A Framework for Sensitivity Analysis in Spatial Multiple Criteria Evaluation

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Abstract The paper presents a framework for sensitivity analysis (SA) in spatial multiple criteria evaluation (S-MCE). The framework focuses on three aspects of S-MCE: spatiality, scope, and cardinality. Spatiality stresses the importance of spatial criteria and spatial weights that should be explicitly considered in GIS-based MCE. Scope relates to the extent of SA, ranging from local one-at-a-time criterion examination to global testing of interdependencies among the multiple criteria model components. Cardinality addresses the duality of motivation for performing SA, namely, single-user learning and group consensus building. The framework organizes the existing SA techniques according to spatiality and scope and can be used as a conceptual guide in selecting SA techniques fitting a task at hand.

Keywords Spatial Multiple Criteria Evaluation, Sensitivity Analysis, SDSS

1 Introduction

Spatial multiple criteria evaluation (S-MCE) belongs to one of the basic analytical methods of GIS (DiBiase et al. 2006). Over the last two decades, much work has gone into integrating MCE techniques with GIS to support formulation, modeling, and evaluation of spatial decision problems (Carver 1991; Jankowski 1995; Laaribi et al. 1996; Eastman 1999; Malczewski 1999; Thill 1999; Malczewski 2006). S-MCE is a method supporting a rational decision process in which a set of geographical options is evaluated based on a number of decision criteria in search of the best choice (Malczewski 1999). Many applications of spatial decision support systems (SDSS), of which S-MCE is a part, suggest that S-MCE has become a well established procedure for solving spatial choice problems. However, S-MCE models have also been criticized for the inadequate treatment of uncertainty present in model outcomes. For example Uran and Janseen (2003), in their assessment of five SDSS models, identify the shortcomings of spatial post-processing analysis of option rankings generated with S-MCE. The uncertainty arises more often than not from the preliminary character of data and unstable human preferences. We may argue that the potential of using S-MCE lies in its exploratory approach to analyzing the decision problem (Malczewski 2006). Thus, ironically, the very essence of S-MCE might be at the same time its weakest point.

In this paper, we argue for strengthening the exploratory role of S-MCE by focusing on sensitivity analysis (SA) as part of the decision support methodology. In response to the lack of systematic treatment of SA in the S-MCE literature, we propose a framework for organizing and guiding the use of SA techniques. According to the framework, the objective of SA in S-MCE is to strengthen the confidence in the obtained solution or, in the case of weak confidence, help to redefine the set of acceptable alternative solutions. In the proposed framework, we extend SA beyond the criterion data uncertainty to account for the spatial characteristics of a geographic decision situation.

The roots of formal SA may be traced to engineering and scientific predictive modeling (French 1992; Pannell 1997; Gómez-Delgado and Tarantola 2006). Its role has been also recognized in decision sciences, where the main purpose of SA is strengthening the bases for a decision recommendation. In Simon's decision process framework (1960) of intelligence-design-choice SA is perceived as the core of the final *choice* stage, where the decision maker evaluates and selects the desirable solution (Jankowski 1995; Malczewski 1999; Feick and Hall 2004). Still, a comprehensive SA included in S-MCE models is more the exception than the norm (Delgado and Sendra 2004).

The importance of SA may be attributed to the complexity of decision processes dealing with spatial choice. Complex spatial problems involve irreducible (aleatory) uncertainty (Helton and Burmaster 1996) caused by the difficulty of arriving at a stable preference structure for decision makers. Aleatory uncertainty is a result of semi- or ill-structured decision problems, where the decision makers are unable to define fully the problem (Densham 1991; Ascough et al. 2002; Malczewski 2006). A semi-structured decision problem may involve, for example, an incomplete or vague knowledge of decision option impacts, in which case SA could be used to examine the sensitivity of evaluation results derived from various plausible impact characteristics.

The spatial nature of geographic problems amplifies the complexity of decision making through spatial interdependencies and spatio-temporal dynamics. Future impacts of proposed choices are often stochastic and deeply uncertain (Lempert 2002). The solutions to such problems should be thoroughly evaluated to ensure their robustness under a wide range of possible conditions (Malczewski 1999; Lempert et al. 2003). Unlike the optimal outcomes, which are based on normative computational tools, there is a need to look for robust solutions in the presence of a broad spectrum of beliefs and values and under varying future conditions. Robustness is defined here as the minimal response of a model solution caused by changing input conditions. In particular, robust S-MCE solutions are characterized by rank-order stability (Jankowski et al. 1997), where the prioritization of options is not significantly affected by minor changes in evaluation components (Andrienko and Andrienko 2005).

Traditionally, SA has been defined as the analysis of response of a model to changes in input parameters (Voogd 1983; Malczewski 1999; Krivoruchko and Gotway-Crawford 2005; Longley et al. 2005). Usually, the general question asked in SA is: *given the outcome, what is its sensitivity to changes in initial conditions?* Therefore, in order to perform S-MCE SA, the decision maker must have a ranking of options already in hand. In this paper, we conceptualize SA more broadly. We define SA in S-MCE as a "thought experiment" (Alexander 1989: 323) or "computer-assisted reasoning" (Lempert 2002: 7309) aimed at quantitative and qualitative assessment of the stability of a given option ranking. This definition is not restricted to the analysis of the stability of ranking given changes in input parameters. Such a strict definition is counter to the uncertain nature of spatial decision making. An overly structured SA does not fit into an often substantially unstructured spatial problem (Feick and Hall 2004). Hence, we should account for various other – intangible and qualitative – decision factors that may influence the choice. Furthermore, the spatially-explicit nature of geographical problems calls for new, spatially-explicit methods of SA (Feick and Hall 2004). The ranking of alternatives should be analyzed based on both site-specific criterion outcomes and on spatial relations, such as proximity, contiguity, or clustering.

Finally, we should distinguish between sensitivity analysis and uncertainty analysis (UA). According to Saltelli et al. (2000) UA is forward-looking in nature. Therefore, performing UA, assumptions are mapped onto inferences (Saisana et al. 2005), whereas in SA a backward-looking or reverse analysis is undertaken. UA embraces multiple solutions and does not refer to any specific (initial) solution. SA focuses on the robustness of a specific solution. This paper focuses on theoretical and methodological foundations of SA in S-MCE.

In the following section we present a framework for SA in S-MCE, followed by a review of SA methods. In the final section, we outline research challenges and recommend directions for further research on SA in S-MCE.

2 A framework of sensitivity analysis in spatial multiple criteria evaluation

The goal of the proposed framework is to provide an organizational outline of SA including many methods and multiple analysis pathways. We start from a three-dimensional conceptualization of SA, followed by a methodology and a review of techniques that may be used to uphold the scope and spatiality perspectives.

The following questions guided the formulation of the framework:

1. *Which elements of the decision process are the least informational and thus especially suited for identification in the course of SA? Are they spatially sensitive? What types of measures should be used to analyze the sensitivity of these decision components?*
2. *What is the informational extent of SA? Does it embrace 'the big picture of the decision problem' or 'a more focused exploration'?*
3. *What is the motivation for performing SA? Is it individual knowledge discovery or group consensus building?*

To address these questions and to present the fabric of SA in S-MCE, we suggest a 3-dimensional representation of SA, called *the SA cube* (Figure 1).

Figure 1 Sensitivity analysis cube of spatial multiple criteria evaluation

2.1 The SA Cube

Each of the axes in Figure 1 represents one of the following characteristics of SA in S-MCE: spatiality, scope, and cardinality. Spatiality stresses the importance of spatial criteria and spatial weights that should be explicitly considered in GIS-based MCE. Scope relates to the extent of SA ranging from local one-at-a-time criterion examination to global testing of interdependencies among the multiple criteria model components. Cardinality addresses the duality of motivation for performing SA, namely, single-user learning and group consensus building.

2.1.1 Spatiality

The spatiality axis comprises both the aspatial and spatial nature of the decision situation and falls under the rubric of technicality proposed by Belton and Stewart (2002). Based on the inventory by Delgado and Sendra (2004), the vast majority of the reported SA studies concern only the aspatial nature of the decision situation. Within this category of SA methods, the major factors analyzed relate to: the diversity of choice alternatives (option list), the choice of attributes (criteria), the stability of solution to changes in weights (weighting), and the uncertainty of evaluation method (e.g. standardization, weighting, and aggregation techniques). The majority of evaluation methods come from general decision theory and embrace spatial variability only implicitly. For instance, in the well-established GIS procedure of weighted overlay, the decision maker *de facto* performs traditional weighting by assigning the same importance value to every spatial unit of a given criterion layer (Lodwick et al. 1990; Lowry et al. 1995).

Only recently it has been recognized that a spatially explicit decision component may potentially influence the rank-order of alternatives (Herwijnen and Rietveld 1999; Feick and Hall 2004; Rinner and Heppleston 2006). Spatial SA involves the use of topological and non-topological relations in S-MCE (Figure 2). For example, the analyst may use GIS to calculate distance between spatial decision alternatives and some attractor. The distance criterion can be further analyzed using traditional SA, for example, by changing its importance and recalculating the weighted option utility. However, given the spatial nature of the problem, the analyst should seek a more geographically oriented SA. Continuing the example, he/she may perform SA by varying the criterion importance over space and assigning different weights to different locations (Feick and Hall 2004). We call this *spatial weighting* (spatial bias) – "a non-uniform *weighting* of the spatial units" (Herwijnen and Rietveld 1999: 78), which is a way of articulating stakeholders' sense of place. Each decision participant may have an individual spatial frame of reference like home, work, daily activity route, or other place of importance, which impacts the perception of the proposed courses of action. Note that this concept of spatial weight involves the perception (judgment) of criterion importance varying over geographical space and it is different from another concept of spatial weights that measure the level of interaction between features in geographical space (Getis and Aldstadt 2004).

A different type of problem arises from the spatial distribution of options and their criteria values. Following the above example, the analyst may be more interested in options that form a cluster because their proximity may reinforce positive or negative effects. Such spatial characteristics (contiguity, compactness, proximity etc.) are called *spatial criteria* (Brookes 1997; Malczewski 2006; Rinner and Heppleston 2006) and are derived from various spatial relations (Figure 2). Consequently, SA applied to spatial criteria does not involve subjective perception of place (spatial weighing), but rather the uncertainty of spatial distributions, interactions, impacts, and relationships, which can be studied by performing repetitive spatial transformations.

Consequently, unlike the geographical SA defined by Lodwick et al. (1990), we argue that spatially explicit SA pertains rather to relative location than to spatial coincidence of absolute location. Absolute location manifests itself in the traditional SA approach of weighted overlay, where the composite score of geographic option is derived by weighting and re-weighting criteria values *at* specific locations. Additionally, it involves the uncertainty of criteria evaluation scores measured at particular sites. Relative location refers to geographical variability, which manifests itself via situational relations (e.g. contiguity, compactness, proximity) representing spatial organization and spatial configuration *in reference to* a particular location (Couclelis 1991). Within the context of GIS, such spatially explicit SA complements traditional (aspatial) SA.

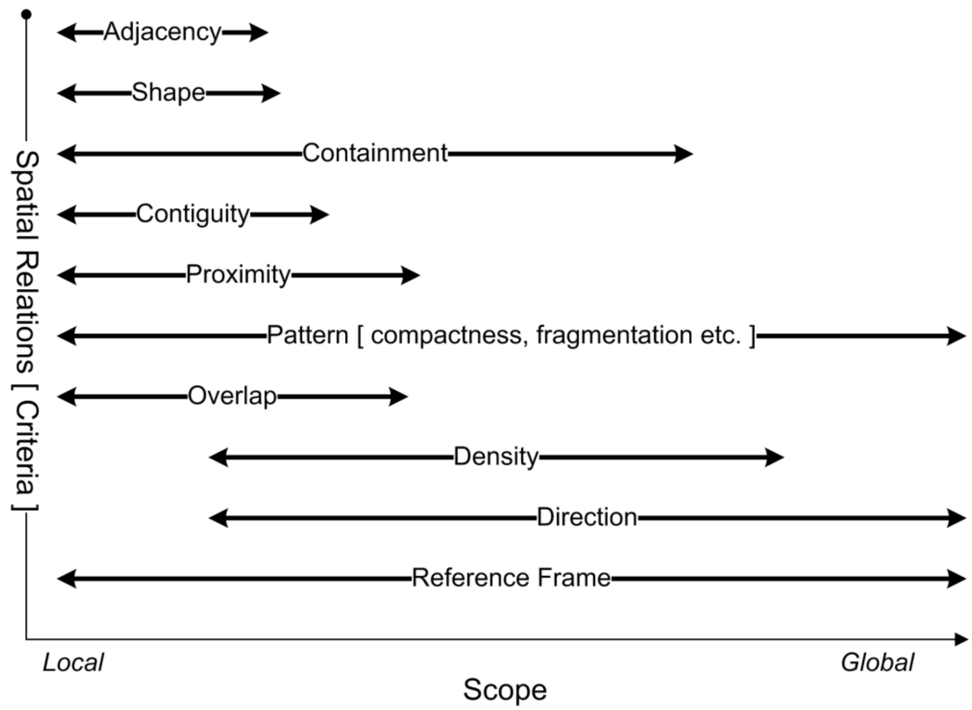

Figure 2 Spatial relations applicable to SA

2.1.2 Scope

Spatiality concerns the structure of the decision process and, in particular, the spatial component of this structure. However, if the objective is to understand the behavior of a selected subset of the criteria and their weights in the decision model (one, few, many, or all) then the scope of SA is more relevant.

Scope may range from a detailed component-focused study to a generalized simultaneous testing of interdependencies among decision elements. Conventionally, the practice of S-MCE treats SA as a method of examining one specific component of S-MCE, where the analyst changes one parameter at a time and evaluates how sensitive the output is to the change (Malczewski 1999; Longley et al. 2005). Additionally, the analyst may vary multiple factors but within a small range around the favored values (Saltelli 2000). This type of SA is very interactive in nature and is termed *local SA* (Saltelli 2000). Conversely, if we perturbate one factor within its whole distribution or vary multiple factors simultaneously over the entire problem space, we perform *global SA* (Saltelli et al. 1999a). The latter is much more data intensive and therefore is usually done through a sampling-based simulation (Saltelli 2000).

The above local-global categorization of SA is specific to an aspatial analysis. The spatiality of geographic problems, however, puts the scope of SA in a different context. The division into local spatial SA and global spatial SA is similar to the local-global notion in spatial statistics. Specifically, spatial SA is defined as the examination of one or more spatial relations (Figure 2) within the extent of either the proximal (neighborhood) space or the whole space of the study area (Lodwick et al. 1990). For example, adjacency and proximity are more neighborhood-related and should be used when dealing with local spatial associations. Conversely, the reference frame may span from a single location to the whole study area. The latter results in a constant spatial weight value, which is simply the traditional weighting in weighted overlay.

2.1.3 Cardinality

The third dimension of the cube, *cardinality,* reflects two potential motivations for SA, namely, 1) insight into individual's values, and 2) learning about the group values. Cardinality follows the line of thought proposed by Belton and Stewart (2002), who divided SA into two distinct perspectives, namely single user and group. The single user perspective of SA deals with intuition and understanding. In this respect, we study the convergence or divergence of our favored options with the options suggested by the model (Belton and Stewart 2002). The user discovers his/her individual viewpoint of the decision problem. In the context of S-MCE, this may manifest itself in the individualistic spatial weighting. Group SA follows a different logic and is concerned more with the perspectives of others than with the individual perspective. Whereas single-user SA has its roots in operations research, the group SA is more related to collaborative learning. Given the value-laden nature of group decision making, group SA should incorporate analytic-deliberative functionality (Nyerges et al. 2006), to enhance place-based qualitative perceptions and consensus building among stakeholders (French 1992; Insua 1999; Andrienko et al. 2003). A possible quantitative application of group SA in S-MCE relates to the analysis of spatial equity (Talen 1998).

3 Methods and measures of SA

This section examines various methodological approaches to SA within the SA cube framework (Figure 1). Since none of the methods developed so far is all-inclusive, and since different methods of SA produce different outcomes, a good understanding of SA methodology and trade-offs involved in using different methods is needed in order to effectively apply SA (Alexander 1989; Saltelli 2000; Andrienko and Andrienko 2005).

3.1 Traditional local and global SA methods

Given an initial decision option prioritization, we may focus on analyzing the sensitivity of various components that contribute to computing the rank-order. Therefore, we divided the methods into four broad, partly overlapping categories of options, criteria, weights, and option scoring/ranking (Figure 3).

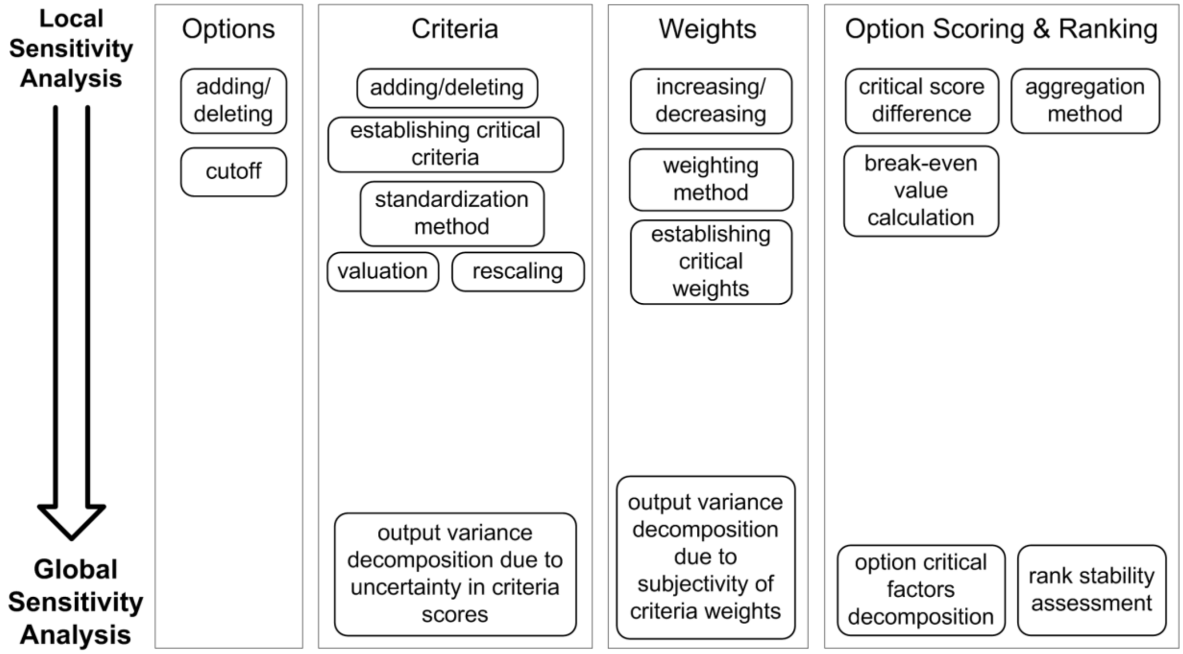

Figure 3 Aspatial SA methods and their scope

The first group of methods concentrates on modifying the list of examined options. The analyst may delete some options which score low or are otherwise inferior or he/she may add back the previously deleted option. It is also possible to impose a constraint on a criterion value and thus modify the ranking by removing these options that do not meet the constraint (Andrienko et al. 2003).

Similarly to adding/deleting options, we may modify the rank-order by deleting or adding a criterion. According to Alexander (1989) a criterion that changes the order of the best option (by being added or deleted) may be termed sensitive. We modify the list of criteria if they do not reflect our values and preferences (Voogd 1983). In weighted overlay, changing the attribute list is equivalent to map removal sensitivity (Lodwick et al. 1990). Additionally, we might be uncertain about criteria evaluation scores (Voogd 1983). This problem is best addressed by using ranges/distribution of values rather than a specific value. With such constructed parameters, we may perform a Monte Carlo (MC) simulation of output variability due to the uncertainty of criteria scores (Saisana et al. 2005).

Criterion uncertainty may also be related to a standardization method used to convert criteria to a common scale (Alexander 1989; Saisana et al. 2005) or the valuation of a criterion (Jankowski et al. 1997). For example, a person may choose to maximize the proximity to a proposed transportation improvement project since the project will benefit him/her by shortening his/her daily commute. Another person may deem such a proximity criterion as cost because it reduces public safety and hence, he/she wants to locate the projects elsewhere (minimize proximity). A novel method of determining the most critical decision criteria was proposed by Triantaphyllou (2000), where the criticality is defined by the minimum change in performance measures (evaluation scores) causing the rank reversal for any two options. For the highly uncertain criteria it may also be useful to perform rescaling (Voogd 1983) from a higher to a lower measurement level, for example from ratio/interval to ordinal scale. The resultant decrease in accuracy may in fact better reflect the true reliability of data.

Weights have often been criticized as the subjective component of S-MCE and hence have been the focus of SA methods. The basic method of examining the sensitivity of weights relates systematic changes in weight values to changes in option ranking. Weighting plays a double role in S-MCE – it either represents a relative criterion importance or a substitution rate among criteria (Feick and Hall 2004). Due to the large number of explicit weighting methods that have been proposed (Malczewski 1999), the choice of weighting method can also be a subject of SA (Saisana et al. 2005). It is also possible to determine critical weights for these criteria for which a relatively small change in the weight value causes the rank reversal of any two options (Triantaphyllou 2000; Bojórquez-Tapia et al. 2005). Additionally, for one parameter at a time weight change analysis, there is a rule of thumb for establishing criterion criticality, which states that if the decision maker changes the parameter by *n*-percent and the result will change by less than *n*-percent then he/she may conclude that this parameter does not significantly influence the result (Longley et al. 2005).

The methods so far discussed are mainly local in scope. A more complex approach to establishing the importance of criteria scores and weights involves global SA, which decomposes the variance of the output of the MCE process into a variety of explanatory factors. An example of a global SA method is the extended Fourier Amplitude Sensitivity Test (FAST). The extended FAST method uses *first* and *total* order indices as SA measures. The first order sensitivity index is defined as a fractional contribution to the variance of MCE model output (e.g. option ranking) due to the uncertainty of a given input parameter treated independently from other parameters (Saltelli et al. 1999a; Saltelli et al. 1999b; Crosetto and Tarantola 2001; Gómez-Delgado and Tarantola 2006; Saisana et al. 2005). The total order index represents the overall contribution of a given parameter (e.g. criterion weight) including its interactions with other parameters. Computation of the indices requires a large number of rank-order calculations performed with weight vectors derived from the decision maker’s weight distribution functions (Saisana et al. 2005).

The key challenge for SA in S-MCE is to determine the stability of the rank-order of decision options. While all four groups of aspatial SA methods in Figure 3 can be used to determine the stability of rank-order, the option scoring and ranking methods address this task directly. Combining weighted multiple criteria values is inherently uncertain since none of the developed aggregation methods is flawless. Thus, SA may also comprise of comparing the stability of the rank-order under different aggregation methods (Massam 1991; Laaribi et al. 1996).

Sometimes, highly ranked decision options are very close to each other in terms of their overall evaluation scores being very similar. Such a situation warrants a careful investigation of critical score difference (Figure 3). For these options, it may be interesting to discover what changes in weights make them score equally well, a procedure which Pannell (1997) calls the “break even value”. If the break even value is within an acceptable range, then we may justify the switch in rank and select an option which we value more given other intangible criteria. The scale of the necessary weight modification may also provide information about options that are more likely to be ranked first – a method called proximity ranking (Wolters and Mareschal 1995).

Insua and French (1991) proposed a more generic framework for SA scoring and ranking. According to their framework, we should first find the non-dominated alternatives, then narrow down the non-dominated set to those alternatives that are optimal, find the adjacent potentially optimal alternatives, and establish for them the least change in weights that is needed to switch the highest ranked option. Such analysis not only pinpoints the most efficient options and their competitors, but also provides information about the minimum tradeoffs between the options (French 1992). A more extensive SA of option scoring relies on the division of multidimensional space into subsections of weight value ranges where a selected favored alternative wins (Belton and Stewart 2002). These subsections are then called preference regions. Sampling-based MC simulation is another useful approach to assessing rank stability (Voogd 1983; Malczewski 1999; French and Xu 2005; Longley et al. 2005). For example, for a large number of rank-orders from MC runs we can calculate different summary statistics like minimum, maximum, and mean position of the option thus revealing how stable the option rank is under changing parameter values (Andrienko and Andrienko 2005).

3.2 Spatial SA methods

Spatial SA is an underdeveloped component of SA in S-MCE. Studies that utilize spatially-explicit SA are rare. Table 1 is a proposition of a GIS-based methodology that addresses spatially-explicit components of S-MCE problems. Based on these components, spatial SA methods are grouped into options, criteria, and weights-focused methods.

The first group of spatial SA methods refers to geographical distributions of the decision options represented in Table 1 by four categories of relations: adjacency, proximity, pattern, and direction. For example, the decision maker may prefer to select high-ranked options because they are located in the direct proximity to other high-ranked options (Rinner and Heppleston 2006). Such spatial autocorrelation can lead to positive spatial externalities. Alternatively, the decision maker may use spatial statistics to analyze and map significant clusters of high scoring options. Other spatial SA operations, pertaining to spatial distribution of options, include map algebra, topology rules, or density analysis. Such operations can be used to derive geographically adjusted option evaluation scores (Rinner and Heppleston 2006).

The sensitivity of decision criteria stems from the uncertainty of the evaluation scores (criteria values). In spatial decision situations, such sensitivity could be analyzed based on traditional value measurement uncertainty (error) or value assessment ambiguity, and spatial uncertainty stemming from the geographical distribution of a given criterion. For example, if the decision maker uses rainfall as a decision criterion in raster-based S-MCE, he/she should consider the uncertainty of the rainfall measure at a particular location, together with the uncertainty associated with a selected interpolation method. One way of analyzing the spatial sensitivity of a criterion involves adding an uncertainty surface to the criterion surface. The uncertainty surface should be derived from a spatial distribution of the criterion under consideration (Krivoruchko and Gotway-Crawford 2005).

Table 1 Methods supporting spatial SA

S-MCE component	Sensitivity	Spatial Relation	SA Procedure	Exemplary Operations
Options	Spatial distribution of options (e.g. dispersed, clustered, contiguous)	Adjacency	Map options that are adjacent	Topology Operations (Share a Line Segment)
		Proximity	Locate proximate options	Spatial Statistics (Measures of Centrality, Cluster Analysis) Distance Decay Functions
		Pattern	Map the dispersion of options and the shape of option clusters	Spatial Statistics (Mapping Clusters) Point/Line/Kernel Density Map Algebra (Neighborhood Operations)
		Direction	Map the direction of options distribution	Directional Distribution Directional Mean
Criteria	Spatial distribution of evaluation scores	Pattern	Modify the criterion layer with an uncertainty ('noise') random layer derived from a spatial distribution of the criterion	Spatial Statistics (Cluster Analysis, Spatial Autocorrelation) Point/Line/Kernel Density Spatial Interpolation
			Use a more generalized criterion layer	Map Algebra (Neighborhood Operations) Reclassify/Remap Aggregate
Weights	Reference frame (point, line or area of interest) and its spatial distribution	Proximity	Use different reference frames as spatial weight layers	Straight Line Distance Distance Decay Functions Spatial Statistics (Standard Distance, Standard Deviational Ellipse)
		Containment		Variable-size Buffer Overlay (Point on Polygon, Line on Polygon, Polygon on Polygon) Map Algebra (Boolean Operations, Zonal Operations)

Another method of analyzing criterion spatial sensitivity involves attribute generalization (Krivoruchko and Gotway-Crawford 2005), similar to the more traditional rescaling proposed by Voogd (1983).

Spatial weight sensitivity pertains to the subjective reference frame of the decision maker. Participants may perceive certain locations as more favorable from a given perspective. For example, they may conceive the rainfall criterion as being more important in rural areas than elsewhere. Consequently, spatial sensitivity of criteria weights may have a direct effect on option scoring and ranking and should be explicitly addressed. Two spatial relations that capture the spatial sensitivity of criteria weights are *the proximity of* and *the containment within* the areas of interest (Table 1). The former can be applied using different distance-decay functions (Rinner and Heppleston 2006) or modeling situation factors (Cromley and Huffman 2006). The latter can be implemented by a variable-size buffer analysis (Halls 2002; Tarantola et al. 2002; Krivoruchko and Gotway-Crawford 2005).

3.3 Methods supporting group SA

The SA methods discussed above support the dynamics of group SA only implicitly. When used in a collaborative setting, the results of individual SA must be aggregated by some means. Jankowski et al. (1997) and Feick and Hall (2004) present consensus maps that show the dispersion of summarized votes using graduated circles or colors. The votes relate to a number of decision elements like option scores, criteria weights or criteria selection. Borda or Copeland voting protocols are used to aggregate the votes. Additionally, the variance of voting results can be displayed to identify the most contentious issues that need further discussion. These analytical techniques rely solely on non-spatial social voting functions. Spatially-explicit and scope-variant group SA remains to be explored in future research.

4 Discussion and challenges

Like any method of S-MCE, SA should embody a range of techniques that fit multiple styles of decision making (Merkhofer 1998; Andrienko et al. 2003; French and Xu 2005) and, thus, the need for appropriate SA methods is self-evident. Many well-developed techniques for SA in S-MCE exist; however, each of them has limitations.

The aspatial methods of SA have been used for years and there is an extensive record of SA applications. However, these methods ignore a geographic aspect of S-MCE expressed by the spatial variability of criteria values and weights. We have suggested that spatial variability and hence, the sensitivity of S-MCE solutions to criteria values and weights can be addressed by the analysis of spatial relations. The methodology of spatial SA is currently still in its infancy and lacks techniques for rank stability testing. Furthermore, not much is known on whether spatial SA can enhance group decision making (Feick and Hall 2004).

Until recently, the majority of studies reported on local one parameter at a time SA techniques. Local SA proved to be useful for human-mediated dynamic testing of rank-order stability. Yet, local SA makes sense only if we deal with perfectly linear models (Saltelli et al. 1999b), which is unlikely in the majority of spatial decision problems. The most appropriate technique for non-linear processes is the model-independent variance-based global SA (Saisana et al. 2005). Also, due to its theoretical underpinnings, global SA constitutes an important advance over the local SA methods.

It is also worth noting the role of qualitative group SA, in which the stakeholders negotiate using in-depth descriptive information that may reinforce or change their initial selection. Although only mentioned in this paper, such *soft* SA presents an intriguing area for future research and has the potential to bridge quantitative and qualitative approaches in decision making (Lempert 2002).

4.1 Visual representations of SA

SA is a useful approach to explore spatial decision options, but its utility can be further enhanced by the use of a cognitively straightforward visual feedback to decision makers. In this respect, the greatest progress has been made in the techniques of traditional local SA. The developments have been based on the principles of human-computer interaction and include user-friendly interfaces, computationally efficient algorithms, data brushing and dynamic linking between the maps, tables, and graphs. A variety of tools are available in today's software including weight sliders (Jankowski et al. 2001; Andrienko and Andrienko 2005), value path plots (Pannell 1997; Belton and Stewart 2002; Andrienko et al. 2003), spider-web charts (Pannell 1997), appraisal roses (Voogd 1983), or pie and bar chart histograms (Chen et al. 2001). More complex display methods have been proposed to account for the interrelated multidimensional nature of a decision problem. Examples include graphs of time-variant decomposition (Saltelli et al. 1999b), decision maps (Jankowski et al. 1999), and policy landscapes combined with policy regions (Bankes 2002).

A future research challenge for visual representations concerns effective techniques of representing the sensitivity of S-MCE solutions at spatial locations. The exemplary cartographic representations of SA in the form of rank maps, rank stability maps, or utility symbol maps should be enhanced with more specific sensitivity maps.

4.2 Representational and computational issues

Krivoruchko and Gotway-Crawford (2005) notice that the results of uncertainty and SA may be numerous and call for creative summary tools. Standards for defining statistical descriptors and improvements in computational techniques bode well for enhancing the ease of use and comprehensiveness of SA (Feick and Hall 2004). An exemplary possibility is the dynamic visualization of global SA in the form of a pre-computed approximation of a solution hypercube, which is dynamically sliceable depending on the specified parameter set. SA creates new information about the decision process (Pannell 1997) and, within GIS, this emergent information can be introduced in the form of maps (Jankowski et al. 1999).

Another important issue to be considered relates to the spatial and aspatial scales of data granularity, representative to a specific decision situation. A possible solution may involve a nondeterministic fuzzy approach to SA in S-MCE (Eastman 1999).

5 Conclusions

This article began with declaring SA as the simultaneous advantage and shortcoming of S-MCE. In the course of the article, we presented a framework for a holistic SA within the context of S-MCE. The goal of this framework is to assist the decision makers with the selection of SA methods and techniques that are appropriate for a specific decision situation. We formalized the structure of SA into spatiality, scope, and cardinality. The first dimension recognizes the duality of the spatial and aspatial nature of geographic decision making. The second dimension relates to analytical methods ranging from the low level exploration of a single decision parameter to the global synthesis of decision situation sensitivities. The final dimension reflects the divergent motivation for performing SA, namely individual learning or group consensus building.

We also discussed a number of SA techniques, delineating the advantages and disadvantages associated with parametric and nonparametric (judgmental) uncertainty. While the spatiality of alternatives is widely recognized, little progress has been made on including spatial aspects of decision criteria and decision weights into MCE-based SA. Therefore, the development of spatially explicit techniques of SA deserves further research. Additionally, the SA cube framework points to the lack of both spatial and aspatial scope-variant group SA methods, which are especially needed to enhance collaborative decision making.

SA is not a substitute for decision making analysis. Instead, it is a way of making the participants of the decision processes aware of the uncertainties inherent in any decision situation. Unlike a ‘typical’ perception of scientific analysis, in which we put probably too much trust in precise (but not necessarily accurate) results, SA emphasizes the impossibility of providing an ‘always-best’ solution (Saltelli et al. 2004). Ascough et al. (2002) state that multicriteria SDSS should be an environment where decision makers can define, explore, redefine and understand the problems they deal with. To accomplish this goal, we need more research into the methods of spatial SA. The SA framework presented here is intended to be a step in building the foundation for further progress in spatial decision support.

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