Decision Support Systems 84 (2016) 41–52

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Key challenges and meta-choices in designing and applying multi-criteria spatial decision support systems

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ARTICLE INFO

Article history:
Received 20 February 2015
Received in revised form 30 October 2015
Accepted 17 January 2016
Available online 25 January 2016

Keywords:
Multiple criteria analysis
Spatial analysis
DSS design
DSS implementation
Decision analysis
Group decision and negotiation

ABSTRACT

There is an increasing use of multi-criteria spatial decision support systems in recent years for dealing with problems that have a spatial distribution of consequences. This growth might be explained by the widespread recognition that there are multiple and conflicting objectives to be considered in spatial planning (e.g. minimizing pollution to air, water and soil, increasing the acceptance of the projects, reducing implementation costs), by new requirements to consider societal values in the evaluation and to increase participation in decision processes, as well as by the crucial role that the spatial dimension plays in such problems. However, we argue in this paper that there are key challenges confronted by DSS designers who are developing such systems and by DSS practitioners who are employing them to support decision making. These challenges impose important meta-choices to designers and practitioners, which may lead to different contents of the evaluation model and to distinctive outcomes of the analysis. In this paper, we present and discuss these key challenges and the associated meta-choices. The contribution that we aim to provide to both researchers and practitioners can be summarized as follows: (i) an increased awareness about choices to be made in the design and implementation of these decision support systems; (ii) a better understanding about the available alternatives for each choice, based on recent developments in the literature; and (iii) a clearer appraisal about the inherent trade-offs between advantages and disadvantages of each alternative.

1. Introduction

Since the 1990s, we have seen an increasing use of multi-criteria analysis (MCA) in spatial planning [58], which has, more recently, been extended to multi-criteria spatial decision support systems (MC-SDSS; [57]). Multi-criteria analysis encompasses a set of methodologies (see [10]) that offer a sound rationale for the assessment of different alternatives, for instance, urban and regional developments plans, according to multiple, conflicting, and often incommensurate dimensions, which are measured via well-specified criteria. One of the strengths of the approach is that it can take into account both qualitative criteria (e.g. specific measurement of impact on the landscape), as well as quantitative ones (e.g. distance to green areas). They overcome some of the shortcomings of traditional economic analysis (e.g. Cost–Benefit Analysis), by allowing the explicit inclusion of intangible and non-tradable goods [42] and by modeling the priorities of decision makers and stakeholders.

Recent technological developments in spatial analysis together with the increased awareness of the importance of taking into account the spatial dimension in planning, have led to the extension of traditional multi-criteria analysis to MC-SDSS [56]. The integration between MCA and Geographic Information Systems (GIS) thus represents an emerging field of research and a very interesting area of application for decision support systems [21,30,31,46].

Over the last 20 years, there has been an exponential growth of theoretical and applied research concerning MCA-GIS integration in many domains [57]. Nevertheless, the field is still very fragmented and, we argue in this paper, there are key challenges confronted by DSS designers and practitioners who are employing, or wish to employ, such methodologies. These challenges impose important meta-choices to analysts, since these choices could lead to different contents of the evaluation model and to distinctive outcomes of the analysis, when designing planning processes adopting MC-SDSS. The time is thus ripe for a formal conceptualization of them and this paper will attempt to lay out these key challenges, as well as the main meta-choices available to cope with them.

Consequently, this article has a dual purpose: (i) to identify and formalize the key challenges involved in the design and implementation of DSSs for spatial multi-criteria evaluation and (ii) to suggest, for each of them, the meta-choices that analysts and systems designers must

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http://dx.doi.org/10.1016/j.dss.2016.01.005
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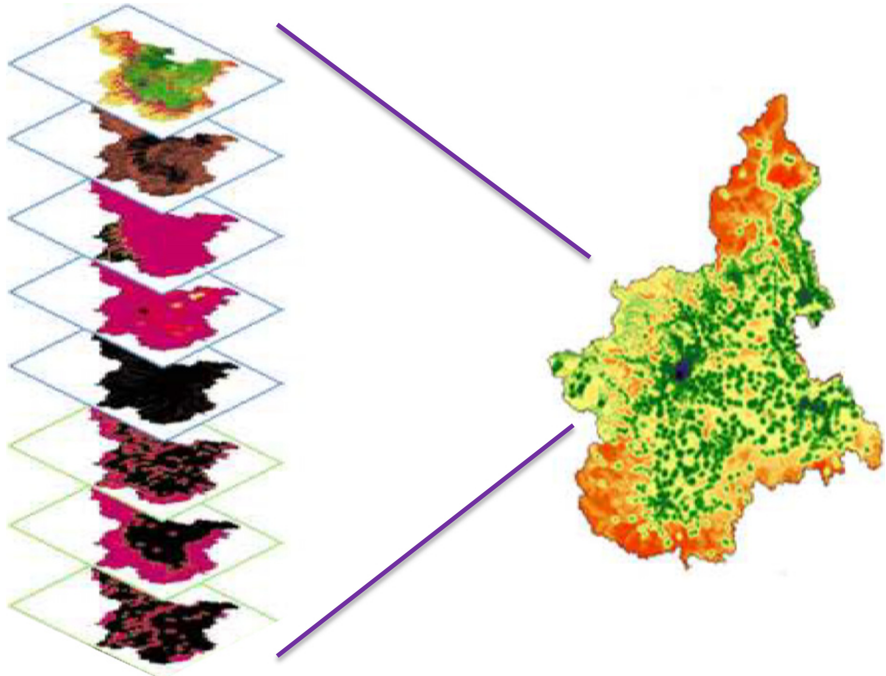

Fig. 1. An example of an MC-SDSS output. On the left are the criteria maps and on the right the overall final map (source: [35]).

make. This may provide to DSS designers and practitioners an increased awareness about choices to be made in spatial planning and decision-making processes, a better understanding about the available alternatives for each choice based on recent developments in the literature, and a clearer appraisal about the inherent trade-offs between advantages and disadvantages of each alternative.

This research thus lies in the interface between two disciplines: on one hand, MC-SDSS users can benefit from a deeper understanding of the assumptions behind multi-criteria methods, and on the other hand, DSS designers can benefit from an in-depth understanding of the intrinsic characteristics of spatial planning processes. This paper is an attempt of bridging this gap.

The remainder of the paper is organized as follows: Section 1 introduces the rationale for the integration between multi-criteria evaluation techniques and spatial analysis tools, as well as the required modeling steps in this kind of analysis. This sets the scene for the subsequent discussion of the key challenges. Section 2 discusses these key challenges for each modeling step and provides guidelines with reference to the available meta-choices. Finally, Section 3 concludes the paper and discusses the opportunities for further research in this field.

1. Multi-criteria spatial decision support systems: Setting the scene

This section presents an overview about MC-SDSS, covering the complexities that call for their use, the rationale for coupling MCA and GIS, as well as the main modeling steps needed to properly develop these integrated models for supporting planning. This section will set the scene for a discussion on the key challenges which follows.

1.1. The need for MC-SDSS

There are several complexities in spatial planning and decision making that may explain the need for MC-SDSS, from both technical and social perspectives.

Starting from a technical perspective, one of the most relevant complexities is the inherent trade-off between socio political, environmental, ecological, and economic factors [51]. Secondly, some of the criteria[2] to be considered in those assessments cannot be easily converted into a monetary value, partly because environmental concerns often involve ethical and moral principles that may not be related to any economic use or value [55], partly because of the difficulties of monetizing intangibles [42]. Thirdly, as mentioned before, the spatial dimension of both the alternatives and the characteristics of the territory plays a crucial role in spatial planning [85]. Fourthly, the increasing volume of data available to support decision making processes emphasizes the need to develop tractable methods for aggregating the information in a way which is meaningful for planners and decision makers [55]. These technical complexities of decision making processes may explain the growing use of MC-SDSS [32,57] to deal both with the spatial characteristics of the land and with the multiple objectives inherent in such contexts (e.g. minimizing pollution to air, water, and soil, increasing the acceptance of the projects, reducing implementation costs).

From a social perspective, there are again several complexities in the context of spatial planning and decision making processes. Firstly, such decision processes often involve many different stakeholders, with different objectives and priorities, thus representing exactly the type of problem that behavioral decision research has shown humans are poorly equipped to solve unaided [55,65]. Secondly, complex decision problems typically draw on multidisciplinary knowledge bases, incorporating natural and social sciences, as well as medicine, politics, and ethics [64]. Thirdly, and associated with the previous complexity, is the tendency of planning issues to involve shared resources and broad constituencies, which means that group decision processes are often necessary [55]. However, groups are also susceptible to establish entrenched positions (defeating compromise initiatives) or to prematurely adopt a common perspective that excludes contrary information and suffer from "group-think" (e.g. [55]). These social complexities may explain the increasing adoption of participative decision processes in those contexts and of facilitated decision modeling to support them [37].

[2] We considered throughout the paper an "objective" as a variable with a direction of preference (e.g. minimize soil pollution) and a "criterion" when this objective is operationalized by an attribute (e.g. particle of contaminant per ton of soil) and normalized by a standardization function.

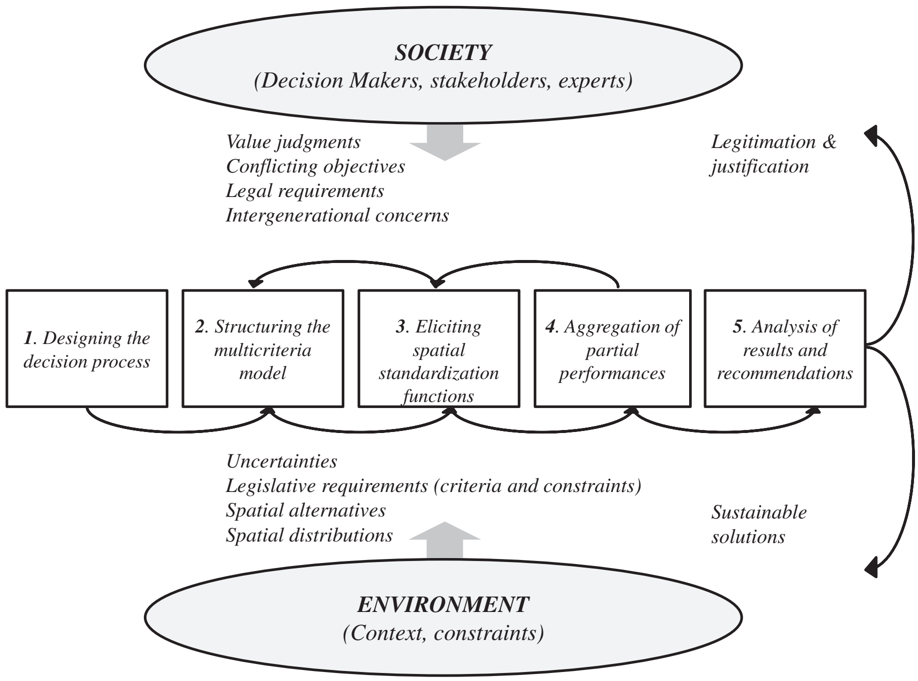

Fig. 2. Modeling steps in a socioenvironmental context.

Following from these considerations, the use of participative MC-SDSS can handle the spatial complexities involved in planning and decision making processes, as well as the societal priorities and preferences[3] of communities.

1.2. The rationale for MCA-GIS integration

How the spatial pattern (e.g., location, proximity, clustering) of development affects critical land components is an important aspect of planning and decision-making processes [40]. The wide availability of GIS provides the technical means to help local and regional planners in better understanding the impacts of development trends, as well as to investigate the interdependencies between the spatial, socioeconomic, and cultural factors in decision-making processes. A drawback of GIS is their lack of decision modeling capabilities, which weakens their ability to support decision processes dealing with conflicting objectives [26,45].

The need to integrate spatial data with algorithmic techniques has thus been recognized and has given rise to a research stream in the context of DSS related to the so-called spatial decision support systems (SDSS, [81]). As mentioned by Maniezzo et al. [59], these systems concern the integration of spatially referenced information in a decision-making environment in order to better support planners and decision makers, showing how spatially integrated DSS can be used to bridge the gap between policy makers and complex computerized models [83]. An emerging subset of these tools is MC-SDSS, which combines GIS and MCA.

From a methodological point of view, MC-SDSS provide a collection of methods and tools for transforming and integrating geographic data (criteria maps, as illustrated in Fig. 1, left-hand side), as well as decision makers' preferences and priorities, to obtain an overall assessment of the spatial decision alternatives (Fig. 1, right-hand side). For example, the overall map might be a land use suitability map for hosting a new development project/infrastructure; or a vulnerability map highlighting areas of high impacts, which need specific mitigation and monitoring measures.

The main rationale for integrating GIS and MCA is thus that they have unique capabilities that complement each other, enhancing the effectiveness and the efficacy of the planning process [57]. On one hand, GIS has good capabilities for storing, managing, analyzing, and visualizing geospatial data required for planning. On the other hand, MCA offers a rich collection of methodologies for structuring planning problems with conflicting objectives, enabling the design, evaluation, and prioritization of decision alternatives [56]. As already mentioned, the literature now contains many developments and applications of MC-SDSS in a variety of domains [57], including territorial and urban development (e.g. [4,34,70]), urban infrastructures (e.g. [21]), siting problems (e.g. [30]), housing policies (e.g. [46]), to name a few. How these models are built up is briefly described next.

1.3. Modeling steps in MCA-GIS

We can divide the process of building an MC-SDSS into five fundamental steps (see Fig. 2). The first step consists in designing the decision-making process, i.e. deciding who should be involved and when, as well as what is the appropriate methodology to be employed. The second step involves structuring the multi-criteria model, by defining a set of fundamental objectives and related spatial criteria, and specifying the options/alternatives.

The third and fourth steps in the process refer to the elicitation of the spatial standardization functions, i.e. functions that allow to translate the raw performances of each spatial criterion into homogeneous dimensionless values varying from 0 (worst performance and low objective achievement) to 1 (best performance and high objective achievement), and to the aggregation of partial performances into an overall performance, respectively. Both these steps underpin the final overlay of the spatial criteria being considered. Due to the inherent subjectivity that characterizes both steps, which require the elicitation of preferences, it is highly recommended to develop them through a participatory approach with the main stakeholders. Finally, in the last step of the process, where the resulting overall map is analyzed, it is always important to perform a sensitivity analysis regarding the key uncertainties associated with the problem (on impacts, standardization

[3] Throughout the paper we intend "priorities" as value trade-offs, which in most MCDA methods are represented by criteria weights, and we intend "preferences" as marginal value over impact on a given attribute, which are represented by spatial standardization functions.

Table 1
Key challenges in MC-SDSS design and application.

Steps	Challenges
1. Designing the decision process	*Challenge 1* (i) Who should participate? (ii) How experts and stakeholders should participate? *Challenge 2* (i) What is the appropriate MCA method, given the plethora of methods available? (ii) Get an off-the-shelf method or design a tailor made one?
2. Structuring the MC-SDSS	*Challenge 3* (i) What sources should we use to define objectives (from experts, public, literature, legislation, etc.)? (ii) How to make sure that all and only the fundamental objectives are included? *Challenge 4* How to deal with the limited availability of spatial data for the criteria?
3. Eliciting spatial standardization functions	*Challenge 5* (i) How to define the appropriate shape of the spatial standardization functions? (ii) How to elicit standardization functions from experts/public?
4. Aggregation of partial performances	*Challenge 6* How to deal with sustainability concerns[1] in the evaluation? *Challenge 7* How to elicit criteria weights from experts/public?
5. Analysis of results and recommendations	*Challenge 8* How to efficiently perform spatial sensitivity analysis?

[1] That is, environmental protection and natural resources consumption, such as soil consumption minimization, agriculture productivity, water resources management, and the preservation of biodiversity, to name a few, against other social and economic criteria that need to be maximized.

functions, and priorities of the decision makers) in order to draw recommendations about the robustness of the solution.[4]

As highlighted in Fig. 2, the whole process is highly iterative and from each step it is always possible to go back to a previous one, to improve the model and allow learning to take place. While these modeling steps have been presented in slightly different ways in the decision analytic literature (e.g. [10,47]) our diagram relates these modeling steps to the socio-environmental context where planning processes take place.

As the diagram shows, two important sources of inputs in this context are the society (e.g. decision makers, stakeholders, experts) and the environment (i.e. the context and the constraints). The former is where the value judgments, the conflicting objectives, the legal requirements, and the intergenerational concerns come from. The latter is where the uncertainties, the legislative requirements about criteria and constraints, the spatial alternatives, and the spatial distribution of their consequences arise. As a result, the process may feedback to society legitimation for and accountability of the final decision. At the same time, it may generate sustainable solutions for the problem, able to take into account the multidimensionality and the interdisciplinary nature of the context. But what are the key challenges confronted by DSS designers and analysts in following those steps in spatial planning and decision making processes? These are discussed in the next section.

2. The key challenges in multi-criteria spatial decision support systems' design and application

Table 1 summarizes the key challenges in MC-SDSS design and application, for each of the modeling steps introduced in Fig. 2. These challenges are based on the relevant literature that we identified in the fields of multi-criteria analysis, planning support systems, and spatial decision support systems, as well as on our experience in conducting multi-criteria assessments in these and in similar contexts. We attempted here to systematically organize the meta-choices that DSS designers need to make when designing this type of interventions and suggest possible alternatives to choose from.

Each challenge will be discussed in detail in the following paragraphs, considering both the reasons why we identified it as a challenge and the meta-choices that are available for coping with it.

2.1. Challenge 1: Who should participate and how can they participate?

Stakeholder[5] involvement is increasingly recognized as an essential element of successful environmental decision making [43]. An early involvement of stakeholders can help in gathering information about concerns and priorities and contribute to an increased acceptance of the final results [5,37]. Stakeholder participation is, however, costly and time consuming. In some cases, it may even lead to stalling the decision process. Therefore, the two variables we identified for this challenge are (i) which stakeholder should get involved and (ii) through which process they should be involved.

Regarding the first variable, despite the crucial role that defining the composition of experts and stakeholders panel has, we cannot prescribe a set of discrete alternatives for this challenge. Nevertheless, stakeholder analysis (e.g. power/interest matrices, see [27]) might help in classifying and selecting them.

Regarding the second variable, i.e. organizing stakeholders' involvement and structuring their inputs to decision making, this task can be accomplished through the use of collaborative decision support systems [55]. The meta-choices available for DSS designers confronted with this challenge concern the means of participation to be employed. Two main alternatives are available here to the DSS designer: (i) online participation or (ii) physical participation. The advantage of online participation is the possibility of a wider and asynchronous involvement of both experts and non-experts. Its drawbacks are limited interaction between participants and the analyst, which miss the benefits of facilitated decision modeling [37], such as a facilitator that can debias decision makers' judgments [62] and the advantages of face-to-face group decision-making [54]; as well as dilution of expertise and power among the group, which might make it difficult to reach an agreement and implement the chosen solution [68]. The advantages of physical participation consist, instead, in enabling facilitated modeling and

[4] For a detailed discussion about robustness in the context of decision aiding see [73].

[5] In this paper stakeholders are defined as any actor having a vested interest in the decision process, either directly affecting or being affected by its resolution, including experts and the public. In the literature experts and citizens are however sometimes viewed as separate categories (see e.g. [48,69]).

promoting interaction among participants. Its drawbacks are the limited amount of people that can be involved and, therefore, the need for selection of members. In addition, it is time consuming, which leads to having, often, only experts participating in the modeling process with the exclusion of other relevant stakeholders.

Some possible best practices that could be helpful for dealing with these challenges are (i) the use of facilitated modeling techniques [37], (ii) the development of stakeholder analysis (e.g. network matrices, power/interest matrices, etc. [1,27]), and (iii) the use of problem structuring methods to structure and facilitate stakeholders' involvement in the decision processes [38], which has been shown to increase the quality of decisions [6].

Some real examples from the authors' experience can offer further insights into the process of identifying the key challenges and shaping the meta-choices and will be mentioned throughout the paper. For instance, one of us has indeed been recently involved in two projects facing Challenge 1 described above. The first project consisted in a multi-attribute location problem for a new parking area inside a UNESCO site [33]. In this case, the participation-related challenge was faced by developing a stakeholder analysis with a power/interest matrix, which supported the identification of objectives and criteria to be later used in the decision making model. Physical participation was selected, given that only key stakeholders were involved, thus leading to a limited and manageable number of participants. In the second project, which relates to the use of a collaborative multi-criteria analysis approach for supporting the development of the new land use plan of a municipality in Italy [14], the team used a combination of both online and physical participation for the following reasons: (i) about 90 participants were involved in the process since the very beginning of the planning procedure (including citizens and associations, environmental authorities, private companies, and practitioners); (ii) the participatory process consisted in several public meetings and debates and in the construction of a web site through which it was possible to share documents, materials, and opinions about the ongoing planning process; and (iii) given the strategic and experimental nature of the project, participatory procedures were planned since the very beginning of the project, i.e. from the identification of the objectives and desired actions to be included in the land use plan, to their prioritization and realization.

2.2. Challenge 2: What is the appropriate MCA method?

There are many different MCA methods, and a detailed analysis of their theoretical foundations is beyond the scope of this paper (see [10] for an overview). Each method has strengths and weaknesses: while some methods are grounded on normative decision theory, others, such as the outranking methods, have more descriptive validity in representing complex preferences and implementing non-traditional aggregation rules. There are also differences in the types of preferences that are elicited by different methods and in the elicitation protocols they employ [10].

Many of these methods can support spatial evaluations using participative decision-making processes, but none of them can be seen as the "super method" appropriate to all decision-making situations [44]. Since the technical choices (typology of the measurement scales, different preference models, different aggregation operators) are not neutral [83], it is important to select the method best fitted to the decision process under consideration.

Moreover, some intrinsic methodological characteristics of the different approaches play a crucial role in determining their suitability to be integrated with spatial analysis: (i) alternative-based methods, in which the different options are directly compared against each other, easily reach their computational limits in a spatial context as every pixel of the map becomes an alternative [18]; (ii) there is a need for coherence between the standardization of the maps and the axiomatic foundations of the methods; (iii) there is a limited availability of built-in MCA methods in GIS software; and (iv) there is a need to avoid the black box effect, by having simplified elicitation protocols and ensuring the transparency of the model.

Choosing among MCA methods is thus an intricate task and there is a strong need for guidelines in the choice of methods, from both the technical and the social point of view. The meta-choices available for DSS designers confronted with this challenge thus concern the process of selection of the method. In particular, the alternatives are (i) use an off-the-shelf method or (ii) design a tailor made approach, by combining components of different methods. The former option implies that a DSS designer tries to select one method, among all the existing ones, by following a checklist of guiding questions, such as those proposed by Roy and Slowinski [75] and adapted by us to the spatial planning context, as shown in Table 2. The latter option means designing an evaluation method by carefully integrating components from different methods in a meaningful way. There are inherent risks in such combinations, for instance in the way that different methods conceptualize criteria weights or represent and elicit preferences [10]. Thus any attempt of combining methods has to make sure that there is theoretical adequacy and logical consistency between the assembling blocks.

A real example in which one of the authors has been involved could help clarify this challenge. In a project concerning the location of a landfill in Italy [31], the team had to develop a land suitability analysis in order to identify the most suitable site for the location of this undesirable facility. Given several features of the problem, such as (i) the type of results needed by the provincial authority (i.e. the choice of the most compatible site); (ii) the existence of many interaction mechanisms between the social, environmental, and economic dimensions of the analysis; and iii) the fact that the decision process was taking place during the strategic macro localization phase of the planning process (thus calling for the need to involve different stakeholders and subsequently to have qualitative elicitation protocols and intuitive models), the team decided to use the Analytic Network Process approach [76], which allows to take interactions among criteria into account, as well as an intuitive approach, and combine it with GIS.

2.3. Challenge 3: What sources should be used to define objectives and how to make sure that all and only the fundamental objectives are included?

Effective spatial decision-making requires an explicit structure for coordinating joint considerations of the environmental, ecological, technological, economic, and sociopolitical objectives relevant to urban and regional planning. This makes the evaluation inherently multi-objective. Integrating this heterogeneous information demands a systematic and understandable framework to organize the objectives and the related criteria that measure their achievement [55].

The meta-choices available for DSS designers confronted with this challenge concern two key variables: (i) the source of provision of the objectives and (ii) the level of objectives being considered in the evaluation.

Regarding the first variable, the alternatives are (i) public-based sources (e.g. the community and the stakeholders) or (ii) expert-based sources (e.g. experts, literature, legislation, etc.). The advantages of using public-based sources are to maintain procedural justice and to take into account local concerns. Their drawbacks are that they are time intensive and they may lead to the generation of objectives that are essential but outside of the specific decision framing of the evaluation or, on the contrary, that are easily measurable but not fundamental aspects in the evaluation (see [49]). The advantages of using expert-based sources are the possibility of taking into account the most well-accepted and up-to-date scientific evidence, as well as the opportunity to have objectives which reflect the best available knowledge. Their drawbacks are the risks of underestimating local concerns and of fomenting social opposition.

The second variable refers to the level of the considered objectives, whether they are fundamental or means. Means objectives (e.g. minimize the walking distance to the subway station) are easier to measure

Table 2
Guiding questions for the selection of an MCA method in MC-SDSS design.

Guiding questions	Specific questions	Solutions
1. What kind of results are needed?	a) Is it conducting a suitability analysis (i.e. choice problem, as for instance the generation of possible alternatives where to locate a new landfill)? b) Is it comparing different existing alternatives (i.e. ranking problem, as for instance comparing two different road layouts)? c) Is it assigning each action to one or several categories which have been defined a priori (i.e. sorting problem, as for instance risk categories or vulnerability categories identification)?	a) Use value-based methods (e.g. [53]). b) Employ outranking/alternative-based methods (e.g. [72]). c) Adopt category-based methods ([86]).
2. How to gather inputs from stakeholders?	How are preferences elicited?	a) Use qualitative elicitation protocols [61]. b) Employ quantitative elicitation protocols.
3. How to share the outputs of the analysis?	How to aggregate the data and display results?	a) Avoid black box methods, use intuitive methods with an easy-to-explain logic [28]. b) Display results in a user-friendly way (e.g. graphical representations, visual use of colors, easy to see changes in the models [8,67]). c) Use methods that support conversation and negotiation of different views [37].
4. What are the relevant characteristics of the problem in terms of compensability, uncertainty and interaction?	a) Is the compensation of bad performances on some criteria by good ones on other criteria acceptable or not (e.g. compensation is not acceptable for emissions of pollutants over regulatory levels or for the number of lives lost; compensation is acceptable between the distance from the subway station and the quality of the landscape)? b) Are there uncertainties (about priorities and the factors) that must be taken into account? c) Is it necessary to take into account some forms of preferential interaction among criteria?	a) If compensation is allowed, one can use compensatory aggregation rules (e.g. [53,76]). If compensation is not allowed, one can use non-compensatory aggregation rules (e.g. [72]). b) Use methods that allow the modeling of non-deterministic impacts (e.g. [53]) and enable an easy sensitivity analysis on criteria weights. c) The DSS designer should try to design a criteria set without preferential dependences. If that is impossible, methods that allow more sophisticated aggregation procedures than a weighted sum are required [75].

and so there is the risk that the planner selects those for which there are data, even if they are not connected with fundamental objectives [49].

The measurement of the level of achievement of each objective in multi-criteria evaluation is done via criteria [52] and, in most spatial applications, this evaluation has to be based on proxy criteria (i.e. they measure the achievement of means objectives). The reason for using proxy criteria is the gap between the information needed and the information available for spatial decisions. The drawback is that the link between a proxy criterion (for example, pollution concentration) and a more natural one (for example, health effects), which could measure the achievement of a fundamental objective, is often tenuous [7].

The alternatives regarding this second variable (i.e. the level of the considered objectives) are (i) top-down structuring of objectives (i.e. decomposing the overall objective into sub-objectives which are easier to measure) and (ii) bottom-up structuring of objectives (i.e. the definition of objectives based on the attributes that distinguish the alternatives – for details see [17]). The advantages of the former are that the structuring of objectives is naturally connected with value-focused thinking [49] as well as with proactive approaches to designing better alternatives [51]. In addition, it makes sure that there is a hierarchical decomposition structure for the criteria set. The drawbacks are that it requires a more abstract way of thinking, which may make stakeholders struggle to provide objectives when prompted [15]. The advantages of bottom-up structuring of objectives are, instead, that it is cognitively an easier approach and it uses a more concrete way of thinking, linked with easily measurable criteria [17]. Its main drawbacks are that it may lead to alternative-focused thinking [49] and to the risk of missing fundamental objectives [15].

A real example in which one of the authors has been recently involved may illustrate this challenge. In the previously mentioned project, concerning the selection of the best location for a new parking in a UNESCO site in Italy [33], the challenge related to the identification of the relevant objectives was tackled in the following way: the team organized a focus group with the key local stakeholders (i.e. we used public-based sources) and employed a participatory and facilitated concept mapping session with them in order to identify the key values and their casual relations and subsequently derive the comprehensive list of relevant objectives and criteria (i.e. bottom-up structuring of objectives). This allowed not only to identify all the relevant concerns since the very beginning of the project, but also to stimulate a learning effect and a sense of ownership of the problem at hand.

2.4. Challenge 4: How to deal with the limited availability of spatial data for the criteria?

The most significant difference between spatial multi-criteria decision analysis and conventional multi-criteria techniques is the explicit presence of a spatial component. MC-SDSS models therefore require data on the geographical locations of alternatives and/or geographical data on criterion values [78]. The issue is that spatial data are usually not publicly available and, in any case, dispersed among different authorities and public offices.

In this situation, the meta-choices available for DSS designers concern the means of defining the spatial distribution for each criterion whenever spatial data are not available. In particular, the alternatives are (i) self-build the maps, using the best available evidence and expert judgment, or (ii) redesign the model, trying to find proxy criteria for those factors for which it is unfeasible to build a spatial map.

The advantage of self-building the maps, by using the best available evidence, is that key criteria, which reflect fundamental objectives, are considered, even for data not readily available. The drawbacks are that the elicitation of expert judgment on the spatial distribution of the values may not be feasible, due to the large number of pixels in the map; as well as the behavioral biases affecting expert judgments (see [41,62]). The advantage, instead, of redesigning the model, by trying to find proxy criteria for those factors for which it is unfeasible to build a spatial map, is that it may enable employing data of better quality. The drawbacks are the need to perform indirect assessments, by using proxy criteria instead of natural ones, and that the achievement of a proxy objective may not fully reflect the achievement of a fundamental one.

Some possible best practices that could be helpful in this context are (i) the use of distributed spatial data access and infrastructures [11], which enables the development of shared geospatial data, and (ii) the development of properly constructed criteria to measure the fundamental objectives [52].

A real example in which one of us has been recently involved could exemplify this challenge. In a project related to the study of the network of actors involved in the design of a spatial decision support system, aiming at understanding the impact of climate change on forestry [12], the team explored the use of distributed spatial data access and infrastructures and its impact on the stability of the network of actors. This meta-choice turned out to have positive effects on the overall design process, as it allowed public authorities and research centers to create an easy-to-update spatial database, which could be used for asynchronous participatory decision processes, as well as for monitoring purposes.

2.5. Challenge 5: How to elicit spatial standardization functions from experts/public?

As previously mentioned, spatial standardization functions are an important component of MC-SDSS models. They are required to make criteria maps comparable and thus they translate the original factor maps scores into a common scale, usually ranging from 0 (worst performance and low objective achievement) to 1 (best performance and high objective achievement). Usually, the standardization functions adopted in MC-SDSS models are linear, which make an implicit, and often unrealistic, assumption that the value of the marginal impact is indeed linear. Most MCDA methods, for example those based on outranking relations or lexicographic rules, among others (see [10]), do not require an elicitation of standardization functions, to assess the value over the marginal impact being assessed. On the other hand, multi-attribute value theory-based methods typically involve an explicit elicitation of such functions, and indeed there is evidence that results are sensitive to their shape [82].

Eliciting spatial standardization functions demands a significant cognitive effort [65] and is inherently subjective. In addition, they should be elicited with proper interviewing protocols, which are psychometrically valid (see [84]).

Spatial standardization functions are typically obtained from decision makers who, sometimes, delegate to experts the provision of such parameters. For spatial planning and decision making processes, often these standardization functions are elicited via surveys with the public (e.g. [16]). Who provides the information, of course, has consequences on the way that the function is structured and assessed [7].

The meta-choices available for DSS designers confronted with this challenge thus concern two key variables: (i) the type of elicitation protocol to be employed in eliciting spatial standardization functions and (ii) the means of eliciting this type of parameter.

Regarding the first variable, the alternatives are (i) using a protocol requiring qualitative statements of preferences with a conversion to a quantitative value function or (ii) employing a protocol requiring quantitative statements of preferences. The advantage of using a protocol requiring qualitative statements of preferences (e.g. AHP, [76]; MACBETH, [3]) is the easiness of this approach for non-technical participants. The drawback is that qualitative–quantitative conversion might be seen as a black box by stakeholders and policy makers. On the other hand, the advantage of using a protocol requiring quantitative statements of preference (for example, the bisection method, see [84]) is the use of a direct elicitation procedure, without artificial conversions, while the drawback is that it is cognitively more demanding.

Concerning the second variable (i.e. the means of eliciting standardization functions), there are two alternatives: (i) using a single expert interview or (ii) employing expert group workshops. The advantage of the former is that it is a faster and less costly process, while the drawback is the risk of missing important value judgment from other experts or stakeholders. Regarding the latter alternative, i.e. employing expert group workshops, the advantage is that it is a more comprehensive involvement, which is likely to provide a better picture of different concerns and values and to allow an exchange of views among experts. Its drawback is the need for either mathematical or behavioral aggregation of the individual preferences [9].

Some possible best practices that could be helpful in this context are (i) using valid psychometric elicitation protocols [84], (ii) controlling the cognitive burden in those elicitations ([65]), (iii) setting up appropriate upper and lower bound limits [52] as they should anchor the criteria weights [53], (iv) using facilitated workshops for their elicitation [37], and finally, (v) designing online surveys for the elicitation of standardization functions (e.g. [24]).

A real example in which one of the authors has been recently involved can illustrate this challenge. In a project related to the study of the suitability of a water basin to be requalified as a wetland with important ecosystem services [20], the team faced the challenge of eliciting spatial standardization functions and decided to employ a group workshop with a limited number of key experts in the different fields important for the decision. This enabled the use of a protocol with quantitative statements of preferences, which provided a better picture of the thresholds of appreciation of the different factors, as well as of the warning levels. The limited amount of experts involved (four) allowed them to agree, via facilitated group discussions, on a single shape for each standardization function without requiring subsequent aggregation. Moreover, by using the bisection elicitation protocol [84], the experts reported a greater sense of understanding of the characteristics of the decision context under analysis.

2.6. Challenge 6: How to deal with sustainability concerns in the evaluation?

When considering sustainability in MC-SDSS models, the evaluation of different decision alternatives requires the consideration of trade-offs between many objectives [23]; factors that range from the reduction of soil consumption to the optimization of the use of environmental resources, from the promotion of economic activities to the requalification of downgraded urban areas, from the endorsement of energy efficiency to the rationalization of transport systems.

In this context, it is worth noticing that there are two competing theories about sustainability, which will influence policy makers and the analysis: the weak and the strong sustainability approaches [22, 60]. Weak sustainability assumes that there is perfect substitutability between man-made capital (e.g. monetary capital, labor) and natural capital (e.g. natural resources and ecosystems services), and thus value trade-offs can be made. In contrast, strong sustainability argues that such substitutability should not be allowed, since it may lead to underestimating issues such as intergenerational equity, resource depletion, ecosystem degradation and/or resilience.

Societal values may direct the adoption of an approach, e.g. the widespread use of Cost–Benefit Analysis in environmental decisions in some countries (see [66]), in which all the impacts are monetized, might reflect the choice of the weak sustainability paradigm. In addition, the context of the problem may lead to a choice of one of the approaches, for instance, in nuclear waste disposal problems [63], trade-offs can be made above safety levels when selecting alternative solutions for storage (thus adopting the weak sustainability paradigm) but not below these safety levels (therefore employing the strong sustainability paradigm).

The concept of weak substitutability thus allows compensability among performances on different criteria, i.e., to compensate a disadvantage on one or several criteria, a sufficient advantage on other criteria is required [50,74]. Many multi-criteria methods are compensatory and, as such, they thus support the evaluation process under weak sustainability assumptions. But non-compensatory methods also exist, for those evaluations that adopt stronger definitions of sustainability (e.g. some outranking methods – see [72]). In addition, non-compensability may occur in situations in which the decision maker is not willing to compensate for anything at all (e.g. due to taboo trade-offs, [36]) linked to societal values as for instance the cost of lives, health issues or environmental damage.

The meta-choices available for DSS designers confronted with the challenge of modeling compensability thus concern the selection and understanding of the sustainability approach. As hinted before, the alternatives here are adopting either: (i) a weak sustainability approach or (ii) a strong sustainability one. The first alternative models the weights as trade-offs, allowing a substantively rational [79] comparison between benefits and costs. The disadvantage of this approach is that it may underestimate environmental consequences, particularly long-term ones. The second alternative (the strong sustainability approach) calls for the use of non-compensatory aggregation rules in a multi-criteria evaluation. The advantage in this case is that it avoids environmental losses when comparing alternatives; while the drawbacks are the use of operators that do not reflect substantive rationality and the risk of over-emphasizing environmental concerns, thus neglecting other consequences and social benefits.

Some possible best practices that could be helpful in this context are (i) the use of screening criteria to remove unsuitable options, allowing compensation only within acceptable ranges of the criteria [3] and (ii) the inclusion of long-term consequences and intergenerational concerns in the multi-criteria model (e.g. [2]).

In order to offer further insights into the process of dealing with sustainability concerns, we share one of the authors' recent experiences facing this challenge. In the previously mentioned project dealing with the land suitability analysis to host a new landfill [31], the team dealt with sustainability concerns by using a compensatory approach (i.e. the Analytic Network Process, ANP). The fact that the decision process was taking place during the strategic and more flexible planning phase (i.e. the macrolocalization phase of undesirable facilities) indeed enabled taking a weak sustainability approach and thus compensating performances on different criteria. It is worth highlighting that specific constraints have been included in the analysis in order to ensure that performances below the regulatory thresholds were considered unsuitable and thus were excluded from the analysis (e.g. all those areas where the groundwater depth was less than 3 m from the surface soil [31]). For these unsuitable areas, compensation could not be made. Moreover, by opting for the complex ANP structuring process (i.e. the benefits, opportunities, costs, and risks network) the analysis enabled the inclusion of long-term consequences and intergenerational concerns in the multi-criteria model.

A different approach was pursued in a project dealing instead with the requalification of an abandoned quarry in Northern Italy, in which one of the authors of this paper has been recently involved [13]. In this case, a non-compensatory approach was used and an extension of the ELECTRE III method was developed, in order to deal with interactions between pairs of criteria, which is a common feature in environmental decision-making. The reason for adopting a strong sustainability approach in this project was linked to the specific characteristics of the geographical context under analysis: the area was characterized by the presence of an important area of high ecological value at the European level and therefore no compensation was allowed in order to ensure the protection of this valuable resource.

2.7. Challenge 7: How to elicit criteria weights from experts/public?

As mentioned before, MC-SDSS models derive an overall value of the spatial characteristics of the land through overlaying the criteria maps (Fig. 1) according to the criteria values and decision maker's preferences. A key modeling step to obtain such overall map is the weighting of the different factors considered in the analysis.[6] Therefore, besides criteria selection, criteria weights severely influence the results provided by MC-SDSS [19].

However, the meaning of weights is different in distinct MCDA methods. While in multi-attribute value theory (MAVT)-based models [84] criteria weights are scaling constants denoting value trade-offs, in other methods, they assume different conceptualizations, such as measurement of "importance" in the AHP [76], or majority rules for comparing outranking relations between alternatives in the ELECTRE methods (which use intrinsic weights in combination with veto thresholds – see [74]). Therefore, the meaning of the criteria is closely connected with the method, and it is therefore crucial that their properties are observed by the decision analyst [10].

The most consolidated approach in spatial MCDA is the use of a weighted sum to aggregate spatial criteria [57]. One way of operationalizing this is employing MAVT, in which weights should denote value trade-offs made by decision makers and/or stakeholders [50]. In addition, the standard preference conditions required in non-spatial multi-criteria value analysis [84] must be extended to the spatial domain. For instance, *pairwise spatial preferential independence* requires that value trade-offs between the criterion levels in any pairs of cells in the map do not depend on the criterion levels in the other cells [80]. This might be hard to check due to the very large number of cells that geographical maps can contain.

In the same way as with standardization functions (see Challenge 5), the elicitation of criteria weights demands a significant cognitive effort from the participants in the analysis [65] and is inherently subjective, since it represents the different priorities in considering the multiple criteria. The meta-choices available for DSS designers confronted with this challenge thus concern two key variables: (i) the type of weight elicitation protocol and (ii) the means of eliciting criteria weights.

The alternatives for the first variable are (i) using a protocol which only requires qualitative statements of preference, with a subsequent conversion to quantitative weights, or (ii) using a protocol which only requires quantitative statements of preference. The advantage of using a protocol requiring only qualitative statements of preferences is its easiness for non-technical participants, while the drawback is that the qualitative–quantitative conversion might be perceived as a black box. The advantage of using, instead, a protocol requiring quantitative statements of preferences is the direct elicitation procedure required, while the drawback is its more cognitively demanding protocol.

Regarding the second variable, i.e. the means of eliciting criteria weights, the alternatives are (i) online collaborative processes or (ii) stakeholders group workshops. The advantage of the former is a wider and asynchronous participation of both experts and non-experts, while the drawbacks are, as mentioned in Challenge 1, a limited interaction between participants and the analyst, missing the benefits of facilitated decision modeling [37], as well as a dilution of expertise and power, which might lead to a lack of agreement about the best option and/or commitment to implement the chosen solution [68]. The advantages of the latter are, instead, enabling facilitated modeling interventions and allowing the interaction among participants. In addition, the use of experts and stakeholders panels expands the knowledge basis and may serve to avoid the limited perspective of a single expert. The drawbacks in this case are limited participation levels and the need for selection of members, as well as planning processes that are more time consuming. Indeed, the use of panels has a range of problems associated with it, such as the panel composition, the interaction mode between panel members, and above all, the aggregation of panel responses into a form useful for the decision [7,54].

Some possible best practices that could be helpful in this context are (i) using valid psychometric elicitation protocols for weights [84], (ii) controlling the cognitive burden in the elicitation processes [65], (iii) using aggregation operators compatible with the preference dependence among the criteria [53], (iv) using facilitated workshops for the elicitation of weights [37], and finally, (v) designing online surveys for their elicitation (e.g. [24]).

[6] While methods that do not employ weights, resorting on concepts of dominance or practical-dominance, are useful for some multi-criteria problems, the large number of cells that geographical maps can contain (i.e. alternatives in the maps) make them easily reach their computational limits in a spatial context [18].

A real example in which one of the authors has been recently involved could help clarify this challenge. In the previously mentioned project about the land suitability analysis for the location of a new wetland [20], the team organized a focus group with a limited number of expert participants, which enabled to also elicit criteria weights employing a quantitative elicitation protocol. In particular, we used the swing weights procedure [7] in a spatial context, which was one of the first experimentations of such protocol in this domain. The lessons that were learned from this experimentation can be summarized as follows: all the experts involved in the process acknowledged the cognitive burden of the elicitation procedure but recognized more awareness of the heterogeneity of the values across the region under analysis and of the effects that this heterogeneity (versus homogeneity) can have on the results of the process.

2.8. Challenge 8: How to efficiently perform spatial sensitivity analysis?

Enhancing MC-SDSS models with sensitivity analysis is crucial, as it enables a better understanding of the dynamics of spatial change [19] and improves the model's transparency. In particular, sensitivity analysis[7] [77] helps planners, stakeholders, and the general public to better understand the consequences of setting up different priorities, varying the shape of standardization functions, and considering the uncertainties in the data. This type of analysis also improves communication and helps in identifying if more data on certain aspects need to be collected [39].

However, sensitivity analysis (on impacts, standardization functions, and priorities of the decision makers) is not a common practice in the field of spatial multi-criteria evaluation [19]; rather, it is still largely absent or rudimentary. This occurs due to the technical complexity of doing this analysis in a spatial context, in comparison with the well-established tools for sensitivity analysis for non-spatial MCDA (see [71]), given (i) the large number of pixels in a map, (ii) the uncertainty range that might be associated to each pixel, which increases the computational time needed for the assessment, and (iii) the lack of prebuilt tools in the GIS software [25].

Indeed, Delgado and Sendra [25] conducted a review on how sensitivity analysis has been implemented in MC-SDSS. They found that little attention had been paid to the evaluation of the final results from these model simulations. In addition, the sensitivity analysis method most frequently used was based on the variation of the criteria weights to test whether different priorities would significantly modify the obtained results. However, according to them, the most critical shortcoming of spatial sensitivity analysis procedures was the lack of insight that sensitivity analysis provided [19].

The meta-choices available for DSS designers confronted with the challenge of efficiently performing spatial sensitivity analysis thus concern the means of representing sensitivity. In particular, the alternatives are (i) an interactive analysis with the decision makers, with real-time visualization of changes in the maps (e.g. using touch screen tables and online tools) or (ii) a back-room analysis and static presentation of a small number of selected scenarios (set of weights). The advantage of the former is the possibility to explore the solution space, which facilitates the understanding of both the results and of the sensitivity analysis itself; while the drawbacks are that it is a time-consuming analysis (i.e. longer computational time for real-time display of spatial results) for both analysts and decision makers. In addition, there is a need for software development which can enable this type of exploration.

The advantages of the latter (i.e. a back-room sensitivity analysis) are, instead, that there is neither need for software development nor very time-consuming presentation and analysis of results to the decision makers, while the drawbacks are that it provides less insights on the robustness of the solutions and less opportunities for group discussions and group learning.

Some possible best practices that could be helpful in this context are (i) enabling weight sensitivity to be visualized geographically by showing interactively the results with reference to key scenarios and making use of visualization tools [29], and (ii) designing the collaborative decision process allocating time for discussion breaks and processing time, so an interactive analysis can be done.

A real example, in which one of the authors has been recently involved, can illustrate this challenge. In the previously mentioned project dealing with the land suitability analysis to host a new landfill [31], the team faced the sensitivity challenge by developing a back-room analysis and presenting to the participants different scenarios arising from new sets of criteria weights, simulating different priorities. This generated more awareness in the participants about the sensitivity of the results and allowed a learning process to take place. In another project, dealing with the development of a land suitability analysis to host ecological corridors [35], the decision analysis team used an aggregation rule (i.e. Ordered Weighted Average, OWA) that allowed to generate a wide range of decision alternatives for addressing uncertainty associated with interaction between multiple criteria. Specifically, OWA scenarios allowed to quantify and analyze the sensitivity of the results as a function of the level of risk taking (i.e., optimistic, pessimistic, and neutral) and to facilitate a better understanding of patterns that emerged from decision alternatives involved in the decision-making process. Table 3 summarizes the key challenges that we have identified as well as the meta-choices to cope with them.

3. Conclusions and opportunities for further research

In this paper, we identified a series of challenges that DSS designers and practitioners employing MC-SDSS models have to address. These challenges are based both on the relevant literature that we reviewed and on our experience in supporting complex multi-criteria evaluation processes in regional planning and similar contexts.

This paper provides three main potential contributions to the literature. The first one stems from the identification and discussion of the key challenges in MC-SDSS design and application. The second is, hopefully, an increase in DSS designers' awareness about the meta-choices available to them, which can make the process of choosing alternative designs more deliberative. We believe that using a deliberative approach, in contrast to an informal one as typically done, is important because these meta-choices have an impact on the quality of the planning process, as well as on the results of the analysis. The third contribution is the generation of interdisciplinary insights in two directions: from decision sciences to spatial planning and decision making and, conversely, from spatial analysis to spatial decision support systems.

We recognize two main limitations to our work. The first one is the relative lack of empirical evidence about the challenges in the relevant literature. We have attempted to address this by drawing on the extensive literature in Decision Sciences, but recognize that other challenges might exist. In addition, we tried here to reach a wider audience and, therefore, a second limitation is that we limited the level of technical explanations about MCA throughout the paper, but attempted to provide the key references for each topic.

We foresee three main directions for further research on this subject. The first one is the generalization of best practices. A better understanding of spatial multi-criteria evaluation applications could (and should) provide significant insights for future developments of DSS. The second

[7] Here we confine the discussion to technical aspects of sensitivity analysis related specifically to the spatial dimension of multi-criteria assessments. We recognize, however, that there are also conceptual issues regarding sensitivity analysis in multi-criteria models, for instance how the parameters should be varied (one-by-one or simultaneously), how to define a robust solution (against worst case scenarios or an 'average' performance), and how recommendations should be drawn from the sensitivity analysis (as ranges in which the preferred alternative remains the best or as robust conclusions covering the robustness of all possible alternatives) – for details see Roy [73] and Rios-Insua [71].

Table 3
Key challenges and meta-choices in MC-SDSS design and application.

Steps	Challenges	Variables	Meta-choices
1. Designing the decision process	Challenge 1 (i) Who should participate? (ii) How experts and stakeholders should participate?	a. Stakeholders' panel composition	1a) Selection of stakeholders to compose the panel
		b. The means of participation	b1) Online participation b2) Physical participation
	Challenge 2 (i) What is the appropriate MCA method, given the plethora of methods available? (ii) Get an off-the-shelf method or design a tailor made one?	The process of selection of the method	(i) Use an off-the-shelf method (see Table 2) (ii) Design a tailor-made approach, by combining components of different methods
2. Structuring the multi-criteria model	Challenge 3 (1) What sources should we use to define objectives (from experts, public, literature, legislation, etc.)? (2) How to make sure that all and only the fundamental objectives are included?	a) The source of provision of the objectives	a1) Public-based sources a2) Expert-based sources
		b) The level of objectives being considered in the evaluation	b1) Top-down structuring of objectives b2) Bottom-up structuring of objectives
	Challenge 4 How to deal with the limited availability of spatial data for the criteria?	The means of defining the spatial distribution for each criterion when spatial data are not available	(i) Self-build the maps using the best available evidence and expert judgment. (ii) Redesign the model, trying to find proxy criteria for those factors for which it is unfeasible to build a spatial map
3. Eliciting spatial standardization functions	Challenge 5 How to elicit spatial standardization functions from experts/public?	a) The type of elicitation protocol to be employed in eliciting spatial standardization functions	a1) Use a protocol requiring qualitative statements of preferences with a conversion to a quantitative spatial standardization function a2) Employ a protocol requiring quantitative statements of preferences
		b) The means of eliciting this type of parameter	b1) Use a single expert interview b2) Employ expert group workshops
4. Aggregation of partial performances	Challenge 6 How to deal with sustainability concerns in the evaluation?	The selection and understanding of the sustainability approach	i) Adopt the weak sustainability approach ii) Adopt the strong sustainability one
	Challenge 7 How to elicit criteria weights from experts/public?	a) the type of weight elicitation protocol	a1) Use a protocol which only requires qualitative statements of preference with a subsequent conversion to quantitative weights a2) Use a protocol which only requires quantitative statements of preference
		b) The means of eliciting criteria weights	b1) Online collaborative processes b2) Stakeholders group workshops
5. Analysis of results and recommendations	Challenge 8 How to efficiently perform spatial sensitivity analysis?	The means of representing sensitivity	i) An interactive analysis with the decision makers, with real-time visualization of changes in the maps ii) A back-room analysis and static presentation of a small number of selected scenarios

one is a clearer appreciation of the implications of different design processes in applying these tools in practice. Further research on spatial multi-criteria evaluations using more systematic observation and analysis, in terms of the meta-choices made and the path dependency of results as a consequence of such choices, will help to develop a theory of practice for this type of application. The third direction is to test the empirical validity of the meta-choices that we suggested here, by means of specific surveys with researchers and practitioners in spatial multi-criteria evaluations, in terms of their occurrence, frequency, and consequences.

Concluding, we hope this paper helps in further consolidating the use of MC-SDSS in planning and decision making processes and provides a useful framework for further research on analyzing and comparing these processes in practice, as well as for supporting the design of a new generation of participative MC-SDSS.

Acknowledgments

The authors wish to thank the helpful comments of three anonymous referees and the area Editor.

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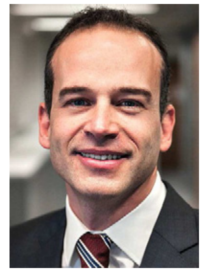

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