# 7

# Insights from an Initial Exploration of Cognitive Biases in Spatial Decisions

Valentina Ferretti

## 7.1 Introduction

Behavioral decision research has demonstrated that judgments and decisions of ordinary people and experts are subject to numerous biases, from both the cognitive and motivational points of view (Tversky and Kahneman 1974; von Winterfeldt and Edwards 1986). This line of research stimulated the study of behavioral issues and their implications across many disciplines, recently reaching the domain of Operational Research (Kunc et al. 2016).

Within the broad field of Operational Research, the domain of spatial multi-criteria decision analysis, i.e. the integration of geographic information systems (GIS) with multi-criteria decision analysis (MCDA) techniques, has been attracting increasing interest in the last two decades, from

V. Ferretti (✉)
Department of Architecture, Built Environment and Construction Engineering, Politecnico di Milano, Milan, Italy
e-mail: V.Ferretti@lse.ac.uk; valentina1.ferretti@polimi.it

Department of Management, London School of Economics and Political Science, London, UK


L. White et al. (eds.), *Behavioral Operational Research*,
https://doi.org/10.1007/978-3-030-25405-6_7

both the research and application points of view (e.g. Malczewski 2006; Ferretti 2013), especially in the environmental decision-making field (e.g. Huang et al. 2011).

Several reasons may explain this growing trend. First, recent technological developments in spatial analysis have allowed to upscale GIS capabilities leading to the embedding of GIS and MCDA within the same software packages (Malczewski 2006). Second, the increased awareness about the important role of the spatial dimension (it has indeed been estimated that 80% of data collected and managed across all sectors of society include geographic references; Williams 1987, p. 151) has led to more integrated decision-making processes (e.g. Ferretti and Gandino 2018). Indeed, combining information on location or geographical extent with structured expert judgment elicitation processes helps analysts fuse disparate data sets into new and valuable information, thus gaining important insights on the decision problems under analysis.

While the attention toward possible biases has already permeated the non-spatial MCDA field (e.g. Morton and Fasolo 2009), the presence of both traditional and possibly new biases has not yet been explored in the growing domain of spatial MCDA. Given how the World Wide Web has profoundly reshaped the public perception and usage of maps making them an ordinary tool across all domains, the time seems ripe to investigate the maps' role as mediators leading to possible behavioral implications for human judgment in spatial decision-making processes.

The objective of this research is thus to initiate the exploration as well as a preliminary discussion of behavioral aspects in both the design of spatial MCDA models and in the interpretation of their results. To detect modelers' behavior trends and patterns, this chapter proposes a review of the recent literature on spatial MCDA processes according to multiple dimensions of interest (field of application, decision problem type, choice of the MCDA method to use in combination with GIS and corresponding justification for its choice, degree of balance of the decision models and type of classification used in the final maps' legend for the interpretation of the spatial results).

The contribution of this study is twofold. First, this chapter will initiate a discussion about the implications of the observed behaviors in GIS-MCDA applications. Second, it will propose preliminary guidelines on how to design spatial decision processes able to convert unconscious effects into beneficial competences.

The remainder of the chapter is organized as follows: Sect. 7.2 illustrates the literature survey method and the study research questions, Sect. 7.3 presents the preliminary results of the review and classification of the literature and, finally, Sect. 7.4 concludes the chapter by discussing implications of the findings and initial guidelines.

## 7.2 Literature Survey Method and Research Questions

This study is the first one to explore the presence and implications of behavioral aspects in spatial decision-making processes. As a consequence, a research based on keywords linked to the fields of behavioral science and spatial decision-making processes is unable to provide relevant results. Authors, spatial decision support systems' designers and modelers are indeed not yet aware of the presence of behavioral aspects (i.e. cognitive and motivational biases) in map-mediated judgments and therefore do not mention them in their scientific papers. This study has thus performed a literature search using the SCOPUS scientific database and the list of keywords from Table 7.1 with the aim of identifying all applications of spatial decision analysis starting from the environmental decision-making domain. The reason for a preliminary focus on the environmental domain is its intrinsic need for the integration between geographical information science and decision science, which results in this field being the most active one in the development of applications of spatial decision analysis (Malczewski and Rinner 2015). Indeed, in environmental decision-making processes all key components of the decision have a spatial nature: from the alternatives under analysis that have a spatial localization, to the geographic distribution of their impact, to the spatially non-homogeneous values of the decision-makers and stakeholders' preferences (e.g. value functions and weights; Simon et al. 2014).

To be able to identify key and recent behavior's trends and patterns associated to the design and use of spatial decision support systems, this study reviewed in detail and classified the literature published between

**Table 7.1** Keywords used for the literature search on the SCOPUS scientific database

| Date of the search | List of keywords | Number of resulting papers published between 1 January 1990 and 31 December 2015 |
|---|---|---|
| May 2016 | TITLE-ABS-KEY ([“MCDA” OR “MCA” OR “MCDM” OR “Multi Criteria Decision Analysis” OR “Multicriteria Decision Analysis” OR “Multi Criteria Analysis” OR “Multicriteria Analysis” OR “Multi Criteria Decision Making” OR “Multicriteria Decision Making” OR “Spatial Multi Criteria Evaluation” OR “Spatial Multicriteria Evaluation” OR “SMCE”] AND [“GIS” OR “Geographic Information Systems” OR “Spatial Decision Support Systems”]) AND (LIMIT-TO [SUBJECTAREA, “ENVI”]) | 539 |

1 January 2013 and 31 December 2015, i.e. 229 papers, which represent 42% of the whole body of literature published on the topic. After removing duplicates, papers written in a language different than English and papers not including an application, 149 articles were left for a full review.

The following three research questions underpin the exploration of the novel field of research of behavioral spatial decision science:

1. How do modelers in spatial environmental decision-making choose the MCDA method to be integrated with GIS?
2. Are decision models in GIS-MCDA studies balanced or unbalanced in terms of criteria structures and what are the associated implications for human judgment?
3. How are the final maps resulting from the spatial decision-making process presented with reference to the class break choice (e.g. equally sized sub-ranges versus use of different cut-off points) and what are the associated implications for human judgment?

The answers to the above questions will be illustrated and discussed in Sect. 7.3.1.

## 7.3 Meta-Analysis of the Literature

The last two decades have experienced a constant and rapid increase in the yearly number of publications dealing with the integration of MCDA and GIS to address decision problems in various domains (e.g. Malczewski 2006; Ferretti 2013).

Table 7.2 shows how the 149 reviewed studies have been classified according to the field of application and the decision problem.

Most decision problems concerned land suitability analyses (49.66%), followed by site selection problems (16.78%), with applications mostly in the water resources/hydrology and environment/ecology domains (22.15% and 20.13%, respectively). These findings confirm the trend highlighted in previous reviews by Malczewski (2006) and Ferretti (2013).

**Table 7.2** Classification of the studies according to the field of application and the decision problem

| | Decision problem | | | | | | Miscellaneous | Total | % |
|---|---|---|---|---|---|---|---|---|---|
| | Land suitability analyses | Site selection problems | Risk assessment | Vulnerability assessments | Plan/scenario evaluations | Impact assessments | | | |
| Water resource/hydrology | 23 | 6 | 1 | 2 | 0 | 0 | 1 | 33 | 22.15 |
| Environment/ecology | 11 | 6 | 1 | 1 | 4 | 3 | 4 | 30 | 20.13 |
| Natural hazard | 0 | 1 | 10 | 10 | 0 | 0 | 2 | 23 | 15.44 |
| Urban/regional planning | 11 | 1 | 1 | 1 | 0 | 0 | 2 | 16 | 10.74 |
| Waste management | 6 | 6 | 0 | 0 | 0 | 0 | 1 | 13 | 8.72 |
| Agriculture | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 6.71 |
| Energy | 6 | 3 | 0 | 0 | 0 | 0 | 0 | 9 | 6.04 |
| Forestry | 2 | 1 | 0 | 0 | 0 | 0 | 3 | 6 | 4.03 |
| Recreation/tourism | 3 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 2.68 |
| Geology/geomorphology | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 3 | 2.01 |
| Miscellaneous | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1.35 |
| Total | 75 | 24 | 14 | 14 | 5 | 3 | 14 | 149 | 100.00 |
| % | 50.34 | 16.78 | 9.40 | 9.40 | 3.35 | 2.01 | 9.40 | 100.00 | |

The term land suitability analysis includes site search problems, with the definitions of land suitability analyses, site search problems and site selection problems being those by Cova and Church (2000, pp. 402–403) and Malczewski (2004, pp. 4–5). Hence, a site selection problem is present, if all relevant characteristics of the candidate sites are known and sites are ranked to find the best one for a certain activity. When a set of alternative sites is not available, a site search problem is present. In this case, the boundaries of the best site are defined within the problem-solving process.

The following paragraphs will illustrate and discuss the answers to the research questions introduced in Sect. 7.2.

### 7.3.1 How Do Modelers in Spatial Environmental Decision-Making Choose the MCDA Method to Be Integrated with GIS?

As highlighted by Hämäläinen (2015, p. 246), there is the danger in environmental decision-making that modelers who only know one modeling technique interpret every problem as solvable with it. Therefore, when faced with the decision problem of a client, they choose the MCDA method they know, even though another method might be more appropriate to provide meaningful recommendations. Focusing on integrated GIS-MCDA approaches, the choice of which MCDA method to combine with GIS has indeed recently been highlighted as one of the key meta-choices for spatial decision support systems designers (Ferretti and Montibeller 2016). The 149 articles resulting from the literature search proposed in this study have thus been reviewed with the aim of identifying which MCDA methods have been integrated with GIS across the many available applications and of highlighting whether a justification for the choice of the particular MCDA method was provided.

Table 7.3 illustrates the results of the literature review from the point of view of the MCDA method being used, while Table 7.4 highlights how many studies provided indeed a justification for the selection of the MCDA approach.

**Table 7.3** MCDA methods used in the reviewed studies

| MCDA method | Frequency | % |
|---|---|---|
| Analytic hierarchy process | 91 | 61.07 |
| Weighted linear aggregation | 20 | 13.42 |
| Fuzzy analytic hierarchy process | 7 | 4.70 |
| Analytic network process | 7 | 4.70 |
| ELECTRE | 4 | 2.68 |
| Ordered weighted average | 4 | 2.68 |
| Compromise programming | 3 | 2.01 |
| Fuzzy overlay | 2 | 1.34 |
| Boolean overlay | 1 | 0.67 |
| Choquet integral | 1 | 0.67 |
| Compound value method | 1 | 0.67 |
| Point allocation method | 1 | 0.67 |
| Ideal point method | 1 | 0.67 |
| Rapid impact assessment matrix method | 1 | 0.67 |
| Not defined | 14 | 9.40 |

**Table 7.4** Number of studies providing a justification for the selection of the MCDA approach

| MCDA method choice justified | Number of studies | % |
|---|---|---|
| Yes | 80 | 53.69 |
| No | 69 | 46.31 |

Some articles used more than one MCDA method, thus leading to a frequency column in Table 7.3 with 158 total cases (from 149 reviewed papers).

Consistently with previous reviews (e.g., Malczewski 2006; Ferretti 2013; Huang et al. 2011), the vast majority of the studies selected the Analytic Hierarchy Process (AHP) (Saaty 1980) as the MCDA approach to be integrated with GIS in spatial decision-making processes (61.07% of the studies). The present literature review tries to look beyond the above descriptive statistics by checking first if a justification for the selection of the specific MCDA method is indeed provided in the reviewed paper and, if yes, by analyzing the type of the provided justification. Table 7.4 summarizes the trends in the 149 reviewed papers with reference to the presence or absence of a justification for the selection of the MCDA approach.

In 46% of the studies in which the applied MCDA method was defined, modelers do not justify their MCDA method selection (e.g. Bagdanavičiute and Valiunas 2013). This may be considered an indicator for the presence of the *hammer and nail bias*, i.e. the tendency for modelers who know only one modeling technique to interpret every problem as solvable with it, which has been highlighted as a key danger in environmental decision-making (Hämäläinen 2015). The hypothesis of the author is that modelers not influenced by the hammer and nail bias would justify the selection of the MCDA method to be integrated with GIS by stating, for instance, its advantages over other MCDA methods (e.g. Dragićević et al. 2014; Malekmohammadi and Rahimi Blouchi 2014).

Moreover, among the 69 studies (46%) which do not provide a justification for the selection of the MCDA method, there is none that uses more than one MCDA approach. Hence, modelers in these studies may just know one MCDA technique and perceive every decision problem as solvable with it.

Zooming into those studies that used the AHP approach (i.e. 61.07% of the total), Table 7.5 shows the frequency of the papers providing a justification for the selection of the method.

As 41% of the studies employing the AHP approach do not provide a justification for its selection (e.g. Gdoura et al. 2015), this trend may suggest the presence of the hammer and nail bias.

After analyzing the arguments provided by the modelers to justify the selection of their modeling approach, it is worth highlighting that among 54 studies which provide a justification for the selection of the AHP, 26 of them (48%) referred only to the popularity of this approach (e.g. Bagheri et al. 2013) and 21 of them (38%) referred to its use in other similar studies (e.g. Esquivel et al. 2015). This trend may also show the presence of a *groupthink bias*, resulting in modelers and

**Table 7.5** Number of studies providing a justification for the selection of the AHP approach

| AHP method choice justified | Number of studies | % |
|---|---|---|
| Yes | 54 | 59.34 |
| No | 37 | 40.66 |

context experts applying popular modeling techniques without questioning them (Hämäläinen 2015, p. 247).

### 7.3.2 Are Decision Models in GIS-MCDA Studies Balanced or Unbalanced in Terms of Criteria Structures and What Are the Associated Implications on Human Judgment?

Recently, Marttunen et al. (2018) highlighted the importance of objectives hierarchy related biases by reviewing the literature on real world applications of MCDA. Key findings from this study show that the hierarchy structure and content can substantially influence weight distributions. For example, hierarchical weighting seems to be sensitive to the *asymmetry bias*, which can occur when a hierarchy has branches that differ in the number of sub-objectives. These results have triggered research question 2 in this chapter with the aim of studying whether the same trends can be highlighted also for spatial applications of MCDA.

To this end, the 149 papers have been reviewed by checking the size and structure of the decision model structures (i.e. value trees, objectives' hierarchies and networks of clusters of objectives). If model structures were only described verbally, they were reproduced based on the provided descriptions.

A GIS-MCDA structure of criteria was considered balanced if it fulfilled two requirements. Firstly, the level of each lowest-level sub-objective should be the same for all sub-objectives. Secondly, the difference in the number of lowest-level sub-objectives between the objective with the most sub-objectives and the objective with the least sub-objectives should not be more than two (see Figs. 7.1 and 7.2 for the visualization of the differences between a balanced and an unbalanced structure of criteria).

Constraints criteria were not considered within the analysis of the GIS-MCDA structure of criteria, as they are typically not evaluated by decision-makers and only used in the screening phase to identify relevant alternatives. For criteria structures different than the hierarchical one

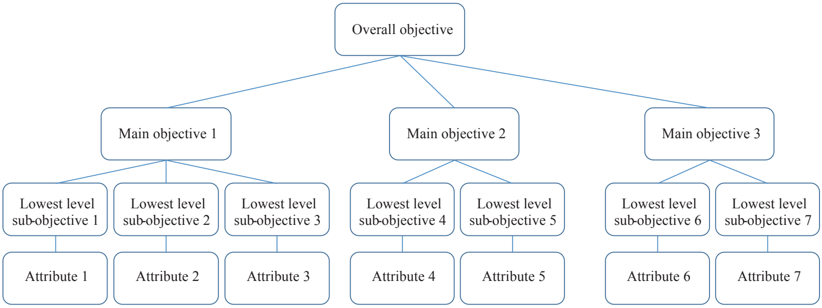


**Fig. 7.1** Example of a balanced value tree

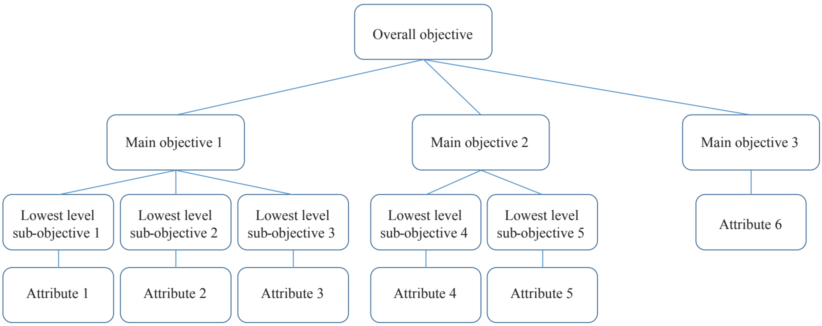


**Fig. 7.2** Example of an unbalanced value tree

(e.g. in the Analytic Network Process models), the number of criteria in each cluster was counted and it was checked whether the difference between the cluster with more elements and the one with less elements was bigger than two.

Table 7.6 summarizes the trends in the 143 papers with reproducible criteria structures with reference to their level of balance.

The results of the review show that 32.17% of the models in GIS-MCDA applications may be considered as based on unbalanced criteria structures (e.g. Yal and Akgün 2013). When criteria structures are not balanced, those objectives which are decomposed into several sub-objectives and are thus defined in more detail, are more likely to receive a higher total weight. This judgment distortion effect is known as the *splitting bias* (Jacobi and Hobbs 2007; Hämäläinen and Alaja 2008).

**Table 7.6** Classification of the reviewed papers according to the structure of the decision criteria

| Criteria structure | Number of studies | % |
|---|---|---|
| Balanced | 97 | 67.83 |
| Non-balanced | 46 | 32.17 |
| Total | 143 | 100.00 |

**Table 7.7** Classification of the studies according to the number of criteria included in the decision structure

| Number of criteria in the decision structure | Number of studies | % |
|---|---|---|
| >7 | 90 | 62.94 |
| <7 | 53 | 37.06 |

**Table 7.8** Justification for criteria selection

| Justification for criteria selection | Frequency | % |
|---|---|---|
| Literature | 81 | 54.36 |
| Expert judgment | 28 | 18.79 |
| Data availability/data driven approach | 28 | 18.79 |
| Legislation/institutional recommendations | 13 | 8.72 |
| No justification | 11 | 7.38 |

When analyzing the trees, Miller's (1956) $7 \pm 2$ rule was also considered. According to this rule, the limit for receiving, remembering and transmitting information on different elements is in the range of $7 \pm 2$ elements. Saaty and Ozdemir (2003) highlighted that the rule is also valid when developing pairwise comparisons and argue that considering more than seven elements in pairwise comparisons leads to inconsistent judgments and hence flawed weights, for instance, within the AHP process. Therefore, the literature review presented in this paper also analyzed the number of criteria included at the same level or within the same cluster in the decision structures, as too large decision structures might lead again to judgment distortion and flawed weights (Table 7.7).

As in 62.94% of the studies the number of criteria on the same level was bigger than seven, there is an additional danger of inconsistent weight judgments in GIS-MCDA studies in environmental decision-making because of too large decision structures.

To explore possible reasons explaining large and unbalanced decision structures, the arguments used by the authors to justify their criteria selection were analyzed. Table 7.8 lists the five most frequent justifications. As authors of some studies used multiple arguments to justify their criteria choice, the total number of studies in the frequency column is bigger than 149.

Interestingly, the "Data availability/data driven approach" category is the second most frequently used justifications for criteria selection. Studies categorized as data driven highlight, for example, that within the process of criteria selection, data availability and quality was an important argument (e.g. Mighty 2015). This may indicate that in GIS-MCDA applications in the environmental decision-making domain a special form of the *availability bias*, i.e. the human tendency to think that examples of things that come readily to mind are more representative than is actually the case, may occur. Indeed, the decision to include or exclude an evaluation criterion when structuring a spatial decision model may be influenced by the easiness with which an evaluation criterion map can be created. Hence, researchers might consider a criterion in their analysis because the evaluation criterion map already exists or is easy to construct, even though the evaluation criterion map indicates spatial homogeneity, or the criterion is not relevant, i.e., it is not referring to a fundamental objective for the decision.

### 7.3.3 How Are the Final Maps Resulting from the Spatial Decision-Making Process Presented with Reference to the Class Break Choice and What Are the Associated Implications for Human Judgment?

In GIS-MCDA applications, modelers usually have to describe the final spatial distribution of the multi attribute aspect under study (e.g. risk index, vulnerability index, suitability index, etc.) by means of a geographical output map (Malczewski and Rinner 2015). For this purpose, common mapping techniques allow them to color areas proportionally to the represented variable by means of classification methods. However, Monmonier (1991) has highlighted that the applied classification method can have effects on the pattern of a map. Therefore, even though different versions of the map provide the same information, decision-makers' judgment about risk/vulnerability/suitability and their associated decisions may be different depending on which classification method is used.

For example, the study by Jung et al. (2013) provides two different final output maps of fire risk in the Kolli Hills in India obtained through a GIS-MCDA approach. Both maps are based on the same final scores, but apply different classification methods. The visual comparison of the two maps shows that when the equal interval method is employed (i.e. the modeler uses the lowest and highest value of the relevant distribution and then divides this range into equally sized subranges; Monmonier 1993), most values fall in the interval belonging to the "high risk" category. When, instead, the map uses the natural breaks method (i.e. the variance within classes is minimized and the variance between classes maximized; Jiang 2013), most areas are categorized as "very high risk" areas.

Imagining a decision-maker who has to allocate a budget for forest fire protection, he/she may perceive the overall risk as higher when visualizing the map obtained using the natural breaks method, as more areas are classified as having a very high fire risk. Therefore, he/she may be willing to invest more in forest fire protection when making a decision based on the latter map, compared to one based on the map where the equal interval method was employed, even though the two maps were generated from the same final data.

To explore GIS-MCDA applications' trends with reference to the map classification approach, this paper reviews the type of legend used in the final output maps of the 149 papers under consideration. When the study used classification methods and provided linguistic labels for the different classes in the legend, the study was categorized as using qualitative output maps (e.g. unsuitable areas, suitable areas, etc.; Akin et al. 2013). When the authors reclassified scores on a numerical scale indicating different levels of intensity, the study was categorized as using quantitative output maps (e.g. Hamzeh et al. 2015). Both qualitative and quantitative maps are based on classification procedures. When the authors used continuous color scales in the final output map to indicate

**Table 7.9** Trends in GIS-MCDA applications with reference to the type of output map

| Type of legend | Frequency | % |
|---|---|---|
| Qualitative legend | 89 | 59.73 |
| Continuous color scale | 19 | 12.75 |
| Quantitative legend | 16 | 10.74 |
| Different maps with different legends | 5 | 3.36 |
| Other | 20 | 13.42 |
| Total | 149 | 100.00 |

the range between the minimum and maximum values (e.g. Wanderer and Herle 2015), studies were categorized as using maps based on a *continuous color scale*. Table 7.9 summarizes the trends in the reviewed papers with reference to the type of output map being generated.

The "Different maps with different legends" category refers to studies in which different final output maps with different types of legends were used (e.g. Romano et al. 2015). At least one of the maps presented in these studies used a classification method.

Considering categories "Different maps with different legends", "Qualitative legend" and "Quantitative legend", 73.38% of the studies applied classification methods when creating the final output map. Thus, in the majority of the GIS-MCDA applications reviewed, class break choice can influence human judgment in the interpretation of the output map. Zooming into those studies that used a classification method to present the final output map, 22 of them (20.18%) used the equal interval method, 46 (42.21%) used a classification method different from the equal interval one and 41 of the studies (37.61%) did not state which classification approach was used. This may suggest poor practice, as not all relevant information to replicate the results of the studies are adequately presented.

## 7.4 Conclusions: Preliminary Guidelines

This section builds on the answers to the three research questions presented in Sect. 7.3 with the aim of suggesting preliminary guidelines for the improvement of judgments and decisions in spatial modeling processes.

Starting from research question 1, key findings highlight that in almost half the applications a justification for the selection of which MCDA approach to integrate with GIS was missing, thus suggesting that a *hammer and nail bias* may exist. When a justification was instead provided, it often referred to the popularity of the method, thus opening the possibility for a groupthink bias. Choosing the right MCDA approach is indeed one of the key meta-choices for spatial decision support systems designers, as recently highlighted by Ferretti and Montibeller (2016). A solution for debiasing the *hammer and nail bias* and *groupthink* might be for modelers to use a set of guiding questions when deciding which MCDA method to combine with GIS (Ferretti and Montibeller 2016). For example, the first guiding question could be "what type of results would you need to obtain?" The possible choices available for this question are land suitability maps (choice problem), or comparison among existing alternatives (ranking problem), or clustering alternatives into predefined categories (classification problem). The second guiding question for the selection of the most appropriate MCDA method to be integrated with GIS could refer to the type of elicitation protocol to be used to gather information from experts/stakeholders. The available choices with reference to this question refer to the use of qualitative elicitation protocols or quantitative elicitation protocols. Another important guiding question for the selection of the MCDA approach in spatial applications considers the relevant characteristics of the problem in terms of compensability, uncertainty and interaction. Indeed, depending on the level of compensation accepted by the decision-maker, the level of uncertainty characterizing the inputs to the model and the level of interaction among the decision criteria, different methods could and should be selected. The interested reader can refer to Ferretti and Montibeller (2016) for a more detailed discussion of the guiding questions and associated meta-choices available for GIS-MCDA designers.

The author believes that this set of guiding questions may help GIS-MCDA modelers to question the MCDA method they know or those approaches that are very popular in their field of research and therefore select the most appropriate one given the characteristics of the decision context under analysis.

With reference to research question 2, 32% of the analyzed spatial models proposed unbalanced criteria structures, which may lead to the splitting bias and important implications on both the elicited weights and on the final results. Possible guidelines to tackle this issue consist in: (i) building concise objectives' hierarchies and considering opportunities to simplify the hierarchy, (ii) carefully considering if asymmetric hierarchies are appropriate and in that case use either weighting procedures which are insensitive to the hierarchy structure or consistency check questions across branches, and (iii) avoiding deep hierarchies as they are more prone to behavioral and procedural biases than flatter hierarchies (Marttunen et al. 2018).

Finally, with reference to research question 3, over 59% of the studies used qualitative legends with ambiguous labels and incomplete information when creating final output maps, which indicates bad practice and may lead to judgment distortion in the interpretation of the results. It is indeed known in the behavioral decision science domain that different people associate different meanings to the same qualitative label (e.g. high risk or medium risk or low risk of a certain event happening) when a clear definition is not agreed, thus resulting in the need to avoid ambiguity as one of the key properties of a good set of attributes (Keeney and Gregory 2005).

A possible recommendation in this case is to always develop a spatial sensitivity analysis over different classification methods, which will allow to detect (i) the presence of significant differences in final output maps when varying the classification approach and (ii) the possibility of consequently different interpretations from the decision-makers.

The following two limitations of the present literature review should be highlighted. First, the search in the SCOPUS scientific database has been limited to the environmental science field of research, but it is not possible to guarantee that all relevant studies were classified as environmental science studies by the database. Second, due to missing information about the evaluation criteria maps in the sample, the analysis of the classification methods was limited to output maps. Yet, different classification methods can also influence the pattern of criteria maps.

In conclusion, the findings from this review and classification of the recent literature on GIS-MCDA in the environmental decision-making field show that spatial multicriteria decision-making processes represent a new and interesting domain of research for behavioral sciences. Indeed, the answers to the research questions explored in this paper have highlighted several biases affecting judgments in GIS-MCDA processes. First, the hammer and nail syndrome and groupthink may be relevant biases playing a role in the design phase of the models. Second, the splitting bias and the availability bias may be relevant biases playing a role in the structuring phase of the models. Finally, ambiguity in the final output maps could be a relevant issue playing a role in the interpretation phase of the model results and in the subsequent recommendation stage. Preliminary debiasing solutions have been suggested for each identified bias in spatial decision-making processes and future developments of this innovative field of research will focus on testing and comparing the efficacy of the proposed debiasing approaches.

**Acknowledgement** The author would like to thank Daniel Pfaller for his support in reviewing the relevant literature.

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