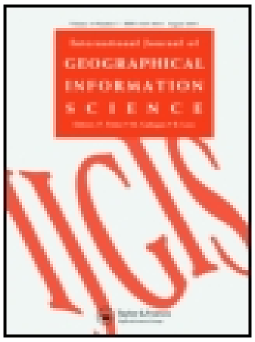

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Emerging trends and research frontiers in spatial multicriteria analysis

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FORESIGHT PAPER

Emerging trends and research frontiers in spatial multicriteria analysis

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ABSTRACT

A majority of research on Spatial Multicriteria Analysis (SMCA) has been spatially implicit. Typically, SMCA uses conventional (aspatial) multicriteria methods for analysing and solving spatial problems. This paper examines emerging trends and research frontiers related to the paradigm shift from spatially implicit to spatially explicit multicriteria analysis. The emerging trend in SMCA has been spatially explicit conceptualizations of multicriteria problems focused on multicriteria analysis with geographically varying outcomes and local multicriteria analysis. The research frontiers align with conceptual and structural elements of SMCA and pertain to, among others, theoretical frameworks, problem structuring, model parameter derivation, decision problem contextualization, scale representation, treatment of uncertainties, and the very meaning of decision support. The paper also identifies research directions and challenges associated with developing spatially explicit multicriteria methods and integrating concepts and approaches from two distinct fields: GIS and multicriteria analysis.

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1. Introduction

Over the last three decades, Spatial Multicriteria Analysis (SMCA), also referred to as GIS-based multicriteria analysis (GIS-MCA), has become a significant part of GIScience (Thill 1999, Malczewski and Rinner 2015). The quantity of publications about SMCA has been increasing exponentially. The total number of refereed journal papers with the keywords {GIS or Geographic Information System} and {multicriteria or multiobjective or multiattribute} has increased from 24 in 1990–1994 to 1537 in the last 5 years (based on a Scopus query for the years 1990 through 2018, executed in August 2019). This trend is likely to persist into the foreseeable future driven by the diversity of SMCA applications (de Brito and Evers 2016, Allain *et al*. 2017, Adem Esmail and Geneletti 2018, González and Enríquez-de-Salamanca 2018, Sallwey *et al*. 2018, Ferretti and Montibeller 2019) and enabled by the steady progress in geospatial technologies and the availability of geographic data/information (Yang *et al*. 2010, See *et al*. 2016, Wang and Goodchild 2018). Although SMCA has been applied in a variety of spatial problems, the decision analysis and support has been the main focus of its applications (Sugumaran and

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Degroote 2011, Ferretti and Montibeller 2016, Rinner 2018, Keenan and Jankowski 2019). Methods of GIS-MCA can be classified into two groups: GIS-based multicriteria evaluation (GIS-MCE) and GIS-based multiobjective optimization. This paper deals with GIS-MCE methods (hereafter, the three terms, SMCA, GIS-MCA and GIS-MCE, are used interchangeably).

While there is a wide range of approaches available for tackling multicriteria decision/evaluation problems (e.g. Malczewski 1999, Malczewski and Rinner 2015), two categories of MCE methods have typically been integrated with GIS. First, *value function* methods such as weighted linear combination (WLC) methods, multiattribute value/utility models, analytical hierarchy/network process (AHP/ANP) and reference point (RP) methods (e.g. Malczewski 2006a, 2010, Ferretti and Montibeller 2016). Second, *outranking relation* methods including ELECTRE (ELimination Et Choix TRaduisant la REalité) and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) (Chakhar and Mousseau 2008, Esmaelian *et al*. 2015). The value-function models require an estimation of value function and criterion weight for each evaluation criterion. The two components are integrated using a model (or a combination rule) to obtain an overall value for each alternative. The outranking methods are based on the process of constructing outranking relations by pairwise comparisons of alternatives with respect to each evaluation criterion. These comparisons allow for the development of outranking relations, which are then used to prioritize alternatives.

This paper discusses a paradigm shift and emerging trends in SMCA (Section 2) and research directions and frontiers (Section 3).

2. Paradigm shift and emerging trends

Currently, the prevalent practice in GIS-MCA is to adapt conventional (*aspatial*) multicriteria methods for analysing spatial problems. An overwhelming majority of GIS-MCA studies involve spatial variability only implicitly by defining evaluation criteria based on the concept of spatial relations such as proximity, adjacency and contiguity (O'Sullivan and Unwin 2010, Ligmann-Zielinska and Jankowski 2012). The GIS-MCA methods usually have been applied at a 'global' level; that is, the methods are premised on the implicit assumption that multicriteria model parameters and results of GIS-MCA do not vary as a function of geographical space. There has recently been a significant paradigm shift in GIS-MCA to address the shortcomings of currently prevalent practices. This shift has been stimulated by two related developments. First, a growing awareness of the limitations and inadequacies of the conventional GIS-MCA methods for tackling spatial problems (e.g. Simon *et al*. 2014, Malczewski and Rinner 2015, Ferretti and Montibeller 2016, 2019, Harju *et al*. 2019) has resulted in the movement away from *spatially implicit* approaches towards *spatially explicit* methods (see Section 2.1). Second, with the advent of the Internet of Things and Big Data, citizens have increasingly been involved in producing and using a new type of data/information useful for analysing spatial problems, and researchers and practitioners increasingly have been confronted with the task of developing methods and approaches for massive data collection, integration and analysis in spatially explicit formats (e.g. Wang and Armstrong 2009, Capineri *et al*. 2016, See *et al*. 2016, Wang and Goodchild 2018). These developments have recently pushed the frontiers of research on SMCA towards big data analytics and CyberGIS-enabled methods (e.g. Andrienko *et al*.

2016, Cerreta *et al*. 2016, González-Ramiro *et al*. 2016, Mele and Poli 2017, Zeng *et al*. 2017, Zhang *et al*. 2018; see Section 2.2).

2.1. Spatially explicit MCA

Two major trends in spatially explicit MCA have been gaining significance in recent years. These emerging trends have focused on developing multicriteria analysis with geographically varying outcomes (MCA-GVO) and local multicriteria analysis (LMCA). First, the works by Simon *et al*. (2014), Keller and Simon (2019) and Harju *et al*. (2019) have charted a new territory for MCA by axiomatizing spatially explicit multicriteria models (see also Ferretti and Montibeller 2016). Simon *et al*. (2014) and Keller and Simon (2019) have proposed spatially explicit multicriteria (multiattribute) value/utility function methods with geographically varying outcomes. The key parameters of MCA-GVO models are *spatial weights* as they represent trade-offs among outcomes at different locations. This approach has been further advanced by Harju *et al*. (2019). Harju and associates have made an eminent contribution to SMCA by developing axiomatic foundations for spatially explicit multicriteria analysis and modelling spatial problems characterized by incomplete preference information. Second, in the direct response to the criticism of prevalent practices, significant advances have been made in developing local forms of MCA models. Malczewski (2011) used the *range sensitivity principle* to develop a local version of GIS-WLC model (see also Carter and Rinner 2014, Tang *et al*. 2018). Subsequently, a local ordered weighted averaging (OWA) was proposed by Malczewski and Liu (2014), Xiao *et al*. (2018) and Jiao *et al*. (2019). Şalap-Ayça and Jankowski (2016, 2018), Jankowski (2018) and Taha *et al*. (2019) advanced GIS-MCA by developing local forms of reference point methods.

Although the two emerging trends share a common premise by acknowledging the presence of spatial heterogeneity of preferences, they differ essentially in their approaches to conceptualizing spatial heterogeneity. The MCA-GVO models have their roots in classic decision analysis and multiattribute value/utility theories (e.g. Fishburn 1970, Keeney and Raiffa 1976), while LMCA is a part of local analysis or local modelling movement within GIScience/spatial analysis (see Fotheringham *et al*. 2002, Lloyd 2010, O'Sullivan and Unwin 2010). MCA-GVO is primarily concerned with preference modelling, while LMCA is mainly concerned with spatial modelling. The former approach focuses on the theory of spatial preferences and has a limited concern for the fundamental properties of spatial data, whereas the latter focuses on GIS-based modelling of multicriteria problems at the expense of 'relaxing' some of theoretical underpinnings behind multicriteria analysis. While GIS provides an effective and efficient platform for the local modelling approach to multicriteria problems, LMCA is based on a hard-to-verify-empirically set of assumptions underlying the principle of range sensitivity (e.g. Fischer 1995, Monat 2009). These contrasts are intrinsically related to the hybrid heritage of GIS-MCA, which creates opportunities and challenges for advancing both conceptual and applied research (see Section 3).

2.2. Spatially explicit MCA with crowdsourced data

The concept of crowdsourcing is often conflated with such concepts as Volunteered Geographic Information – VGI (Goodchild 2007), contributed data (Harvey 2013), neogeography (Turner 2006), Public Participation GIS (Ramsey 2010), and the use of social media platforms employed in data production through photos, video and text (Leung *et al*. 2018). Although these concepts are not necessarily synonymous, they all describe data contributed by the public at large leveraged by wide-spread technologies such as GPS, mobile devices, Internet connectivity, and Web-2 apps. The emerging trends pertinent to crowdsourced data and SMCA are the employment of: (i) crowdsourced geographical data (CGD) on criteria, for which there are no authoritative geographical data (AGD) available, and (ii) crowdsourced preference data (CPD) substituting for or augmenting traditional preference data (TPD) provided by experts. While CGD comes in similar forms to AGD and can involve geographical object attributes of qualitative and/or quantitative nature, CPD substantially differs from TPD in representing revealed rather than stated preferences (see Upton *et al*. 2015, Pritchard 2018). The revealed preferences typically take a form of object selection or sentiment expression that is location-specific (e.g. by sharing via social media apps the name and location of one's favourite service facility or marking object location on a map). Contrary to this, stated preferences take a form of criterion trade-offs or weights numerically expressing a relative criterion importance vis-à-vis the other criteria in a SMCA model. The affinity of AGD and CGD and the difference between CPD and TPD present a challenge and an opportunity to adopt the existing and develop new SMCA methods integrating different yet complementary types of data. The potential integration strategies are outlined in Table 1.

The strategies in Table 1 can be categorized into three groups. Group A, comprised of a single strategy *type 1*, represents prevalent practices involving the combination of AGD with TPD. Methods representative of *type* 1 involve spatially implicit/explicit MCA, in which criterion data come from authoritative sources and preferences are typically stated by experts as weights, trade-offs, or value functions. The vast majority of present and past publications reporting on research and applications of SMCA falls into this group.

Group B, comprised of types 2–6, represents emerging trends in SMCA incorporating crowdsourced data. The strategy *type 2* (CGD + TPD) was used, for example, by Bordogna *et al*. (2014) for evaluating the quality of crowdsourced geographic data by employing traditional MCA techniques. Lyu *et al*. (2019), used *strategy 3* combining AGD with CPD to develop a point-of-interest (POI) recommender system. Their system harnesses POI-specific preferences of individuals from popular POI web services such as Yelp and Instagram and integrates them into crowd-averaged preferences to deliver POI

Table 1. Strategies for combining authoritative and/or crowdsourced geographic data with traditional and/or crowdsourced preference data. Note: Authoritative Geographic Data (**AGD**), Crowdsourced Geographic Data (**CGD**), Traditional Preference Data (**TPD**), Crowdsourced Preference Data (**CPD**).

		Preference Data (PD)		
		Traditional (TPD)	Crowdsourced (CPD)	Mixed (TPD+CPD)
Geographic Data (GD)	Authoritative (AGD)	*Type 1* **(AGD)+(TPD)**	*Type 3* **(AGD)+(CPD)**	*Type 6* **(AGD)+(TPD+CPD)**
	Crowdsourced (CGD)	*Type 2* **(CGD)+(TPD)**	*Type 4* **(CGD)+(CPD)**	*Type 8* **(CGD)+(TPD+CPD)**
	Mixed (AGD+CGD)	*Type 5* **(AGD+CGD)+(TPD)**	*Type 7* **(AGD+CGD)+(CPD)**	*Type 9* **(AGD+CGD)+(TPD+CPD)**

recommendations tailored to individual preferences. A different type of recommender system substituting CGD for AGD, representative of *type 4*, was proposed by Bordogna *et al*. (2014). The strategy *type 5* augmenting authoritative geographic data with crowd-sourced data and relying on stated preferences (TPD) has been the most common emerging trend. Examples of this strategy include using public-contributed photos to derive the characteristics of tourist accommodations and restaurants (González-Ramiro *et al*. 2016) and to assess the attractiveness of landscape (Mele and Poli 2017). The same authors (Mele and Poli 2017) used OpenStreetMap to obtain data for ecosystem services (water), infrastructure (railways, roads, public transportation), recreation (cultural sites) and soils (waste disposal sites). Another emerging trend has been the integration of authoritative data (AGD) with revealed by crowd preferences (CPD) and expert-elicited stated preferences (TPD) in *type 6* strategy. Examples of this strategy can be found in SMCA of natural disaster evacuation shelters guided by people's shelter preferences contained in Tweets and combined with stated expert preferences for suitable shelter locations (Kusumo 2016). Another example is presented in SMCA of site selection involving a geo-social network (Neisani Samani *et al*. 2018).

Group C, comprised of *types* 7–9, does not have published exemplars – at least to our knowledge, and thus suggests directions for future SMCA research on ways to conflate authoritative with crowdsourced geographic data, and approaches to integrating revealed with stated preferences.

3. Research directions and frontiers

Here, we highlight some of new research directions that emanate from the hybrid nature of GIS-MCA. The research directions can be characterized by a series of shifts from the currently prevailing practices to emerging trends and research frontiers in spatially explicit MCA. The discussion is organized around core concepts and elements of SMCA including theoretical frameworks, problem structuring, combination rules, model parameters, contexts, scales, uncertainties, decision support and visualization (see Table 2).

Table 2. Spatial multicriteria analysis: prevalent practices and emerging trends/research frontiers.

Concepts/elements of SMCA	Prevalent practices	Emerging trends/research frontiers
Theoretical frameworks	Normative/Prescriptive	Descriptive/Behavioural
Problem structuring	Well-structured	Networks
	Hierarchies	Ontology-driven
Combination rules	Single-method	Mixed-methods
(methods, models, procedures)	Single-agent	Multiple agents/Citizens
Model parameters	Knowledge–driven	Data–driven
(criteria weights, value functions, etc.)		Knowledge/Data-driven
Contexts	Context-independence	Context-dependence
		Context-awareness
Scales	Single-scale	Multi-scale/Spatio-temporal
(spatial, temporal)		
Uncertainties	Deterministic	Non-deterministic
	One-parameter-at-a-time sensitivity analysis	Integrated uncertainty and sensitivity analysis
Decision support	Decision support systems	Recommender systems
Visualization	Visualizing situational awareness	Geo-visual analytics

3.1. Theoretical frameworks

3.1.1. Rationality and modelling frameworks

There are three main types of theoretical frameworks for GIS-MCA: descriptive, normative and prescriptive (Bell *et al*. 1988, Malczewski and Rinner 2015). Descriptive models are concerned with actual behaviour of decision-making agents. Normative theories are built on the basic axioms that should be considered as rational guidance for making decisions. While descriptive or pragmatic rationality attempts to explain how agents actually make their decisions, normative rationality addresses the question of how agents ought to make their decisions. The prescriptive approaches focus on the insights into the decision-making process rather than on the axioms underlying the normative modelling. These insights are enhanced by a synergetic effect of combining normative and descriptive approaches (Bell *et al*. 1988).

Models and methods of GIS-MCA share the elements of rational decision-making and bounded/procedural rationality theories. A (theoretically) rational decision-maker has an unambiguous understanding of the nature of a decision problem, is capable of identifying all feasible decision options, and knows their outcomes (Edwards 1961). It follows that the rational decision maker is fully capable of discriminating among decision options by evaluating their trade-offs, integrating them in an overall measure of the worth of a decision option, and consequently producing an ordered list of choice alternatives. Importantly, choice preferences of the rational decision maker are transitive (i.e. if one prefers option *A* to *B* and *B* to *C*, then he/she must prefer *A* to *C*).

These assumptions are reflected in the conceptual and structural elements of GIS-MCA including preference, trade-off, objective, criterion, constraint and decision rule. Additionally, value functions in GIS-MCA directly borrow from the concept of utility functions in utility theory (Fishburn 1970). The assumptions of the rational decision-making model are also reflected in procedural steps of GIS-MCA such as comprehensive search for decision options, known or expected decision option outcomes, discrimination among the decision options by evaluating their trade-offs, and integration of multiple tradeoffs into an overall measure of decision option worth (Jankowski 2018). That said, GIS-MCA also embraces some of important points of the critique levied on rational decision theory by, among others, Herbert Simon who offered bounded and procedural rationality theories (Simon 1957). These elements include making provisions in GIS-MCA for overcoming incomplete search for decision alternatives, biased evaluations including violations of preference transitivity, and support for satisficing behavior characterized by setting goal/aspiration levels. Examples of the latter are reference point methods.

3.1.2. Behavioral turn

Behavioral turn implies the acceptance of behavioral concepts such as bounded rationality, prospect theory, regret theory, disappointment theory, etc. in mainstream decision science/multicriteria analysis (e.g. Morton and Fasolo 2009, Franco and Hämäläinen 2016). Behavioral theories attempt to improve understanding of decision-making process by combining theoretical foundation of normative methods with empirical findings of descriptive research. One of the most prominent contributions to behavioral turn in decision analysis came from prospect theory and its extensions (Kahneman and Tversky 1979, Tversky and Kahneman 1992, Schmidt *et al*. 2008). These theories challenged the normative approaches based on expected utility in arguing and demonstrating in a number of experiments that gains have different utility functions than losses. When measured in absolute values and given a typical risk aversion, the utility of gaining $100 is less than the disutility of losing $100. In utility theory, the utility of gain cancels out the disutility of loss if the gain equals the loss (in absolute terms). This implies that given a 50–50 chance of ending up at location *A*, characterized by the positive utility of $100, versus ending up at location *B*, characterized by the disutility of -$100, one should be indifferent to such a gamble – according to utility theory. However, according to prospect theory, most people will require a higher payoff at *A* to offset the prospect of ending up in *B* before they take the gamble. This trivial example becomes more interesting when extended to a more realistic situation of more than two locations evaluated under multiple criteria. Clearly, in such a case criterion trade-offs should consider differential perceptions of gains and losses. The present GIS-MCA methods, however, make no provisions for such a calculus. Hence, there is a research opportunity to develop new GIS-MCA methods consistent with the cornerstone of prospect theory, namely the recognition that people tend to treat gains differently than losses by applying different utility functions. There are two areas ripe with opportunities for future research. First, prospect theory has not been validated in the context of spatially explicit, multicriteria choice situations with risky outcomes (i.e. entailing both a chance of gain and loss). Although nothing at this point indicates that prospect theory would fail to explain such choice behaviors, demonstrating that it does would provide a theoretically valuable proof. Second, vast amounts of data about individual choices including location choices (e.g. points-of-interest or POIs) and navigational choices could be leveraged to estimate the parameters of utility functions for gains and losses that can be attributed to specific places in geographical space. Moreover, such utility functions could conceivably by estimated for individuals who are interested in receiving recommendations for POIs (i.e. *recommender systems* – see Section 3.8.2).

3.2. Problem structuring

Problem structuring is a process that aims at defining and representing a research (decision) problem in a format acceptable and manageable by all involved in the process. Although problem structuring has been recognized as a crucial component of or prerequisite for multicriteria analysis (e.g. Belton and Stewart 2010), a very limited attention has been given to the significance of problem structuring in SMCA (Ferretti and Montibeller 2016, Adem Esmail and Geneletti 2018). Typically, GIS-MCA takes a well-structured problem as a starting point and/or a simple hierarchical structure approach is used for representing the problem situation (see Table 2). Only recently, methods for structuring multicriteria problems have gained attention as an integral part of SMCA (Bottero and Ferretti 2011, Argyris *et al*. 2019). The SMCA literature reports a variety of problem structuring methods including soft systems methodology (SSM), strategic options development and analysis (SODA), strengths, weaknesses, opportunities and threats (SWOT), and strategic choice approach (SCA) (Lami *et al*. 2014, Oppio *et al*. 2015, Uhde *et al*. 2015, Ferretti and Gandino 2018). Also, Analytical Network Process (Saaty 2001) has been increasingly used in the process of problem structuring for SMCA (Bottero and Ferretti 2011, Bojórquez-Tapia *et al*. 2011, Oppio *et al*. 2015). The main advantage of network approach is its capability of dealing with complexity by representing a problem situation as a network of elements (e.g. objectives, criteria, alternatives) that are grouped into clusters including inter-relationships within and between clusters (Bottero and Ferretti 2011).

3.2.1. Spatial data

A common characteristic of all problem structuring methods for SMCA is that they combine problem structuring with spatially implicit multicriteria analysis. The traditional methods of problem structuring – are, however, of limited applicability for spatially explicit MCA. This is because the process of structuring spatial problems should involve explicit considerations of 'the special nature of spatial data' (Haining 2009) as well as the special nature of spatial preference data/information (Simon *et al*. 2014, Ferretti and Montibeller 2019, Harju *et al*. 2019). The fundamental (i.e. special) properties of spatial data, *spatial dependence* and *spatial heterogeneity*, are inherent in the nature of attributes (criteria), and they depend directly or indirectly on the model of spatial data (Haining 2009). Consequentially, a central question in the process of spatial problem structuring is that of how to represent spatial properties of decision/evaluation alternatives and how to elucidate spatial preferences within the frame of spatial dependence and spatial heterogeneity.

3.2.2. Social networks

The notions of social networks, both physical and virtual, can be incorporated into the process of multicriteria problem structuring. The networks, within which nodes (representing decision-makers, stakeholders, participants, or citizens) are connected and influence one another can be used as a platform for supporting decision-makers' reasoning, which, in turn, can be structured in terms of a network of means-and-ends (i.e. cognitive/causal mapping) approaches (e.g. Montibeller and Belton 2009). Social networks can also incorporate interactions among nodes (changing preferences over time and space) and contextual factors (Giacchi *et al*. 2016) into the process of structuring multicriteria problems. Such an approach can provide an effective way for developing procedures for spatial problem structuring by considering not only the spatial-temporal nature of the interactions among nodes (e.g. spatial social networks) and the nodes' context-awareness (social and spatial) but also the fundamental properties of spatial data (see Section 3.2.1).

3.2.3. Qualitative-quantitative approach

The current GIS-MCA methods and practices impose the notion of geometric primitives (points, lines, polygons and pixels) on the process of problem structuring; and subsequently, the multicriteria modelling procedure and its outcomes are positioned in an absolute space, which is 'static, deterministic, and asocial' (Warf and Sui 2010). This generates an incompatibility between processing and analysing geographic data, and the requirements of SMCA for processing and analysing preferences on criteria and alternatives (Ferretti and Montibeller 2016, Malczewski 2017). Some evidence suggests that the concept of relational (cognitive) space provides an effective foundation for structuring problems in GIS-MCA (Ferretti 2016, Bojórquez-Tapia *et al*. 2019, Giuffrida *et al*. 2019). Unlike the absolute models of space, which require measurements referenced to constant base, implying nonjudgmental observations (Peuquet 1994, Wachowicz 1999), the relational spaces of critical/qualitative GIS allow for value judgments (Elwood *et al.* 2011); that is, concepts such as location, distance, direction, connectivity, adjacency, neighbourhood, proximity can be specified in terms of an agent's preferences, beliefs, opinions and perceptions. Emerging from arguments about the complementarity of absolute and relational models of space, a qualitative-quantitative approach to spatial problem structuring should be developed in order to bridge not only methodological but also ontological and epistemological divides between GIS and MCA.

3.2.4. Ontology-driven approach

One of the most challenging issues in developing the qualitative-quantitative SMCA approach is the problem of semantic heterogeneity caused by different meanings of data, terminologies and models used in GIS and MCA. It has been only recently recognized by researchers how the problem of semantic heterogeneity inherent in conventional GIS-MCA affects the quality of spatial decision-making process (Bojórquez-Tapia *et al.* 2011, Jelokhani-Niaraki 2018, Jelokhani-Niaraki *et al.* 2018). We suggest that an ontology-driven approach for spatial problem structuring (and solving) is needed to make substantial progress in spatially explicit MCA. A generic framework proposed by Smith and Shaw (2019) can be adapted to this end. The framework should be organized around a set of assumptions related to spatially explicit MCA including ontological assumptions describing the reality and leading to a definition of spatial problem, epistemological assumptions and theories underlying GIS and MCA, and methodological assumptions about the models and methods of GIS and spatially explicit MCA.

3.3. Combination rules

3.3.1. Comparison, augmentation, and integration

Spatially explicit MCA has typically been a single method analysis (see Table 2); that is, a specific multicriteria combination (or decision) rule has been integrated into GIS for analysing a given spatial problem (Malczewski 2006a, 2017). The single-method approach can significantly be enhanced by developing GIS-based procedures that combine multicriteria model(s) with other method(s) (e.g. Uhde *et al.* 2015). The research should proceed in three main directions (see Howick and Ackermann 2011): (i) *comparison* (using two methods separately, for the purpose of comparing them or solving different aspects of a spatial problem, which either method used on its own could not tackle), (ii) *augmentation* (enhancing one method by using elements of the other), and (iii) *integration* (developing new methods by integrating or unifying the existing methods).

Mixing methods may simply involve a comparison of the GIS-MCA outputs or an improvement of a SMCA method by using elements of another method. Spatially explicit methods can be advanced by using other methods for estimating the parameters of MCA models. For example, mathematical programming procedures can be used for estimating criterion weights in spatially explicit models (Ferretti and Montibeller 2019) and for defining order weights in GIS-OWA models (Malczewski and Liu 2014, Jiao *et al.* 2019). There is empirical evidence to show that applying different GIS-MCA methods for a given spatial problem can generate significantly different results (e.g. Elaalem *et al.* 2011, Feizizadeh and Blaschke 2013). Although this is often seen as a drawback of GIS-MCA, a comparative analysis of spatially explicit MCA methods may provide us with diverse insights into the results generated by different methods and is one way of analysing the sensitivity of problem solution (see Section 3.7.1). Moreover, it can also reveal whether methods are compatible or complementary. Of particular significance are comparative studies of global and local MCA models; this type of modelling creates opportunities for the synergistic accumulation of insights from spatially implicit and explicit MCA methods.

A robust framework for analysing spatial problems can be developed by mixing spatially explicit multicriteria models with other GIS-based modelling procedures. The most prominent example of this approach has been the use of multicriteria methods for defining agent's decision rules in geosimulation models such as cellular automata and agent-based models (Li and Liu 2007, Yu *et al*. 2011, Sabri *et al*. 2012). While geosimulation methods provide a platform for making conventional MCA spatially explicit (Ford *et al*. 2019), they can be enriched by using spatially explicit MCA. Conversely, decision rules used in MCA models can be enriched by adopting rules of behaviour developed for agent-based models (ABM). One of the most promising research directions in GIS-MCA is integrating local MCA models with geosimulation procedures and ABM.

An integrated mixed-method involves combining elements of different multicriteria methods to develop a new approach for tackling spatial problems (e.g. Moradi *et al*. 2017, Dragićević *et al*. 2018). Yet, there is a contradiction between GIS-MCA studies focusing on the uniqueness of different approaches and similarities between ostensibly very different methods. The value function methods provide a good example of this. Specifically, there are several parallels between WLC, AHP/ANP and RP methods (see Malczewski and Rinner 2015). We hint that these MCA methods along with Boolean operations can be unified within the framework of OWA (Malczewski 2006b, Boroushaki and Malczewski 2008). A unified GIS-OWA framework can in turn provide a tool for further advancement by developing an integrated global and local MCA modelling system.

3.3.2. Multiple agents

Recent approaches to computer-based modelling have taken a broader perspective on decision-making to include the concept of decision-making agent. An agent can be an organization (government, corporation, or non-government organization – NGO), a person (stakeholder, expert, citizen) or a computer program characterized by such properties as autonomy, reactivity and rationality including humanistic characteristics (preferences, beliefs and opinions). Spatially explicit multicriteria methods have been designed to deal with single-human-decision maker problems (Malczewski 2011, Simon *et al*. 2014). Hence, an obvious direction for future research is to extend single-decision-maker methods such as MCA-GVO and LMCA to spatially explicit multi-agent MCA. The main difficulty in developing a spatially explicit multi-agent MCA model is associated with estimating its parameters (values/utilities, criterion weights). A way to deal with this difficulty is to operationalize spatially explicit multi-agent MCA in terms of multicriteria group decision-making under incomplete preference information (e.g. Salo and Hämäläinen 2010). For example, a multi-agent MCA-GVO procedure can be developed by using a method of preference programing with incomplete information (Harju *et al*. 2019). LMCA can also be used in group, participatory and collaborative settings by enhancing local models with voting procedures.

The integration of multicriteria decision rules into geosimulation (agent-based) models (Yu *et al*. 2018, Ford *et al*. 2019) and the use of crowdsourced data/information in SMCA (González-Ramiro *et al*. 2016, Mele and Poli 2017) have stimulated the development of multi-agent MCA. Spatial perspective, often implicit in conventional MCA, can be made explicit through geosimulation and crowdsourced geographic data (CGD). Indeed, geosimulation has emerged as a platform for integrating MCA into group (social or collective) decision-making. Likewise, conventional MCA can be made spatially explicit through integrating CGD into multicriteria analysis (CGD-MCA). A limitation of CGD-MCA models has been their reliance on traditional methods of eliciting preferences. CGD-MCA models have so far combined authoritative and crowdsourced geographic data with expert-based preferences (see Section 2.2). This limitation can be addressed by developing methods that combine authoritative and crowdsourced geographic datasets with traditional and crowdsourced preference data. This type of approach would open new opportunities for advancing research on participatory (collaborative) GIS and usher in new perspectives on spatial group decision-making by incorporating place-based knowledge of people into SMCA. It can potentially be employed not only for operationalizing multicriteria combination rules for group decision-making but also for examining behaviour of decision-making agents.

3.4. Model parameters

Parameters of multicriteria models are typically estimated by knowledge-driven approaches, which rely on the decision-making agents' knowledge, experience, value judgements, opinions and perception of the problem at hand (Malczewski 2006a, Stevens and Pfeiffer 2011, Veronesi *et al*. 2017). A drawback of knowledge-driven methods is that the agents (decision-makers, stakeholders, experts, citizens, etc.) find it difficult to elucidate their preference and in effect provide inconsistent judgments under different schemes of estimating model parameters (Ferretti and Montibeller 2016). Parameters such as criteria weights (criteria 'importance') and value functions (values associated with criteria scores) are as much properties of the criteria as they are of the agents. This implies that model parameters can be estimated by knowledge-driven approaches (which rely on the agents' knowledge of a problem at hand) or they can be derived from data.

3.4.1. Data–driven approach

The data-driven procedures such as entropy methods, correlation and standard deviation methods (Wang and Luo 2010) have sporadically been used for estimating parameters of GIS-MCA models (Veronesi *et al*. 2017). We suggest, however, that the data-driven framework can provide a valuable platform for advancing spatially explicit GIS-MCA. For example, a data-driven approach can be used for developing local forms of outranking methods. Arguably, the main limitation of integrating this class of MCA methods into GIS is a large number of pairwise comparisons of alternatives with respect to each evaluation criterion. This problem can be overcome by aggregating spatial analysis units (e.g. Marinoni 2006, Chakhar and Mousseau 2008), but the downside is potential information loss. This shortcoming provides a motivation for further research. Specifically, the outranking relations can be modelled locally. For example, a local form of PROMETHEE can be developed by estimating local weights and local binary preference functions. The concept of local outranking relations opens the door for developing spatially explicit outranking methods for choosing the best alternative, ranking the alternatives from best to worst, and sorting (or classifying) the alternatives into homogeneous groups.

3.4.2. Combining knowledge- and data-driven approaches

There are contrasting suppositions on the merits of data- versus knowledge-driven models (Stevens *et al*. 2013, Veronesi *et al*. 2017, Rohrbach *et al*. 2018). On the one hand, there is a notion of the superiority of data-driven approaches due to their objectivity and replicability of results; on the other, data-driven approaches are criticized for their limited ability to tackle problems involving hard-to-quantify preference information and intangible aspects of a spatial problem situation. In contrast, the knowledge-driven methods are perceived to be inferior because of their subjectivity and low replicability; however, they are superior in their ability of dealing with preferences and intangibles. These conflicting properties provide a good starting point for advancing SMCA by developing methods that combine the knowledge- and data-driven methods. For example, local RP models can be developed by using the entropy or correlation and standard deviation methods for estimating local criterion weights, and the maximum and minimum criterion values can be employed for approximating local value functions. Data- and knowledge-driven methods can be combined by employing Bayesian updates. For example, criterion weights can be elicited through a knowledge-based approach (i.e. pairwise comparison or value function) and treated as *a priori* information. Then, using the Bayes Rule, data-based methods can be employed to derive an alternative set of weights that will serve as *a posteriori* information and be used to update the initial set of weights. There is also another justification for a hybrid approach combining data-based with knowledge-based methods. Complex decision problems involving multiple stakeholders with often divergent interests can hardly be reduced to hard data. Soft data representing beliefs, preferences and sometimes intangibles should have a way to be included into SMCA calculus, along with hard data, in order to operationalize such problems.

Knowledge/data-driven approaches can be developed using authoritative and crowdsourced data for estimating model parameters (e.g. Cerreta *et al*. 2016; see Section 2.2). The former is a theory-driven approach that is concerned with stated preferences, while the latter involves data-driven analytics aiming at constructing revealed preferences. These two very different ways of parameterizing multicriteria models provide new opportunities for advancing GIS-MCA. They also make the procedures for estimating model parameters more challenging. Future research should strive to advance GIS-MCA through a combination of theory-driven and data-driven approaches. Combining authoritative with crowdsourced preference data is of particular significance in situations requiring real-time estimation of model parameters. That said, there is a need for developing a theoretically and practically sound protocol for validation and verification of SMCA models involving both stated and revealed preferences.

3.5. Contexts

3.5.1. Context-dependent preferences

An important and often ignored aspect of SMCA is the context of decision-making processes. Broadly speaking, the context of spatial multicriteria problems is a set of factors (or characteristics) of an individual agent or group of agents that have the potential to change the preferences about decision alternatives. It is important, however, to make a distinction between the notions of context-dependent preferences and heterogeneity of preferences. While the former articulates how preferences are adjusted by the decision situation, the latter captures differences in preferences across a study area independent of context. Spatially explicit models including LMCA and MCA-GVO are concerned with spatial heterogeneity of preferences (see Section 2.1). While these models are derived from context-dependent spatial analysis (Fotheringham 2000), they do not directly consider contextual factors. One of the underlying assumptions of spatially explicit MCA models is based on the principle of rational choice – a corner stone of neoclassical decision theory (see Section 3.1.1); stating that an individual's preferences over a set of alternatives can be completely rank-ordered and the highest-ranked alternative is declared to be the best alternative (Keeney and Raiffa 1976). This implies the property of independence of irrelevant alternatives: preference ranking between any pair of alternatives is not influenced by the decision context. We suggest that the property of independence of irrelevant alternatives deserves more attention in spatially explicit MCA. For example, we argue that any change in the spatial scale results in a new set of alternatives (see Section 3.6.1) and therefore the principle of independence of irrelevant alternatives may not hold for spatial context-dependent SMCA solutions. An important contribution to context-dependent spatial analysis can be made by contextualizing spatially explicit MCA and analysing the relations between spatial heterogeneity of preferences and contextual factors.

3.5.2. Contextualizing SMCA

Contextual factors are operationalized by data about characteristics of an individual or group of individuals. The data can be obtained from traditional (authoritative) sources such as population censuses, surveys, questionnaires, etc. (Cabrera-Barona *et al*. 2018) and/or extracted from unstructured crowdsourced data (Robertson and Horrocks 2017). An effective way of integrating contextual factors into SMCA is through the use of multi-method approach in which SMCA is hybridized with a method for analysing authoritative contextual data. This approach is proved to be highly effective in developing GIS-MCA procedures for the construction of composite socio-economic and socio-environmental indices, such as the indices of vulnerability, liveability, deprivation, environmental quality and sustainability, just to name a few (e.g. Schuurman *et al*. 2007, Miller *et al*. 2013, McHenry and Rinner 2016). For example, GIS-MCA can be used for constructing a deprivation index and statistical methods can be employed to examine the sensitivity of the index values to the contextual factors (e.g. Cabrera-Barona *et al*. 2018). One way of refining this approach is to use the concept of localized contextual factors within the framework of LMCA. There is some evidence suggesting that the size and shape of a neighbourhood are the critical parameters of LMCA (McHenry and Rinner 2016, Taha *et al*. 2019). The parameters are problem specific and context dependent. We suggest that a constructive approach can be developed by examining how the results of LMCA are influenced not only by the parameters of neighbourhood but also by the contextual factors.

SMCA can be contextualized by extracting contextual factors from volunteered crowdsourced data with explicit or implicit geographic references collected through social networks or mobile applications and then by linking those factors to multicriteria procedures. This approach is of particular importance for emergency management applications to reduce the detrimental effects of natural disasters such as floods, hurricanes, earthquakes, tsunamis, landslides and forest fires (e.g. Wood *et al*. 2014, Zhang *et al*. 2018). One of the main tasks in this type of applications is selecting an efficient and effective method for combining authoritative and crowdsourced datasets to obtain useful information for emergency management (see Section 2.2). The most challenging questions for SMCA-based emergency management applications are how to derive contextual factors from unstructured crowdsourced data and incorporate them into SMCA procedures in real-time and capture dynamically changing preferences and priorities.

3.6. Scales

3.6.1. MAUP and rank reversals

The results of multicriteria analysis of spatially aggregated data are sensitive to the modifiable areal unit problem (MAUP); that is, the scale effect (the size of the zones) and the zoning effect (the shape of the zones) (Wong 2009). Every change in the shape and size of zones creates a new set of geographic data (and different set of decision/evaluation alternatives). Consequently, the results of GIS-MCA are sensitive to the rank reversal problem; that is, the change in ordering/ranking of the alternatives is a consequence of modifying the set of spatially defined alternatives (Nijssen and Schumann 2014, Malczewski and Rinner 2015, Taha *et al*. 2019). Future research can make an important contribution to GIS-MCA by demonstrating how do scale/zonation changes influence the outcomes of GIS-MCA procedures, and examining how MAUP relates to the rank reversal problem. The scale and zoning effects should not be regarded solely as 'problems', but as a research opportunity for contributing to GIS-MCA. The process of detecting an appropriate scale of analysis must be considered as an essential component of the exploratory analysis of spatial problems.

3.6.2. Multi-scale spatio-temporal analysis

GIS-based multi-scale MCA (MS-MCA) models use geographic data/information for two or more spatial and/or temporal scales simultaneously or sequentially to analyse decision/evaluation problems (e.g. Schuurman *et al*. 2007, Scolozzi and Geneletti 2012, Delmotte *et al*. 2013, Dragićević *et al*. 2015). GIS-MCA can be advanced by integrating multicriteria models into multi-scale spatiotemporal analyses. The triangle and pyramid models (Van de Weghe *et al*. 2014, Qiang *et al*. 2018) can potentially be used to develop a multi-scale spatiotemporal GIS-MCA framework. The inherent complexity of this type of GIS-MCA analysis brings about conceptual and operational challenges in the process of estimating spatio-temporal parameters of multicriteria models. An estimation of parameters requires not only data about four spatio-temporal elements (e.g. location, spatial resolution, temporal interval and temporal unit of aggregation), but also a choice of spatial and temporal, observational and analytic extents. In addition to the conceptual and operational complexities, the major challenge here is the development of efficient computational procedures for tackling multi-scale spatio-temporal multicriteria problems.

3.7. Uncertainties

3.7.1. Uncertainty and sensitivity

Uncertainty in geography is an umbrella term for describing problems that arise from the inherently incomplete representations of the world (Longley *et al*. 2010). In GIS-MCA, uncertainty permeates problem structure, combination rules, data and model parameters (Ligmann-Zielinska and Jankowski 2008). Some parameter uncertainties, such as those concerning criterion weights, can be subdivided into scalar and spatial (i.e. global and local), which is reminiscent of the distinction between attribute and positional errors in spatial data. Both scalar and spatial model parameters can be represented using probability distributions, or as multiple realizations of a geographic theme (Liburne and Tarantola 2009).

A comprehensive approach to dealing with SMCA parameter uncertainties involves an integrated uncertainty analysis (UA) and sensitivity analysis (SA) (Feizizadeh *et al*. 2014, Ligman-Zielinska and Jankowski 2014). UA and SA are two complementary ways of evaluating the uncertainty present in model parameters and by extension in model results (Saltelli *et al*. 2004, Saltelli and D'Hombres 2010). UA quantifies outcome variability given model input uncertainties. UA is therefore forward-looking as it focuses on the evaluation of how the uncertainty of parameters (e.g. criterion weights) propagates through the model and affects its output. Typically, UA produces an empirical probability distribution of model result(s), accompanied by descriptive statistics and confidence bounds for the output. UA, however, does not provide information on the magnitude of the influence of individual parameters, which is the objective of SA. Consequently, SA evaluates how much each source of parameter uncertainty contributes to model output variability; it is therefore backward-looking (Saisana *et al*. 2005). With SA one aims at identifying those parameters that are mostly responsible for the uncertainty of model results. This can be done by quantifying the contribution of each parameter to model output variability.

Numerically, uncertainty can be expressed, among others, through the variance of model output. In spatially explicit models, the variance is represented by a variance layer as the model output is spatially distributed. One can subdivide the variance and apportion it to uncertain parameters effectively expressing the (relative) share of model output variability due to each of the uncertain input parameters (Saltelli and Annoni 2010). Arguably, this method of SA, called *variance decomposition*, is highly advantageous for GIS-MCA for a number of reasons. First, it enables a global approach to SA that allows the exhaustive examination of model input parameters, rather than selected 'best-guess' parameter values, as is the case in frequently used one-parameter-at-a-time (prescriptive) approach (Gomez-Delgado and Tarantola 2006, Chen *et al*. 2013). Next, variance decomposition is agnostic of model formulation. Last (but not least), it accounts for the contributions of a given input parameter to model output uncertainty owing to this parameter only and additionally due to its interactions with other parameters.

The use of integrated UA-SA in GIS-MCA is still an exception rather than the rule. Many researchers still publish results of SMCA as if the underlying model was clear-cut and the input data error-free. Some plausible reasons for this are (i) lack of expertise in the use of uncertainty and sensitivity analysis methods, (ii) lack of efficient computational methods for spatially explicit UA-SA, and (iii) the challenge of finding effective ways of communicating the uncertainty of model parameters and the sensitivity of model output due to uncertain parameters. While the first reason can be rectified through the UA-SA literature readings, the latter two present a research frontier.

3.7.2. Integrated spatially explicit UA-SA

Spatially explicit UA-SA is computationally costly (Ligman-Zielinska and Jankowski 2014). Computational cost increases exponentially with the simultaneous consideration of model parameters (e.g. criterion weights) and data (criterion values) uncertainties. Two research directions that address the issue of computation cost are: (i) accelerating UA-SA with high-performance computing, and (ii) meta-modelling approaches. Graphic Processing Units (GPUs) offer powerful and relatively affordable high-performance computing infrastructure that has been used in various research fields. Erlacher *et al*. (2017) have shown that GPUs can accelerate up to 150 times computationally-demanding calculations of sensitivity indices in spatially explicit UA-SA. Other high-performance architectures such as Hadoop should also be explored. Meta-modelling approaches approximate the full solution space typically explored by global UA-SA, but as shown by Şalap-Ayça *et al*. (2018) the accuracy of approximation may be sufficient even for complex spatio-temporal models.

The effectiveness of communicating model output uncertainty, both numerically and visually, is of paramount importance especially in spatial decision-making problems where model results fail to disclose full information by falsely conveying the sense of certainty and reliability. There is a need to build on the existing body of work on visualizing information uncertainty (MacEachren *et al*. 2005) and systematically evaluate the effectiveness of various visualization techniques in communicating the results of spatially explicit uncertainty and sensitivity analysis. Future research efforts should be directed at investigating, which of map designs are effective in helping to understand distributional patterns of model variances and the link between parameter uncertainties and model sensitivity. The link, which is fairly easy to understand in non-spatial model, becomes much more complex in spatial and even more so in spatial-temporal models. Still, an effective visualization could illuminate the relationships between the parameter uncertainty and model sensitivity and thus, contribute to an effective decision support.

3.8. Decision support

3.8.1. Decision support as structuring the decision space

The conventional approach to decision support in GIS-MCA follows a model, under which a spatial decision support system (SDSS) is developed and deployed to organize the decision space by identifying feasible (meeting all salient constraints) decision alternatives and systematically evaluating their performance. Hence, the essence of decision support lies in assisting and not necessarily in recommending a choice. This approach is justifiable for high stake situations characteristic of institutional decision-making environment, in which political context and other intangibles often limit the role of SDSS to structuring a complex decision space. Typical structural elements of decision space include objectives, criteria, alternatives and trade-offs.

3.8.2. Decision support as choice recommendation

An alternative approach to spatial decision support has recently emerged as a result of growing data accumulation about personal choices and choice object characteristics. Under this model, choices that are made by individuals (not agencies) on a frequent rather than infrequent bases, are typically low-stake in comparison with institutional choices. SMCA can be used in this approach for recommending the 'best alternative' (multicriteria *recommender* systems) rather than supporting decision-making process (multicriteria *decision support* systems).

MCA-based systems for recommending spatially explicit points of interest (POI) (Liu *et al*. 2013, Lyu *et al*. 2019) offer a personalized decision support by taking advantage of big data created by millions of users accessing online services such as Yelp or Instagram. By accessing information on specific POIs such as restaurants, shops, service providers, etc., users effectively reveal their preferences instead of stating them through value judgements, which is the traditional way of eliciting the decision-maker/stakeholder preferences. The preferences revealed through the user check-in frequencies can be leveraged to develop personalized preference profiles useful in making POI choice recommendations on individual bases. A recent example of MCA-based recommending system is the work of Lyu *et al*. (2019). The system integrates user preferences for geographical location, POI category and POI's attributes, which are treated as three top-level criteria. Limiting spatially explicit criteria to location only is a shortcoming of the system. A potentially promising research direction is the exploration of spatial relations, such as proximity and inclusion (e.g. inclusion in a specific geographical zone of interest), as additional spatially explicit criteria (Mazumdar *et al*. 2018). One of the challenges in MCA-based recommending systems is how to keep updating criterion preferences in light of changing user experiences, trends and influences exerted by ever-evolving popular culture. To this extent, Bayesian updating new knowledge on the relevance of salient criteria affecting people's choices might be a promising approach.

3.9. Visualization

3.9.1. Visualization of multicriteria problem structure and solution

A hallmark of GIS-MCA from its early days has been the integration of maps, afforded by GIS, with MCA data processing. Typically, maps represent criteria and their spatial distributions (aka spatial variables), locations of alternatives (e.g. sites) and MCA results (e.g. locations of rank-ordered alternatives). Choropleth maps and raster-based surfaces, used in early GIS-MCA visualization, were extended into interactive visualizations by linking maps with graphs and tables (Andrienko and Andrienko 1999), which in turn afforded simultaneous visual exploration of criterion and decision spaces (Jankowski *et al*. 2001).

A criterion space in GIS-MCA encompasses criterion values and their ranges that can be easily obtained by taking max and min values from a column in a GIS attribute table. In a similar fashion, a decision space representing alternatives and their criteria-based characteristics can be constructed by taking the attribute values from table's row. The visual exploration of both data spaces contributes to understanding patterns and relationships among the criteria and alternatives and hence, supports understanding of the decision problem structure. Tools that can be used to explore both criterion and decision spaces include parallel coordinate plots, unclassified and classified choropleth maps, dynamic map query, bi-variate maps and multiple maps with pie-, bar- and column charts (Andrienko and Andrienko 2006).

Similar to exploring problem structure, the results of SMCA can be visually explored and analysed. By employing a bivariate map, the overall estimate of decision alternative's performance and the uncertainty of the estimate, quantified by mean alternative rank and its variance, can be simultaneously visualized and contextualized by the distribution pattern of mean ranks and their variances. A different, but complementary visualization of SMCA results can be achieved by a pie chart map, in which the pie size reflects the position of a given alternative in the rank order, and the pie wedges representing the evaluation criteria are scaled to reflect the weighted contribution of each criterion to the overall performance of alternative.

3.9.2. Towards geo-visual analytics in SMCA

The visual-analytic capabilities described above are aimed at developing a situational awareness in a decision problem, which roughly follows a sequence of steps comprised of (i) perception of structural elements comprising the decision problem, (ii) comprehension of relationships between the structural elements, and (iii) projection of the hierarchy among choice alternatives (Luo and MacEachren 2014). While the visual exploratory techniques described above can support the first step, there is a need to develop effective visualization techniques and tools to support steps two and three. Such techniques and tools could focus, for example, on visual analysis of trade-offs among the evaluation criteria, visualization of uncertainty and sensitivity analysis results (see Section 3.7.2), and visual exploration of what-if scenarios.

In charting future research directions for geo-visual exploratory techniques for SMCA, it is worth acknowledging that decision-makers frequently have reasons to keep certain decision criteria implicit (Andrienko *et al*. 2007). Hence, the decision support approach requiring the complete knowledge of problem structure is unlikely to succeed. Given that tacit criteria are common in decision processes, future techniques and tools should allow the flexibility in introducing such criteria and their values into SMCA and exploring their impacts on the suitability assessment of each alternative.

4. Conclusion

This paper has examined the shift in paradigm from spatially implicit to spatially explicit multicriteria analysis. It has identified the emerging trends and research frontiers and pointed out the challenges that come along with the development of spatially explicit approaches to GIS-MCA. Presented herein the analysis of the changing paradigm has allowed us to identify key research directions with opportunities for advancements. We have argued that the future development of GIS-MCA can be organized around a series of moves from the currently prevalent practices to new approaches for advancing spatially explicit MCA. More specifically, we have proposed ways of moving towards spatially explicit MCA by modifying/augmenting existing approaches or developing new methods for spatial problem structuring, combining geographic and preference data, estimating model parameters, defining contexts and spatial/time scales, dealing with uncertainties, supporting decision-making and geo-visualizing multicriteria spatial problems and solutions.

The research on integrating GIS and MCA is an example of how linking concepts and methods from two distinct fields (GIScience/GIS) and (Decision Science/MCA) can yield new approaches for analysing and solving complex spatial problems. We believe that advancing GIS-MCA requires more attention to the interdisciplinary character of GIS-MCA research. The process of merging traditionally distinct approaches calls for a tight collaboration among researchers and practitioners with different areas of expertise. We would therefore hope that the growth of interest in spatially explicit modelling will encourage more mutually beneficial interactions between GIS and MCA communities.

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Appendix: List of acronyms

AHP (Analytic Hierarchy Process)
ANP (Analytic Network Process)
ELECTRE (ELimination Et Choix TRaduisant la REalité)
GIS-MCA (GIS-based Multicriteria Analysis)
LMCA (Local Multicriteria Analysis)
MAUP (Modifiable Areal Unit Problem)
MCA (Multicriteria Analysis)
MCA-GVO (Multicriteria Analysis with Geographically Varying Outcomes)
MCE (Multicriteria Evaluation)
OAT (One-parameter-At-a-Time)
OWA (Ordered Weighted Averaging)
POI (Point of Interest)
PSM (Problem Structuring Method)
PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations)
RP (Reference Point)
SCA (Strategic Choice Approach)
SDSS (Spatial Decision Support System)
SMCA (Spatial Multicriteria Analysis)
SODA (Strategic Options Development and Analysis)
SSM (Soft Systems Methodology)
SWOT (Strengths, Weaknesses, Opportunities and Threats)
TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)
UA-SA (Uncertainty Analysis and Sensitivity Analysis)
VGI (Volunteered Geographic Information)
WLC (Weighted Linear Combination)