure of the decision problem. This structure can contain up to three levels, with the bottom level holding what we call individual decision models, the mid level holding the group decision models, while the top level holds the overall decision model. The individual decision models may correspond to either one or several different DMs separately tackling decision problems which are in their area of expertise, the group decision models are used to aggregate the results of the individual models that are directly linked underneath them while the overall decision model is used to aggregate the results of all the group decision models.

Finally, the third step is concerned with constructing each model in the hierarchy. Note that each decision model requires that all the underlying decision models inside the hierarchy have been previously constructed. Constructing a decision model is done in two parts: structuring the model and then tuning it.

The first part consists in building the structure of the model from the input data, if we are dealing with an individual decision model, or from the decision maps of the models directly linked below the considered model, if we are dealing with models from the top two levels of the hierarchy.

The input data may be transformed into: *intermediate data*, *criteria* or *filters*.

One or more pieces of data may be processed into an intermediate piece of data using any type of logic that can be written as an algorithm, as long as the resulting data is numerical. In the MODEL tool we have implemented this by allowing the user to enter these rules using Python syntax. The intermediate data built in this way will contain features resulting from the geometrical operations of intersection and difference between the features of the data referenced in the construction rules, as seen on the top of Fig. 5.

A second type of intermediate data can be constructed by buffering the features inside a single piece of input data with a certain distance. The resulting intermediate data will contain the buffered features, but also a series of features corresponding to the areas

outside them. This type of data is textual, denoting whether a feature is inside or outside the buffered areas. Fig. 5 (bottom) illustrates this.

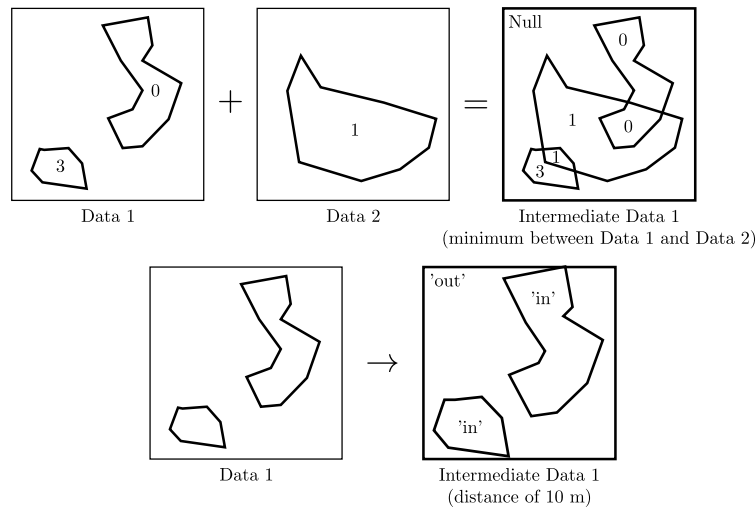


Figure 5. Constructed intermediate data (top) and distance intermediate data (bottom);

Criteria are also built from both the initial data and the intermediate data in a way similar to the first type of intermediate data. However, they are merged into a single layer called the multi-criteria layer, as seen in Fig. 2. The only difference between a criterion and a constructed intermediate data is that a criterion also holds a direction of preference with respect to its values. For example, when dealing with a cost criterion, a DM may prefer higher or lower values if the criterion refers to either a benefit or a penalty.

Filters may be built from both the initial and the intermediate data. Filters may be seen as templates that are used to cut away portions of the decision map that are not of interest for a model. Each filter uses the features from a single piece of data, which may be themselves filtered with respect to their attributes. A filter may either use the features it has selected to cut away portions from the decision map (filter out), or to cut away the decision map around these features (filter in), as seen in Fig. 6.

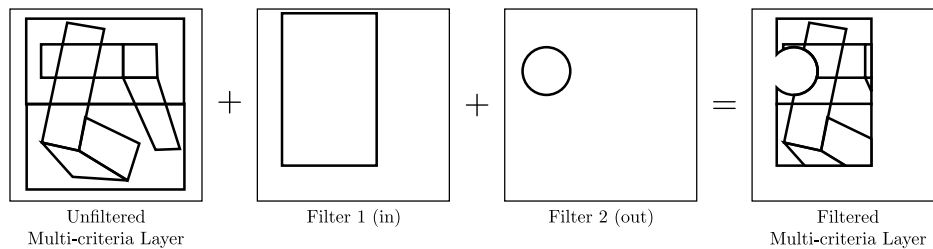


Figure 6. Filters;

After structuring the model, we tune its parameters either directly or indirectly as described in Section 2. These parameters are the majority threshold, criteria weights and category profiles, although we allow also to replace the first two with a more robust set of parameters in the form of majority and minority coalitions of criteria, which can be easily deduced from them. The direct approach allows the DM to give the exact values of these parameters, while the indirect approach takes input from the DM in the form of assignment examples (Mousseau and Slowinski 1998) and runs an algorithm to infer the model parameters (see Olteanu and Meyer (2014) for further details).

4. An illustrative example

In what follows, we present an illustrative example of the use of the MODEL tool in relation to a practical application of the SHOM. While this is a real-world application, the example will only illustrate a small portion of the decision problem over a set of artificial data. An in-depth discussion on the problem will follow in a subsequent paper.

4.1. Initial discussions

In order to help the SHOM with their problem, we have followed the general structure of the decision aiding process, as presented in Section 2. Their problem revolved around deciding which areas of the marine environment they should target in order to make surveys leading to the acquisition of data that would be then used for a wide range of purposes. We continued by asking about the existing procedures in order to identify the criteria they currently considered as important as well as imagining different scenarios where data on the marine environment would be useful to them. The latter exercise allowed to identify a large number of scenarios, separate one from the other, where a decision would be made using generally different criteria. In Fig. 7 we present a summary of 4 scenarios containing the areas of interest and the criteria that would make certain areas more important than others. Following these descriptions we have also identified datasets from the SHOM that would be needed for modeling each scenario.

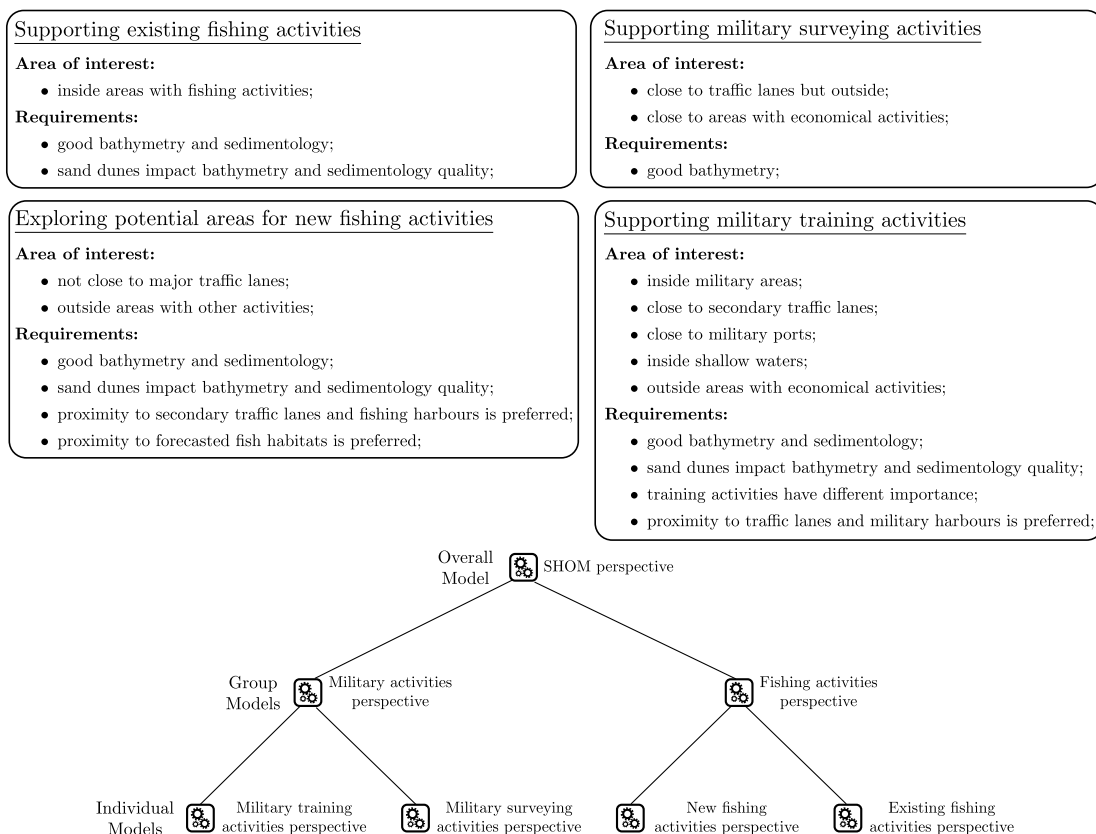


Figure 7. The survey scenarios and structure of the decision problem;

Based on the 4 scenarios, the SHOM representative additionally expressed the desire

to aggregate the results of the scenarios related to fishing activities and those related to military activities, before proceeding to reaching a global decision. This led to the structure of the decision problem and the required models also presented in Fig. 7.

We consider that for each model, a different expert (or DM) may be involved, although the same expert may be used for all the problems within each group, or even across the entire set of decision problems. In this example, we are in the last situation. In Appendix A we illustrate how the hierarchical structure of the decision problem is defined in MODEL, as well as how the input data is loaded. Fig. 8 illustrates this data.

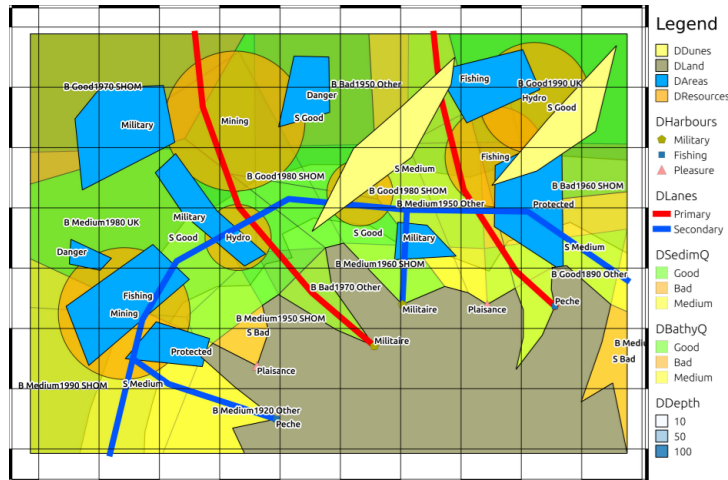


Figure 8. Data layers for the SHOM test problem;

We observe that only the presented 4 scenarios already bring a high level of complexity if a DM were to take all these data layers into account simultaneously.

4.2. Constructing the individual models

Following the construction of the hierarchical structure of the decision and the definition of the input data, we proceed to modeling each of the 4 individual models.

We start with the first model related to fishing activities. This model corresponds to the desire of the SHOM to improve data inside regulated fishing areas. Looking at the description of the use case for this model, as seen in Fig. 7, the points under *Area of interest* are used to construct a set of filters, which will limit the decision map to only the concerned areas, while the points under *Requirements* are used to construct the criteria. At this stage we also determine whether the needed input data also needs to be preprocessed into the set of intermediate data. We therefore identify the intermediate data, filters and criteria listed below.

- **Intermediate data:**
 - IDC1: Bathymetry quality derived from survey dates (DBathyD), authors (DBathyA) and quality (DBathyQ);
- **Filters:**
 - F1: filter inside fishing areas(DAreas);
 - F2: filter outside land area(DLand);
- **Criteria:**
 - C1: overall data quality using IDC1, DDunes, DSedimQ(ordinal scale with 6 levels; to be maximized);

In Appendix B we illustrate the way in which the intermediate data, filters and criteria for the first scenario are defined in MODEL.

Following the structuring of the model we then construct the MC layer which will

contain features having geometries that derive from the intersection and difference between all the features from the data layers and the intermediate data layers that were referenced by the criteria. These features will be described through their attributes by the values of they receive on the set of criteria. In the considered model, the MC layer is a mono-criterion layer. We then continue with tuning the parameters of the model, which can be done either directly or indirectly. However, as we are only dealing with a single criterion, we may easily define how each of its values will be represented inside the decision map. We illustrate this step in Appendix C. The MC layer and the resulting decision map containing 6 ordinal categories are presented in Fig. 9.

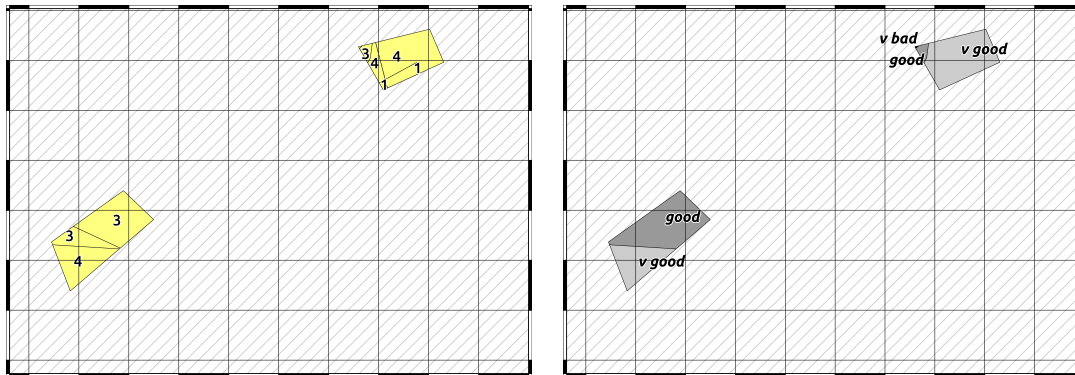


Figure 9. MC layer (left) and Decision map (right) for the first decision model;

At this point, the DM may analyze further the decision map and confront it with the input data that has been used in its construction in order to better understand the result. Simply looking at the map, we notice that the considered regulated fishing areas are generally well described by the existing data.

We continue with the second model which corresponds to modeling the interest of the SHOM in performing surveys in areas that might be transformed into regulated fishing areas but which lack a good description of the marine environment. From Fig. 7, we extract the following set of intermediate data, filters and criteria for this model:

- **Intermediate data:**
 - IDC1: Bathymetry quality derived from survey dates (DBathyD), authors (DBathyA) and quality (DBathyQ);
 - IDB1: buffer of 100 km around main traffic lanes (DLanes);
 - IDB2: buffer of 50 km around estimated fish habitats (DResources);
 - IDB3: buffer of 100 km around secondary traffic lanes (DLanes);
 - IDB4: buffer of 3000 km around fishing harbours (DHarbours);
- **Filters:**
 - F1: filter outside main traffic lanes (IDB1);
 - F2: filter outside other areas with activities (DAreas);
 - F3: filter outside land area (DLand);
- **Criteria:**
 - C1: overall data quality using IDC1, DDunes, DSedimQ (ordinal scale with 6 levels; to be minimized);
 - C2: accessibility using IDB3 and IDB4 (ordinal scale with 2 levels; to be maximized);
 - C3: probability of high fish densities using DResources and IDB2 (ordinal scale with 3 levels; to be maximized);

IDC1 and C1 are constructed in the same way as those in the previous model. The second criterion reflects the ease of access by fishing boats, focusing mostly on areas close to secondary traffic lanes and fishing harbors. This criterion contains only two ordinal levels (0 when not close to either a fishing harbor or a secondary traffic lane, and 1 otherwise). The third criterion reflects the probability of an area to contain dense fish populations. These areas are present in DResources, however we have also added a buffer around these areas in order to simulate uncertainty in the exact delimitation of these areas. The criterion contains three ordinal levels, with 2 being inside the areas from DResources, 1 being inside the buffer around them and 0 otherwise.

The resulting MC layer is depicted in Fig. 10. As the problem is a multi-criteria one, rather than trying to build a decision rule which takes all the criteria into account in order to construct an ordinal evaluation of the territorial zones, we proceed to using the implemented outranking model. This is depicted in Appendix D, where the DM assigns a subset of territorial zones to one of 3 classes (*no interest*, *neutral*, *interest*), while an underlying algorithm uses this information in order to extract the model parameters leading to a set of assignment rules. The resulting decision map is illustrated in Fig. 10.

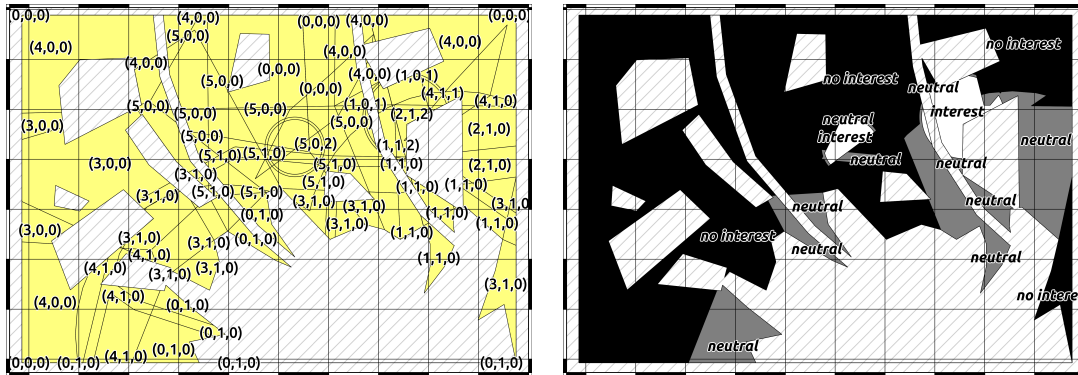


Figure 10. MC layer (left) and Decision map (right) for the second decision model;

We notice that only a small set of areas are considered as being of interest for making new surveys from this perspective.

We continue with the remaining two individual decision models related to military activities. The first one concerning surveying activities is similar to the first individual model that we have described above. In this case too we have only one criterion which reflects the quality of the existing data on the marine environment inside areas where surveying activities may be held. Hence, we only present below the resulting decision map which contains the same 6 ordinal categories as the first constructed decision map. The second model concerning training activities is similar to the second individual model that we have described above. This model has three criteria, the first reflecting the quality of the existing data, the second highlighting the ease of access, while the last gives different importance to the training activities that may take place in different areas. We have used in this case the same 3 categories as in the second individual decision model and we have extracted the parameters of the model through the approach of using assignment examples. In Fig. 11 we present the decision maps for these two models.

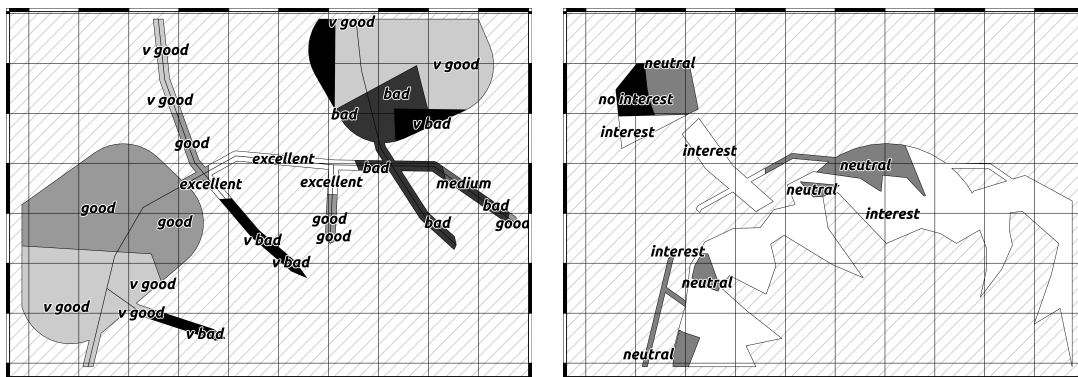


Figure 11. Decision maps for the Surveying (left) and Training (right) models;

4.3. Constructing the group and overall models

With all the individual decision models completed we now look at how their decision maps may be combined in order to model an overall perspective on them. While inside each individual decision model one or several DMs have considered only their perspective on that particular problem, a group decision model considers all the different underlying decision problems at once, however without going into detail for each of them but using only the resulting decision maps. The same DMs that have modeled the individual decision models may now form a group and decide on a way to combine their decision maps together, or a different set of DMs may take their place such as for instance a board of higher ranked individuals within a company.

A group decision model only has access to the decision maps from the individual models underneath as input data. This is due to the fact that we consider that at this level the DM or DMs involved in the group decision model may not hold extensive knowledge of the underlying decision problems. A group decision model may use different aggregation methods in order to remap the features from the underlying decision maps and their corresponding categories into a new decision map and a new set of categories. We have previously seen that the categories for the individual decision maps within the same group may be heterogeneous. For instance, the decision model concerned with assessing the quality of the data in regulated fishing areas outputs a decision map with categories as degrees of quality, a higher degree denoting a higher satisfaction with the quality of the data and therefore a lower need to survey that particular area, whereas the decision model concerned with identifying potential fishing areas which are not properly described by the existing data outputs a decision map with categories as degrees of interest, a higher degree denoting a higher need to survey the concerned area.

We illustrate below the construction of the first group decision model. This model is concerned with building a unified view on what areas hold an interest for the SHOM to survey from the perspective of supporting both the existing fishing areas but also the potentially new ones. The model has two pieces of input data based on the decision maps from the two individual models linked to it. As the two maps are completely disjoint, we may easily construct a new criterion which remaps the values from the input data into a new scale. The way of doing this in MODEL is illustrated in Appendix E.

We continue with the second group model and aggregate the two decision maps concerning the two military activities in a similar fashion. In this case the decision maps overlap, therefore we apply a weighted average between the remapped categories of the features of the two decision maps. We also use the same categories as the previous group model. In Fig. 12 we illustrate the decision maps for the two group models.

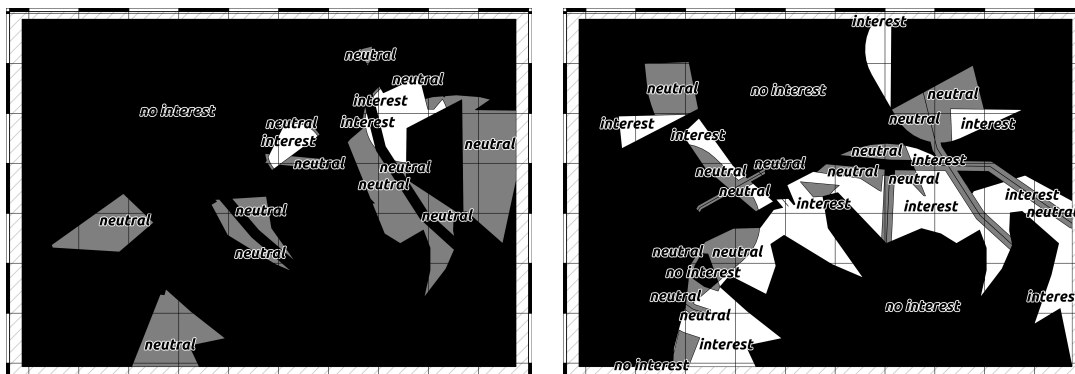


Figure 12. Decision maps for the Fishing model (left) and the Military model (right);

Finally, we construct the overall decision model by using a max operator on the categories of the decision maps from the two group models. The final decision map as well as an illustration of the process of reaching it is presented in Fig. 13.

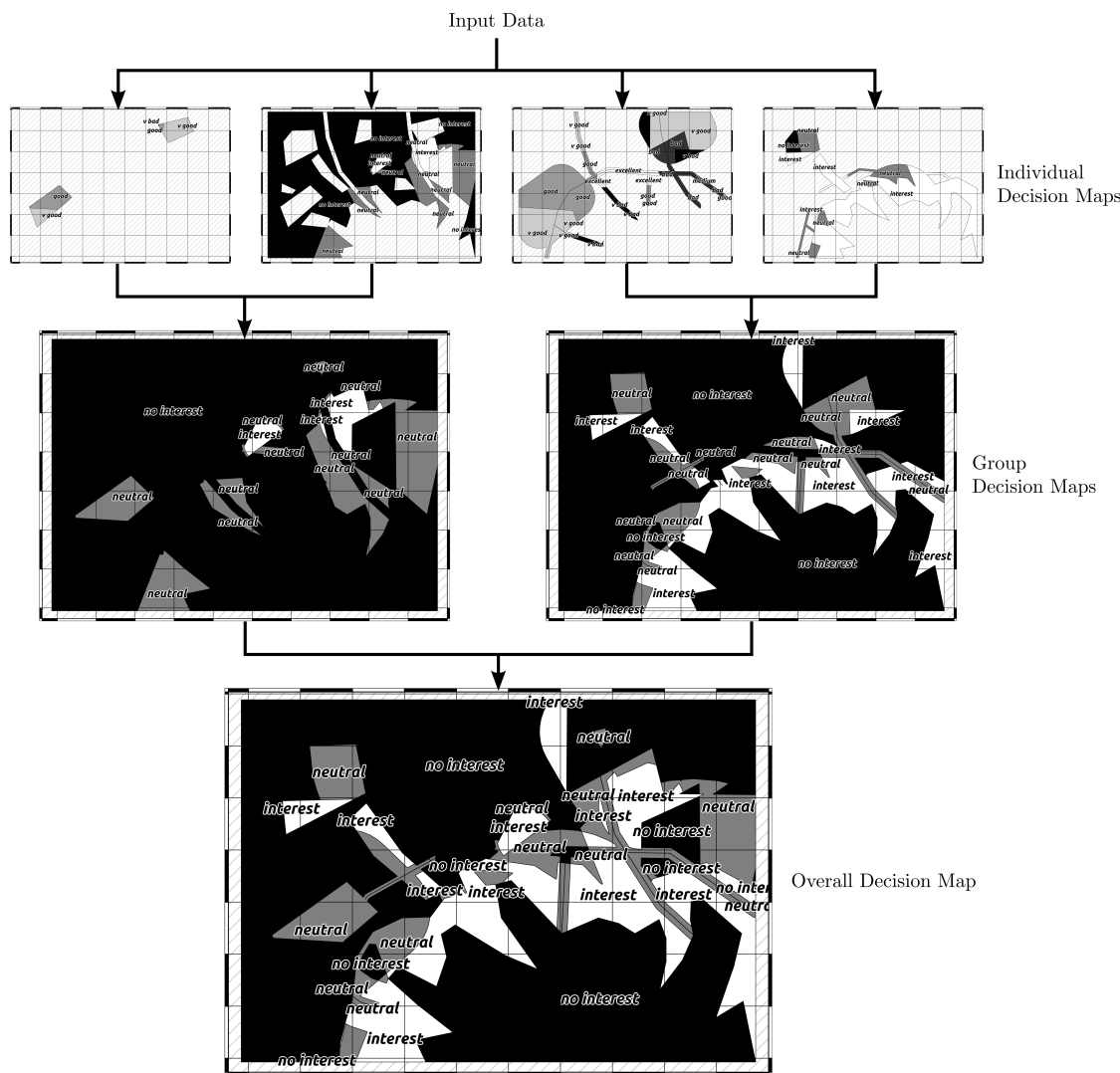


Figure 13. Overview of the MODEL process and final decision map;

Using the overall decision map, the SHOM may at this point plan their survey so that the areas with maximum interest are targeted, although other criteria may be additionally used in their decision. Furthermore, if a certain distribution of their efforts with respect to the two group perspectives is required, the group decision model maps may be used in a multi-objective optimization approach in order to provide surveying recommendations which satisfy this distribution. Finally, the individual decision maps may also be used separately, for instance in order to plan surveying activities for the military in areas where they have good knowledge on the marine environment.

5. Discussion, limitation and perspectives

The MODEL decision aiding methodology combined with the MODEL plug-in, provide a generic toolbox for solving spatial decision problems, involving multiple points of view and decision makers. As it is grounded on real-world requirements expressed by the SHOM, we are confident that it can be applied on other actual decision problems, respecting, among other things, the constraints listed in Section 2.2. While the presented tool may benefit from additional development in order to make it applicable to even a wider range of problems, it may nevertheless already be used to solve problems within several other domains than the maritime one illustrated here. Among these we wish to mention territorial risk assessment, land-use planning, acoustic nuisance management and others. The specific structure of these problems may contain a hierarchy of decision-makers, each potentially involved in a separate decision problem whose aim is to build an ordinal qualitative scale to evaluate a set of alternatives, and combine these evaluations in an overall recommendation according to the hierarchical structure. Naturally, simpler problems containing a single DM or a single decision-problem may also be modeled.

The advantage of using an outranking-based model is mainly its ability to take into account qualitative evaluations of the territorial zones on various points of view and to generate robust decision recommendations. Besides, as mentioned in Malczewski (2006), the confidence of the DM in the output of the decision aiding process is enhanced if a clear feedback from the system is given. This feedback helps him to understand the recommendation, gives him the ability to defend it in an organization, and facilitates the justification of his choices. The combination of the proposed hierarchical structuring of the decision problem with the outranking-based sorting model allows us to generate a clear and readable feedback for the DM in this work methodology.

Moreover, the preference elicitation algorithm implemented in the MODEL plug-in has been extensively validated in Olteanu and Meyer (2014) on a large number of artificially generated data sets. This allows us to be confident that this metaheuristic performs well and that it provides preference models which fit well to the preferences of the DMs.

At the moment, the tool provides support for alternatives corresponding to territorial zones, however we envision that other types of geometries (points and lines) may be added at a later time. Furthermore, additional preference models may be added to the existing two that are currently implemented, as well as making the hierarchy of decision-makers more customizable (e.g., adding or removing nodes).

Currently no sensitivity or robustness analyses are implemented in the proposed methodology and software. The iterative elicitation process should lead to a quite robust decision recommendation, however we plan to explore this in our future work.

Appendix A. Defining the hierarchical structure and input data in MODEL

In the MODEL process, the first steps consist in defining the hierarchical structure of the decision and selecting the input data. These steps are illustrated in Fig. A1.

On the left we find the panel where the hierarchy of models may be defined. At the moment this hierarchy is limited at 3 levels, however following further development we believe this could be made more general. In the middle we observe the panel containing a list of the imported data while on the right we find the panel where each piece of data is imported and edited.

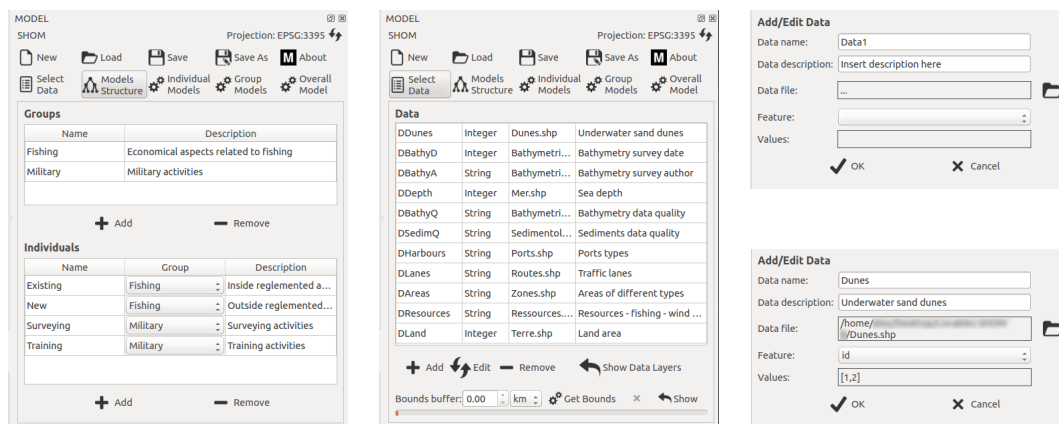


Figure A1. Constructing the structure of the problem and adding data in MODEL;

Appendix B. Defining the intermediate data, criteria and filters in MODEL

In Fig. B1 we illustrate how the intermediate data, criteria and filters may be defined inside MODEL, using the scenario of the SHOM related to existing fishing activities.

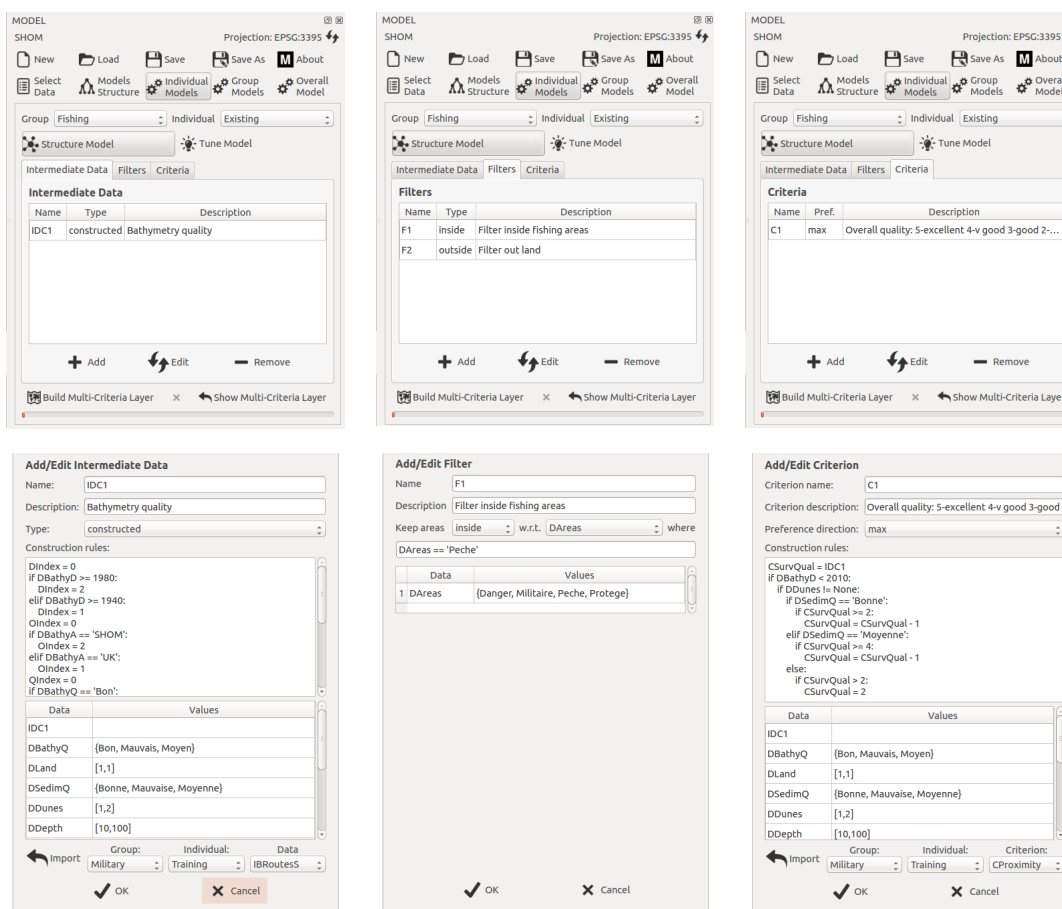


Figure B1. Adding and editing intermediate data, filters and criteria in MODEL;

On the first column we have on the top the panel containing a view of the existing

intermediate data, and the functions to add, remove or edit one of them. Below we observe a panel containing a detailed view of one intermediate data, which in this case is constructed through a set of decision rules.

The middle panels illustrate a view of the filters at the top and a detailed view of one filter at the bottom. In this case, the filter is also used to select a subset of features from the DAreas data, which correspond to fishing areas.

Finally, on the right, we illustrate the view of the criteria, which in this case consist of only one criterion which uses the previously constructed intermediate data and complements it with data related to sand dunes in order to degrade the quality of the existing data on the marine environment wherever sources of uncertainty exist (sand dunes and poor data related to sediments on the bottom of the ocean), and construct a final ordinal measure with 6 levels.

Appendix C. Directly tuning the parameters of a model

When tuning the parameters of a model, inside the MODEL tool we first need to define the number of ordered categories that will be represented in the decision map and their labels, followed by the criteria weights and majority threshold, or alternatively the majority and minority coalitions of criteria, while finally fixing the values of the delimiting category profiles on each criterion.

In the case of the model corresponding to existing fishing activities, as the only criterion contains 6 values we also define 6 categories labeled as: *v bad*, *bad*, *medium*, *good*, *v good*, *excellent*. The 6 levels and their labels have been decided by the DM from SHOM. As we only have one criterion, the second set of parameters are not relevant for the model. Finally, we fix the values of the 5 delimiting category profiles from 1 for the profile delimiting the *v bad* and *bad* categories (ex. the 0 value is not at least as good as 1 therefore it belongs to the *v bad* category, whereas the 1 value belongs to the *bad* category), up to 5 for the profile delimiting the *v good* and *excellent* categories. We illustrate how this is achieved within the MODEL tool in Fig. C1.

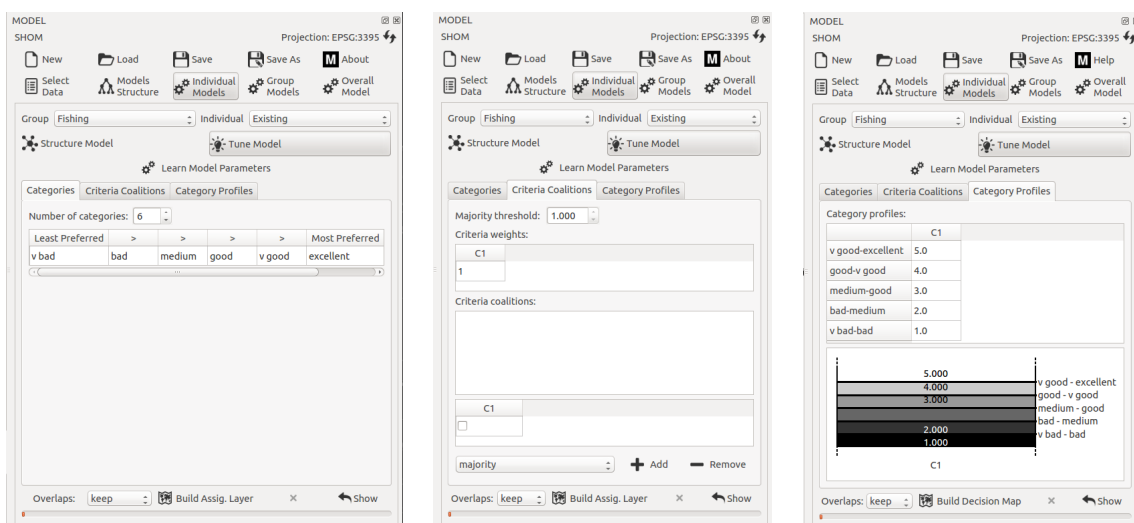


Figure C1. Fixing the parameters of the decision model;

Appendix D. Indirectly tuning the parameters of a model

As with tuning any model, we start by defining the categories in which the DM wishes to place the territorial areas. In this case we have only three categories which reflect the interest of the DM to perform surveys in a given territorial zone: *no interest*, *neutral*, *interest*. We skip over defining any criteria coalitions or setting the values of the two category profiles as we will learn these parameters by assigning a subset of the territorial zones to the defined set of categories and running an algorithm within MODEL. In Fig. D1 we illustrate on the left the assignment examples for which the algorithm managed to find a set of parameters fulfilling all the constraints except one. The images to the right contain the resulting set of parameters of the model.

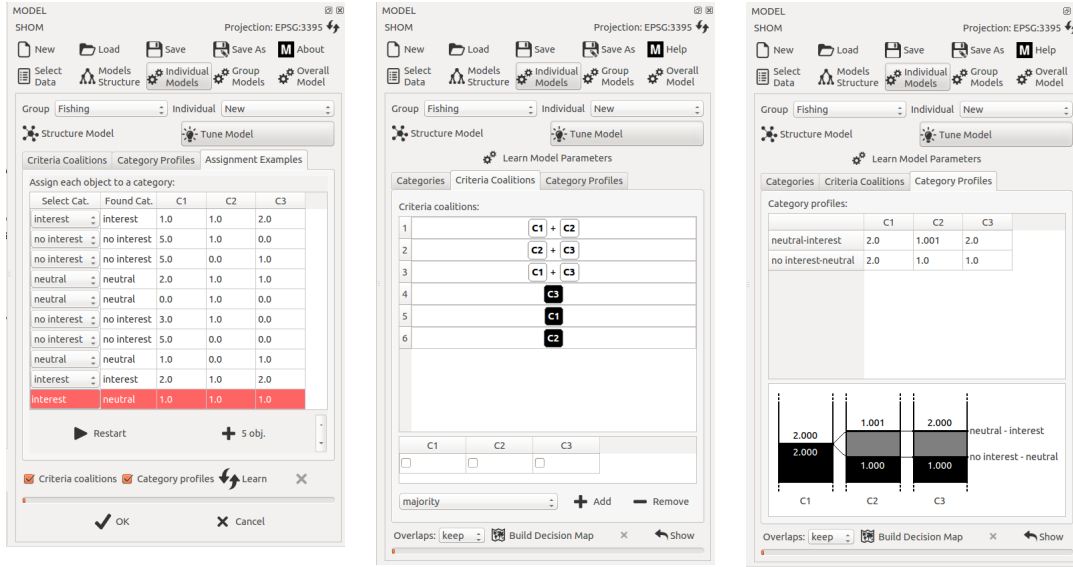


Figure D1. Learning the parameters of the decision model;

The results show that the criteria are not dictators and need to be paired with at least another one in order to validate an 'at least as good as' assertion. This, in combination with the two delimiting profiles for the three categories, gives rise to the following decision rules:

- *no interest* when:
 - when $C1 > 2$ and $C2 = 0$; (*medium-good survey quality and difficult to access*)
 - when $C1 > 2$ and $C3 = 0$; (*medium-good survey quality and low fish probability*)
 - when $C2 = 0$ and $C3 = 0$; (*difficult to access and low fish probability*)
- *neutral* when:
 - when $C2 = 1$ and $C3 = 1$; (*easy to access and medium fish probability*)
 - when $C1 \leq 2$, $C2 = 1$ and $C3 = 0$; (*poor survey quality, easy to access and low fish probability*)
 - when $C1 \leq 2$, $C2 = 0$ and $C3 = 1$; (*poor survey quality, difficult to access and medium fish probability*)
 - when $C1 > 2$, $C2 = 1$ and $C3 = 2$; (*medium-good survey quality, easy to access and high fish probability*)
- *interest* when:
 - when $C1 \leq 2$ and $C3 = 2$; (*poor survey quality and high fish probability*)

Naturally, we may refine this model by either directly changing some of the parameters, or by adding more assignment examples so that a larger and more representative sample of the territorial zones is used when learning the parameters. The topic of selecting a representative sample of territorial zones has not yet been explored in this work.

Appendix E. Structuring and tuning a group model

In Fig. E1 we illustrate the structuring and tuning of the group model related to fishing activities.

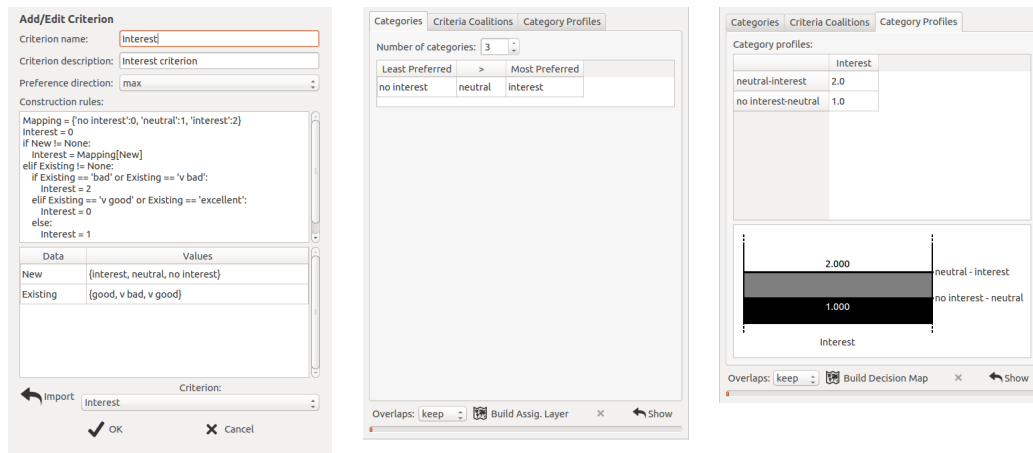


Figure E1. Structuring and tuning a group decision model;

The single criterion that we construct uses the decision maps from the two underlying models, which contain territorial areas assigned to different categories. A decision rule is defined in order to aggregate these results into a single measure or interest for performing surveys for supporting fishing activities. This new criterion is used for assigning the areas to a new set of categories, which in this case are identical to the second individual decision model. On the right we then tune the model by defining the required levels of the criterion for each of the three categories.

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