DOCTORAL THESIS NO. 13

Computational and Visual Tools for Geospatial Multi-Criteria Decision-Making

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UNIVERSITY
OF GÄVLE

Gävle University Press

Dissertation for the Degree of Doctor of Philosophy in Geospatial Information Science to be publicly defended on Tuesday 21 April 2020 at 10:00 in Room 13:111, University of Gävle.

External reviewer: Professor Gennady Andrienko, Fraunhofer Institute for Intelligent Analysis and Information Systems IAIS

Gävle University Press
ISBN 978-91-88145-44-4
ISBN 978-91-88145-45-1 (pdf)
urn:nbn:se:hig:diva-31928

Distribution:
University of Gävle
Faculty of Engineering and Sustainable Development
Department of Computer and Geospatial Sciences
SE-801 76 Gävle, Sweden
+46 26 64 85 00
www.hig.se

Svanenmärkt trycksak, 3041 0736 Kph Trycksaksbolaget 2018

Abstract

Geospatial multi-criteria decision-making usually concerns quasi-continuous choice models, with the number of alternatives constrained only by the limits of the used representation model. This sets high demands on the decision-making methods used in the context. The most commonly used approach in geospatial decision-making is combining a method for assigning criteria weights with an aggregation method. As pairwise comparison of alternatives is not feasible when the number of alternatives is large, the weights are usually assigned to criteria without considering the values or the value ranges of the alternatives, an approach often criticized in the decision analysis literature. Apart from criteria weighting controversy, this approach does not allow for advanced use of interactive visualization in the choice phase of the decision-making process. In this thesis, two alternative methods for geospatial decision-making based on the *even swaps* method are developed. The first method relies on automation of swaps, which makes this method viable for decision problems with any number of alternatives. The second method emanates from the findings of behavioral decision theory, and combines even swaps with reduction of large data sets through *quasi-satisficing*, allowing for efficient use of interactive visualization in the choice phase of the decision process. Visualization frameworks for both methods are also developed in the thesis. They include both geo-specific representations, such as interactive maps, and information visualization techniques such as graphs, diagrams, scatterplots and parallel coordinates. Two studies concerning the impact of interactive visualization on decision-making are presented in the thesis: a study concerning the impact of interactive visualization on geospatial decision-making, and a study concerning potential effects of *visual saliency* on decision-making. The results of the first study indicate positive effects of interactive visualization on coherency and consistency in performing trade-offs. The results of the second study suggest that saliency can increase attention and decision quality in MCDM for certain visualization techniques and forms of saliency. The work presented in this thesis contributes to method development and the use of interactive visualization in the context of geospatial decision-making.

Keywords: geographic information systems, multi-criteria decision-making, interactive visualization, even swaps

Sammanfattning

Multikriterieanalys i geospatialt kontext avser oftast kvasi-kontinuerliga valmodeller, där antal alternativ endast definieras av gränserna av den använda representationsmodellen. Detta ställer höga krav på beslutsmetoder som används i geospatialt sammanhang. Den ansats som oftast används är att kombinera någon kriterieviktningsmetod med en aggregeringsmetod. Eftersom det är orimlig att utföra parvisa jämförelser av alternativ när antalet alternativ är stort, bestäms oftast kriterievikter utan att hänsyn tas till de faktiska värdena, eller värdeintervallen – ett angreppssätt som ofta kritiserats i litteratur inom beslutsanalys. Detta angreppsätt gör det även svårt att använda avancerade interaktiva visualiseringar i beslutsfasen av beslutsprocessen. I denna avhandling har två alternativa metoder, baserade på *even swaps,* utvecklats för geospatial beslutsanalys. Den första metoden baseras på automatisering av swaps, vilket gör den tillämpbar på beslutsproblem oavsett antal alternativ. Den andra metoden utgår från behavioristiska beslutsteorier och kombinerar even swaps med reducering av stora datamängder genom s.k. *quasi-satisficing*. Båda metoderna är interaktiva, vilket gör dem lämpliga för effektiv användning av interaktiva visualiseringar i beslutsfasen av beslutsprocessen. I denna avhandling har också visualiseringsramverk för de båda metoderna utvecklats. De inkluderar både geo-specifika representationer, dvs. interaktiva kartor, och visualiseringar i form av bl. a. diagram, spridningsdiagram och parallella koordinater. I avhandlingen presenteras två studier om effekten av interaktiv visualisering på beslutsfattande: en studie om effekten av interaktiv visualisering på beslutsfattande i geospatial kontext, och en studie om effekter av *visual saliency* på beslutsfattande. Resultaten av den första studien indikerar att interaktiv visualisering kan hjälpa beslutsfattaren göra mer koherenta och mer konsekventa avvägningar. Den andra studien indikerar att visual saliency kan ha positiv effekt och hjälpa beslutsfattaren att fatta bättre beslut. Forskningen presenterad i denna avhandling bidrar till utvecklingen av nya beslutsmetoder och effektiv användning av interaktiv visualisering inom geospatial beslutsanalys.

Nyckelord: geografiska informationssystem, multikriterieanalys, interaktiv visualisering, even swaps

List of Papers

This thesis is based on the following papers, which are referred to in the text by Roman numerals.

Paper I
Milutinović, G., Ahonen-Jonnarth, U., and Seipel, S. (2018). GISwaps: A New Method for Decision Making in Continuous Choice Models Based on Even Swaps. *International Journal of Decision Support Systems Technology*, 10 (3), 57-78.

Paper II
Milutinović, G. and Seipel, S. (2018). Visual GISwaps – An Interactive Visualization Framework for Geospatial Decision Making. In: D. Bechmann, A.P. Cláudio and J. Braz, eds. *Proceedings of the 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*. SCITEPRESS.

Paper III
Milutinović, G., Ahonen-Jonnarth, U., Seipel, S., and Brandt, A. (2019). The impact of interactive visualization on trade-off-based geospatial decision-making. *International Journal of Geographical Information Science*, 33:10, 2094-2123, DOI: 10.1080/13658816.2019.1613547

Paper IV
Milutinović, G., Seipel, S., and Ahonen-Jonnarth, U. (manuscript). Geospatial decision-making framework based on the concept of quasi-satisficing and even swaps.

Paper V
Milutinović, G., Ahonen-Jonnarth, U., and Seipel, S. (submitted). Does visual saliency affect decision-making?

Notes on contributions

Paper I

Milutinović conceptualized the method, designed and developed the prototype, and did the major part of writing. Ahonen-Jonnarth contributed with writing, comments and revision. Seipel contributed with comments and revision. Milutinović is the principal author of the paper.

Paper II

Milutinović designed and developed the prototype, and did the major part of writing. Seipel contributed with writing, comments and revision. Milutinović is the principal author of the paper.

Paper III

Milutinović planned and carried out user studies, analysed the data, and did the writing. Seipel and Ahonen-Jonnarth contributed with comments and revision. Brandt contributed with revision. Milutinović is the principal author of the paper.

Paper IV

The method and the visual framework were jointly designed by Milutinovic and Seipel. Milutinović designed and developed the prototype, and did the writing. Seipel and Ahonen-Jonnarth contributed with comments, suggestions and revision. Milutinović is the principal author of the paper.

Paper V

Milutinović participated in planning and carried out user studies, participated in data analysis, and did major part of writing. Ahonen-Jonnarth and Seipel contributed with writing, comments, suggestions and revision. Seipel contributed with study design and data analysis. Milutinović is the principal author of the paper.

Acknowledgements

First and foremost, I would like to thank my supervisors, Prof. Stefan Seipel, Dr. Ulla Ahonen-Jonnarth and Assoc. prof. S. Anders Brandt for all the insightful comments and suggestions, and all the support they provided when I needed it the most. Their ability to find mistakes, inconsistencies and ambiguities in my reasoning was sometimes frustrating, but always welcome, and always helpful.

I would also like to thank Gunilla Mårtensson, faculty manager of the Faculty of Engineering and Sustainable Development, and Jonas Boustedt, head of the Department of Computer and Geospatial Science, for their support and understanding. A very special 'thank you' goes to Bengt Eriksson, former faculty manager of the Faculty of Engineering and Sustainable Development, for believing in me enough to grant me the opportunity to engage in doctoral studies. Thanks also to all my colleagues at the department, simply for being the best colleagues one could ever hope for. Special thanks to Magnus Hjelmblom, whose comments, made casually during a coffee break some years ago, came to shape the direction of my research.

My deepest thanks to Danny Popovich, who did a fantastic job proofreading paper III in this thesis.

It has always been difficult for me to be kind and to say "thank you" to those who deserve it the most. Maybe it's the Slavic gene, or maybe it's just me, I don't know. However, here I am – sitting quietly, hoping that all the 'thank-yous' I want to say to my family will somehow come from nowhere, that the words will in some mysterious way appear in the text without me actually writing them… but they never do. In my whole life I've experienced nothing but love and support from my family, and I wish to express, in my own inadequate words, my deepest love and gratitude to you all: my mother Dobrica – a poet with a beautiful heart, hurt one too many times; my late father Drago – a kind and understanding man, always trying his best not to show it, and always failing; my sister Sanja, whom I love as only a brother can love a sister; my beautiful daughter Ena – a rebellious angel who can never even come close to understanding how much I love her and how much she means to me… zlato tajino; and finally my love Sanja who, some thirty years ago, patiently picked up pieces of me scattered all across the streets of Sarajevo, put them back together, and has been holding them together ever since. Sanja, I know that the last four years have been as tough on you as they have on me, and I admire you for being able to cope with me during that time (actually, I admire you for being able to cope with me, period!, but that's a whole another book). And, just in case you're wondering: yes, I do love you.

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1 Introduction

Making a decision, any decision, is hard. We need to carefully define our objective(s) – what we want to achieve. We need to decide on minimum conditions that an alternative needs to meet in order to be considered, and discard the ones that do not meet those conditions. Then we need to decide on which criteria we will base our decision – which aspects of the available alternatives are important to us. The next step is to analyze the alternatives and see how well each alternative performs in terms of each of the aspects, i.e. what are the consequences of each of the alternatives. In the best of all possible worlds, there will be an obvious choice, an alternative which is superior to all other alternatives on every aspect. This, however, rarely happens, and if it does, then we are not really making a decision – we are simply finding the best alternative. In reality, we will probably need to choose one amongst a number of alternatives, none of which is superior to all the others on every aspect. In order to do that, we will need to make trade-offs, i.e. to decide how much we are ready to give up on one aspect in order to achieve more in terms of another (Hammond, Keeney, and Raiffa, 1999). The more alternatives and aspects we need to consider, the harder it is to make a decision… and even harder to make a *good* decision. And that does not even include the issue of uncertainty, when the consequences of alternatives are not known in advance. Thankfully, there are a number of methods, techniques and tools which can provide support for decision-making.

When it comes to spatial decisions, supporting methods and techniques are usually integrated in tools referred to as *geographic information systems* (GIS). The ultimate goal of geographic information systems is to provide support for making geospatial decisions. For the last couple of decades there has been a growing interest in the subject of integrating multi-criteria decision-making (MCDM) with GIS. The need to address the all-important issue of applying the established concepts of multi-criteria decision-making to spatial problems and adapting them with respect to the nature and the format of GIS data has resulted in a whole new interdisciplinary field of study. There is a vibrant community within the field conducting research related to a number of application areas, such as environment, transportation, urban planning, waste management, hydrology, agriculture, forestry etc.

Malczewski and Rinner (2015) define GIS-based multi-criteria decision analysis (GIS-MCDA) as *"... a collection of methods and tools for transforming and combining geographic data and preferences (value judgments) to obtain information for decision making*", where the central task is evaluating a set of alternatives in terms of a number of conflicting criteria (Zavadskas, Turskis, and Kildienė, 2014). Virtually all MCDM methods can be applied to spatial problems. That does not mean that any MCDM method can be applied to any spatial problem, though. The method-related research within the field has shown that different MCDM methods often are inconsistent and tend to yield different results for the same decision problem, which makes the choice of method itself a source of uncertainty (Greene, Devillers, Luther, and Eddy, 2011). There are a number of factors that may affect the choice of the method for a particular spatial problem, such as uncertainty, number of alternatives, measurement scales, computational requirements and capacities, number of objectives, the type of criteria used to rank the alternatives, and last but not the least, the decision maker's acquaintance with available tools. It is, however, important to emphasize that regardless of which method we choose for a particular decision problem, it is not aimed to solve it for us, but simply to help us make the best possible choice, based on our knowledge and preferences. It is therefore of great importance that these methods are designed in such a manner that a user's preferences can be expressed and quantified in an intuitive and transparent way.

1.1 Problem definition

Geospatial multi-criteria decision-analysis is based on three main concepts: criteria weighting, value scaling (standardization) and combination rule (Malczewski and Rinner, 2015). A random search of literature shows that the majority of both theoretical and applied research on GIS-MCDM focuses on a limited number of methods, such as *Weighted Linear Combination* (WLC) and *Analytic Hierarchy Process* (AHP), which deploy these concepts. Although this approach is well established and accepted, it is not uncontroversial. Geospatial multi-criteria decision-making usually concerns quasi-continuous choice models, where the number of alternatives is only constrained by the limits of the used data representation model. For large sets of thousands or even millions of alternatives, it is not feasible to perform pairwise comparison of alternatives, as it would require $\sum_{i=1}^{n-1} i$ comparisons for *n* alternatives. In such conditions, criteria weighting, i.e. the decision maker's estimate of relative importance of criteria, is often done without taking into account the values of the alternatives. The rationality of comparing the importance of different criteria without considering the actual degree of variation among the consequences of the alternatives under consideration may be questioned (Hammond, Keeney, and Raiffa, 1998; Keeney, 2013; Korhonen, Silvennoinen, Wallenius, and Öörni, 2013). Suppose that a person wants to book a hotel room and decides that, for him or her, price is more important than size. Assuming that there are two rooms between which the person needs to choose: room A with the size of 12 m^2 at a price of $85, and room B with the size of 22 m^2 at a price of $90, and that they are equal on all other criteria, what would be the rational choice? Obviously, most people would agree that it would be room B, since we get a nice, large enough room instead of extremely small room for only five dollar in price increase. If so, then – what is the meaning of a priori deciding that price is more important than size?

Another important aspect of GIS-MCDM is the use of interactive visualization. Andrienko and Andrienko (2003) point out that, while visualization plays an important role in the initial phase of the decision-making process, it has rather limited use in the choice phase. GIS decision-making would certainly benefit from more extensive use of visualization and interaction even during the decision process itself, i.e. during making the actual choices. In order to decide whether or not a trade-off to be made is feasible or admissible, the decision maker needs to see how an option is positioned in both the geographical and the attribute space, as well as how it compares to other options (Andrienko and Andrienko, 2003). Limited use of visualization in the choice-phase in geospatial decision-making is in part related to the choice of multi-criteria decision-making methods used in GIS-MCDM. This phase of the decision-making process in GIS context is most commonly performed using some weighting method to derive the weights associated with attribute map layers, and some compensatory aggregation method to obtain the score for each alternative in the set. This non-interactive approach leaves the decision maker with little or no control over the score calculation once the criteria weights have been set, and the role of visualization is thus reduced to presenting the final results of the computations.

1.2 Objectives

The objectives of this study are threefold. The first objective is to develop methods for geospatial multi-criteria decision-making which will not be based on the assessment of relative importance of criteria through criteria weighting. The second objective is to design and develop interactive visualization frameworks based on the developed methods, that will offer interaction opportunities in the choice-phase of a decision-making process. The third objective is to evaluate the impact of interactive visualization on geospatial decision-making. In order to meet the objectives, the following questions will be addressed:

1. How can trade-off methods, which do not utilize criteria weighting, be adapted, in order to be applicable to spatial multi-criteria decision problems with large number of alternatives?
2. How can findings of behavioral decision theories and the concept of satisficing facilitate the GIS-MCDM method development?
3. How can interactive visualization be used during the choice phase of a decision-making process?
4. What is the impact of the form of visual representation on decision-making?
5. How can interactive visual decision support systems be evaluated? What are the important evaluation issues, and how should they be handled?

1.3 Scope and limitations

The most commonly accepted generalization of the decision-making process is suggested by Simon (1960), with *intelligence, design* and *choice* as three major phases. During the intelligence phase, a problem or a situation that calls for a decision is identified and formulated. This phase involves data collection, exploration and pre-processing. The alternatives, or the set of possible solutions, are defined in the design phase. Finally, in the choice phase, the alternatives are evaluated and the most appropriate alternative or set of alternatives is selected. The work presented in this thesis concentrates on the choice phase of the decision-making process.

Multi-criteria decision-making is often classified as either multi-attribute decision-making (MADM) or multi-objective decision-making (MODM). A comparison between MADM and MODM decision problems with respect to the relevant factors is suggested in Malczewski (1999) (c.f. Table 1, p. 7). In this comparison, MODM is considered to be applied to decision problems concerning infinite or large number of alternatives, and MADM should be applied to problems concerning small number of alternatives. This distinction is most common (Greene et al., 2011; Malczewski, 1999; Tavana, Khalili-Damghani, and Abtahi, 2013). Another, more strict view, is that MODM deals with the design process rather than concrete alternatives; the predefined set of alternatives is non-existent and the number of alternatives is continuous, or infinite (Zavadskas et al., 2014). In this thesis, the term multi-attribute decision-making is used for any decision situation where the number of alternatives is discrete, regardless of whether it is small, moderate or large. The term multi-objective decision-making is used for decision situations with no predefined set of alternatives. The work presented in this thesis concerns multi-attribute decision-making in quasi-continuous choice models. This term is used to describe the type of decision problems where the outcome space, though conceptually containing an infinite number of alternatives, is constrained by the resolution limits of the used data representation model, making the number of alternatives in fact finite. Multi-objective decision-making, as well as MODM-related methods such as goal programming, compromise programming or reference point method, are outside the scope of this thesis.

2 Theoretical background

Research in the field of geospatial decision-analysis is, almost by definition, interdisciplinary. It usually has its starting point in general decision-making concepts and methods, and relates them in some way to geographical context. Whether it concerns development of new methods, or analysis and adjustments of existing methods, or simply some specific application of generic methods in the GIS context, it will rely on both decision analysis and geographical information science. The research presented in this thesis does indeed fall into these categories, but it also includes a third important topic, namely data visualization. In this chapter, theoretical concepts and methods of importance for the research related to each of the three disciplines are presented and explained. Section 2.1 is a short introduction to decision analysis and multi-criteria decision-making. A brief introduction to behavioral decision-making is given in Section 2.2. The concepts of GIS-MCDM which are important for this research are presented in Section 2.3, and Section 2.4 covers relevant aspects of visualization in GIS.

2.1 Multi-criteria decision-analysis

The objective of decision analysis is to help a decision-maker analyze a specific problem, including the overall structure of the problem, as well as his/her preferences and beliefs (Clemen and Reilly, 2014). A more philosophical definition of the term decision analysis, given in Howard (1968), defines it as *"... a term that describes a combination of philosophy, methodology, practice, and application useful in the formal introduction of logic and preferences to the decisions of the world.*". This paradigm of decision analysis was in Keeney and Raiffa (1976) summarized in a five-step process:

1. *Preanalysis*. In this step, the decision-maker identifies the problem and detects viable alternatives.
2. *Structural analysis*. In this step, the decision-maker creates a decision tree to structure the qualitative anatomy of the problem: what are the choices, how they differ, what experiments can be performed, what can be learned.
3. *Uncertainty analysis*. The decision-maker assigns probabilities to the branches emanating from chance nodes.
4. *Utility or value analysis*. The decision-maker assigns utility values to consequences (alternatives) associated with paths through the tree.
5. *Optimization analysis*. The decision-maker calculates the optimal strategy, i.e. the strategy that maximizes expected utility.

Making a decision may be relatively easy, if it entails making a choice between a small number of options, considering only one aspect, or attribute. However, such a scenario is not really a decision scenario. Suppose that you are one of very few people in the world that can afford to buy a new car considering nothing but the maximum speed. Do you need to make a decision which car to buy? Obviously not – you just need to know which car is currently the fastest, and that is the car you will buy… or decide not to buy, in which case you do make a decision. For most of us, deciding which car to buy would not be as easy. We would need to choose between a number of alternatives, considering at least price, size, and fuel consumption. In short, we would have to take into consideration *multiple criteria*, and as none of the cars is best in all considered aspects, we would need to make some *trade-offs* in order to decide which of the cars best suits our needs. We would have to perform a multi-criteria decision task.

According to Hammond et al. (1999), the following five elements can be considered the core elements of any multi-criteria decision problem: *problem, objectives, alternatives, consequences, and trade-offs*. A list of important elements suggested in Po-lung (1985) consists of four elements: the set of *alternatives*, the set of *criteria*, the *outcome* of each choice (consequences), and the *preferences* of the decision maker (trade-offs). Notably, Hammond et al. (1999) do not include criteria, but do include objectives, while Po-lung includes criteria, but not problem and objectives. The exclusion of any of the three mentioned elements may be unjustified. Defining and structuring the problem is an important first step of every decision process. Furthermore, defining criteria is the prerequisite for a successful evaluation of the alternatives. Finally, defining criteria without first establishing what the objectives are is both counter-intuitive and unreliable. Consequently, the list of core elements relevant for multi-criteria decision-making should include all suggested elements from both lists combined: *problem, objectives, criteria, alternatives, consequences, and trade-offs*.

The classification of multi-criteria decision-making as either multi-attribute or multi-objective is based on the nature of the set of considered alternatives, or the number of alternatives to be considered. This topic is covered in the next section.

2.1.1 Multi-attribute vs. multi-objective decision-making

Multi-criteria decision-making is often classified as either multi-attribute decision-making (MADM) or multi-objective decision-making (MODM). While generally accepted, this distinction is not easily explained, and there is no universally accepted definition of the two types of MCDM. Colson and de Bruyn (1989) define MADM as *"...concerned with choice from a moderate/small size set of discrete actions (feasible alternatives)"* and MODM is defined as the method that *"...deals with the problem of design (finding a Pareto-optimal solution) in a feasible solution space bounded by the set of constraints."*. A similar view is expressed in Zavadskas et al. (2014). According to this view, while MADM assumes a finite set of alternatives, MODM deals with design process rather than concrete alternatives; the predefined set of alternatives is non-existent and the number of alternatives is continuous, or infinite (Zavadskas et al., 2014). A different view on the distinction between MADM and MODM does not pose the same requirements regarding alternatives. From the comparison of decision problems in Malczewski (1999) (see Table 1), it appears that the author sees the size of a set of alternatives, rather than whether it is discrete or not, as one of the criteria for the distinction. This distinction is most common (Greene et al., 2011; Malczewski, 1999; Tavana et al., 2013). This lack of a commonly accepted definition of the distinction between MADM and MODM may be caused by the lack of commonly accepted definitions of the terms *objective* and *attribute*, and the distinction between the two. Indeed, there is no universally accepted definition of the terms. The MADM – MODM distinction implies that both objectives and attributes are types of criteria, which is a generic term. Keeney and Raiffa (1976) see objectives as indicators of direction – minimize cost, maximize comfort, etc., while attributes are measurable descriptions associated with objectives – dollars, comfort factor, etc. However, they do not use the term criterion as a generic term, but rather as a synonym for the term attribute. Indeed, the terms attribute and criterion are often used interchangeably, and they are used interchangeably also in this thesis.

Table 1: A comparison between MADM and MODM decision problems in Malczewski (1999)

	MODM	**MADM**
Criteria defined by:	Objectives	Attributes
Objectives defined:	Explicitly	Implicitly
Attributes defined:	Implicitly	Explicitly
Constraints defined:	Explicitly	Implicitly
Alternatives defined:	Implicitly	Explicitly
Number of alternatives:	Infinite (large)	Finite (small)
Decision-maker’s control:	Significant	Limited
Decision modelling paradigm:	Process-oriented	Outcome-oriented
Relevant to:	Design/search	Evaluation/choice

2.1.2 MCDM methods

The distinction between MADM and MODM is the basis for the most common classification of decision-making methods. MADM methods concern decision-making with discrete number of alternatives, while MODM methods facilitate decision-making in a continuous domain (infinite number of alternatives). Different classifications of MADM methods have been suggested. One of the first attempts to make an extensive classification of MCDM methods was presented in Hwang and Yoon (1981), who grouped different methods based on the information available to the decision-maker (no information, information about criteria, information of alternatives). Greene et al. (2011) classify decision-making methods in six groups: compensatory methods, non-compensatory aggregation methods, weighting methods, outranking aggregation methods, mathematical programming methods, and heuristic methods, whereas Carlsson and Fullér (1996) suggested four distinct classes of decision-making methods: outranking methods, methods based on the value and utility theory, multiple objective programming methods, and group decision and negotiation theory based methods.

There are a large number of decision-support methods available, and deciding which method is most suitable for a particular decision problem may in itself be considered a decision-making problem. An overview of all commonly used decision-making methods regardless the application area is beyond the scope of this thesis. However, two methods are, for different reasons, particularly important for the work presented in the thesis: *Analytic Hierarchy Process* (AHP), which is subjected to criticism in the articles included in this thesis, and *even swaps*, on which the methods presented in this thesis are based. Even swaps is presented in this section, and AHP is covered in Section 2.2 which includes an overview of the methods most commonly used in the context of geo-spatial decision-making.

Even swaps

One of the difficulties related to MCDM is comparison of criteria that are measured using different scales, for example metric and monetary scale. In even swaps, this issue is not considered a problem, but rather the main strength of the method. The decision maker is encouraged to think about the value of one criterion in terms of another, and this approach provides a practical way of making trade-offs among any set of criteria across a range of alternatives (Hammond et al., 1998). The main principle of even swaps is adjusting the consequences of considered alternatives in order to render them equivalent in terms of a chosen criterion. When all alternatives have the same value on a certain criterion, that criterion becomes irrelevant for further analysis and can be cancelled out. In Hammond et al. (1999), the method is defined by the following five steps:

1. Determine the change necessary to cancel out criterion R (reference).
2. Assess what adjustments need to be done in another criterion, M (response), in order to compensate for the needed change.
3. Make the even swap. An even swap is a process of increasing the value of an alternative in terms of one criterion and decreasing the value by an equivalent amount in terms of another. After the swaps are performed over the whole range of alternatives, all alternatives will have the same value on R and it can be cancelled out as irrelevant in the process of ranking the alternatives.
4. Cancel out the now-irrelevant criterion R.
5. Eliminate the dominated alternative(s). Alternative *a* is said to be dominated by alternative *b* if it is inferior to *b* on at least one criterion and not superior to *b* on any of the criteria.

These steps are repeated until a single alternative remains. The process is explained in the following example:

John plans for a short vacation, and he needs to choose one among four available hotels. John is only interested in price, room size, and distance from city center. The values of considered hotels in terms of the considered criteria are given in Table 2.

Table 2: Vacation problem; initial state

	A	**B**	**C**	**D**
Price ($)	105	110	100	115
Room size (m^2)	14	18	16	26
Distance (km)	3.5	0.8	5.2	1.2

John decides to use room size as the reference criterion, compensating on price. For John, increasing the room size from 14 m^2 to 26 m^2 is worth increasing the price from 105$ to 135$, increasing the room size from 18 m^2 to 26 m^2 is worth increasing the price from 110$ to 130$, and increasing the room size from 16 m^2 to 26 m^2 is worth increasing the price from 100$ to 120$ (Table 3).

Table 3: Vacation problem; adjustments have been made on room size, and compensation values have been assigned on price.

	A	**B**	**C**	**D**
Price ($)	~~105~~ 135	~~110~~ 130	~~100~~ 120	115
Room size (m^2)	~~14~~ 26	~~18~~ 26	~~16~~ 26	26
Distance (km)	3.5	0.8	5.2	1.2

Now that all four alternatives have the same value on room size, room size can be cancelled out from further analysis. Furthermore, alternatives A and C are now dominated by alternative D, and can be discarded. John continues using distance as the reference, compensating on price. For John, decreasing the distance from 1.2 km to 0.8 km is worth increasing the price from 115$ to 125$ (Table 4).

Table 4: Vacation problem; dominated alternatives have been removed, adjustments made on distance, and compensation values assigned on price.

	B	**D**
Price ($)	130	~~115~~ 125
Distance (km)	0.8	~~1.2~~ 0.8

Now that both remaining alternatives have the same value in terms of distance, distance is cancelled out and John chooses hotel D, which has the best value (the lowest price) on the only remaining criterion, price (Table 5).

Table 5: Price is now the only remaining criterion, and the alternative with the best value, D, is chosen.

	B	D
Price	130	**125**

A number of enhancements of the method, as well as new methods based on even swaps, were proposed in recent years (Bhattacharjya and Kephart, 2014; Dereli and Altun, 2012; Elahi and Yu, 2009; Li and Ma, 2008; Mustajoki and Hämäläinen, 2005, 2007). However, all referred methods, including even swaps, operate in discrete choice models, where the number of criteria and the number of alternatives are reasonably small.

2.2 Behavioral decision-making

When we talk about decision-making methods or models, we usually think of prescriptive models which tell us how we *should* make decisions, i.e. in which way we should work with a decision problem. Prescriptive methods offer support in making rational decisions, assuming that human behavior is rational and that the deciding subject always tries to make the optimal choice. In order for a choice to be considered rational according to these models, the deciding subject needs to perform complex analysis and computations. This notion of maximizing expected utility was questioned and criticized by many (Gigerenzer, 2001; Klein, 2001; Simon, 1955). In contrast to this assumption and proposed models of rational behavior based on it, Simon (1955; 1956) argues that, rather than trying to obtain the optimal outcome, we tend to perform a simpler decision-making process with *satisficing* as a stop rule. The process stops when "*a solution has been found that is good enough along all dimensions*" (Simon, 1979). The satisficing model is based on the concept of *bounded rationality*, as presented in Simon (1955). According to Simon, rationality can be bounded by a number of factors. Rationality is limited by imperfection of the actor's knowledge, which arises as a result of risk and uncertainty. Furthermore, it can be limited by the incomplete information about alternatives. Finally, it can be limited by complexity of the task which demands cognitive capabilities which the actor does not possess (Simon, 1972). The concept of satisficing as a model for behavioral decision-making has been evaluated in a number of studies (Agosto, 2002; Giegerenzer and Goldstein, 1996; Nakayama and Sawaragi, 1984; Zhu and Timmermans, 2011). The results showed that different implementations of the satisficing model matched, and in some cases even outperformed, more rational inference procedures.

Although Simon's theory of bounded rationality has been widely recognized, it seems to have had little influence on the development of decision-making models and methods. The development of prescriptive decision models and methods shifted the focus from theoretic concepts of decision-making towards algorithmic and computational aspects of modelling (Jankowski, 2018). Behavioral decision theory has been marginalized in prescriptive models, which often adopt a utility maximizing stance. This applies not least to spatial decision support systems and GIS where, despite the findings in the field of behavioral decision-making, the rational model of decision-making persisted as a theoretical construct used in normative models (Jankowski, 2018).

2.3 Geospatial multi-criteria decision-making

A geographic information system, or GIS, is a system used for collecting, storing, manipulating, analyzing and presenting geographic data (Borrough, McDonnell, and Lloyd, 2015; Malczewski, 1999; Malczewski and Rinner, 2015), with the ultimate goal to provide support for making spatial decisions. In its pure form, GIS offer limited support for decision-making, as they lack the capabilities to consider the decision-maker's preferences and value judgments, and decisions that may be generated are those based on purely spatial relationships. These capabilities may be enhanced by integrating MCDA in GIS (Malczewski and Rinner, 2015). This integration constitutes the framework for development of spatial decision support systems (SDSS) – interactive, computer-based systems designed to facilitate decision makers in solving semi-structured spatial decision problems (Malczewski, 1999). MCDA and GIS in an SDSS may be linked through either *loose* coupling, where two separate systems exchange files, or *tight* coupling, with different modules integrated into a single system with common user interface (Jankowski, 1995; Malczewski, 2006).

2.3.1 Basic concepts

GIS-based multi-criteria decision analysis (GIS-MCDA) includes geographical data and the decision-maker's preferences, as well as combination of data and preferences in accordance with specified decision rules (Malczewski, 2006a). It is based on three basic concepts: value scaling, criteria weighting and combination rules (Malczewski and Rinner, 2015). Value scaling is a process of standardizing raw data to comparable units, usually by the value function

$$v(a_k) = \frac{a_k - k_{min}}{k_{max} - k_{min}}$$

or

$$v(a_k) = 1 - \frac{a_k - k_{min}}{k_{max} - k_{min}}$$

if criterion k is of "the less, the better" type. Criteria weights are values which indicate the relative importance of criteria. It applies that, for n criteria,

$$\sum_{i=1}^{n} w_i = 1$$

where w_i is the weight of the i-th criterion. A combination rule, or decision rule, is a method for evaluating and ordering decision alternatives. In the context of GIS-MCDM, a combination rule is a rule which combines information and data about the alternatives with the decision-maker's preferences to produce the overall assessment of alternatives (Malczewski and Rinner, 2015). In Section 2.3.2, some of the most frequently used methods are presented.

2.3.2 GIS-MCDM methods

The most general classification of GIS-MCDM methods is a division into GIS-MADM and GIS-MODM methods. As multi-objective decision analysis is beyond the scope of this thesis, only the methods applied in multi-attribute decision-making are covered in this section. Weighted summation methods are covered in Section 2.3.2.1, ideal point methods in 2.3.2.2, outranking methods in Section 2.3.2.3, and AHP in Section 2.3.2.4.

2.3.2.1 Weighted summation methods

Combining a weighting method, most commonly AHP, and an aggregation method, is the most common approach in GIS decision-making (Drobne and Lisec, 2009; Eastman, Jin, Kyem, and Toledano, 1995; Malczewski, 2006b; Malczewski and Rinner, 2015; Shahabi, Keihanfard, Ahmad, and Amiri, 2014). It includes the following four steps:

1. Preparing criteria maps
2. Generating alternatives
3. Deciding relative importance of criteria
4. Creating the overall utility layer

This process is shown in Figure 1. In step 1, criterion maps are created. Each raster cell in a criterion map contains the value in terms of a given criterion for the geographic point referenced by the cell. In step 2, the alternatives which do not conform to previously defined constrains are discarded, and the values of the remaining alternatives are normalized over a common scale. In step 3, the criteria weights are assigned. The most often used method for assigning weights is AHP (see Section 2.3.2.4). Other weighting methods, such as ranking and rating, are also used, but far less frequently than AHP. Finally, the utility value $u(a)$ of each alternative a is calculated in step 4 through aggregation. Weighted linear combination (WLC) and boolean overlay operations are the most often deployed aggregation methods, as they are most intuitive and most straight-forward (Malczewski, 2004). In WLC, a total score for each alternative is obtained by multiplying the weight assigned to each criterion by the scaled value given to the alternative on that criterion, then summing the products over all attributes:

$$u(a) = \sum_{i=1}^{n} w_i * v(a_i)$$

where w_i is the weight of criterion i, and $v(a_i)$ is the scaled value of alternative a in terms of criterion i.

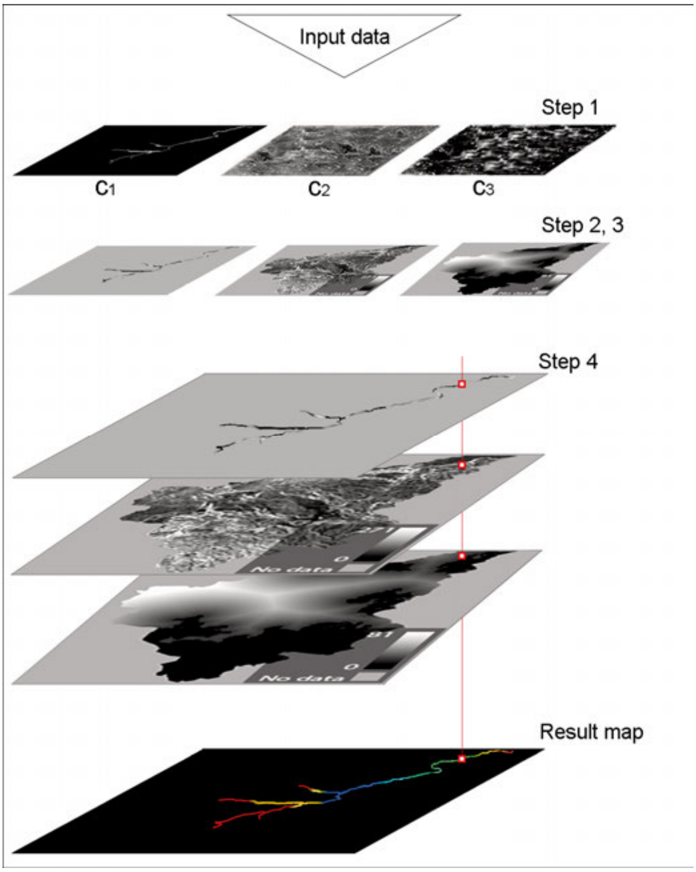

Figure 1: Four steps of weighted summation methods: preparing maps (Step 1), generating alternatives (Step 2), assigning criteria weights (Step 3), and creating overall utility layer (Step 4).

Another popular aggregation method is *ordered weighting averaging* (OWA) that uses a fuzzy approach based on Yager's work on ordered weighted aggregation operator (Jiang and Eastman, 2000; Yager, 1988). OWA extends the WLC model by introducing order weights. While criterion weights are assigned to the criteria and all alternatives are evaluated using the same weight on a certain criterion, order weights are associated with the criterion values on location-by-location basis (Malczewski, 2006a).

2.3.2.2 Ideal point methods

In ideal point methods, alternatives are evaluated through judging their multidimensional distance to a specific target, referred to as ideal point. The core of the ideal point methods lies in the intuitive concept that the chosen alternative should be as close as possible to the hypothetical alternative considered to be the best solution, and as far away as possible from the worst solution (Jankowski, 1995). This hypothetical ideal alternative, not feasible in general, provides the highest score in terms of each considered criterion (Zeleny, 1976). Ideal point methods differ mainly in the applied separation measures, i.e. the way in which they calculate the separation of an alternative to the ideal solution. However, regardless of the way in which this separation is calculated, the effectiveness of any ideal point method is largely dependent on the weighting method used to assign criteria weights – a problem which is often overlooked.

2.3.2.3 Outranking methods

Outranking methods are based on building a preference relation among alternatives on several attributes (Bouyssou, 2001). This relation is constructed through pairwise comparison of alternatives, usually applying the concordance-discordance principle, which states that an alternative *x* is not dominated by an alternative *y (xSy)* if *i)* a majority of the attributes supports this assertion, and *ii)* the opposition of the attributes which do not is not "too strong" (Bouyssou, 2001). The model of preferences, which is the basis of outranking methods, consists of three cases (Roy, 1991, 1996):

$a'Ia$: a' is indifferent to a
$a'Pa$: a' is strictly preferred to a
aPa': a is strictly preferred to a'

Apart from *indifference* and *strict preference*, this model implicates two more types of preferences, depending on hesitations we might have between two of the mentioned cases: *weak preference Q*, and *incomparability R*. Weak preference is the case where

$a'Qa$: either $a'Ia$ or $a'Pa$, but surely not aPa'
or
aQa': either $a'Ia$ or aPa', but surely not $a'Pa$

and incomparability is the case where

aRa': either $a'Pa$ or aPa'

This IPQR model constitutes the basis for ELECTRE (*Elimination EtChoix Traduisant la REalite* [ELimination and Choice Expressing REality]) – a family of multi-criteria decision-making methods based on outranking, first introduced in Benayoun, Roy, and Sussman (1966). Another popular outranking method is PROMETHEE (Preference Ranking Organization METHod for Enrichment of Evaluations), often used for group decision-making (Brans and Vincke, 1985; Brans, Vincke, and Mareschal, 1986). The method is often referred to as PROMETHEE-GAIA, as it is usually used with its descriptive complement GAIA (Geometrical Analysis for Interactive Aid) that allows the decision maker to visualize the main features of a decision problem.

Just as with weighted summation methods and ideal point method, the efficacy of outranking methods is effectively dependent on the efficacy of the applied criteria weighting method. In addition, applicability of outranking methods in the GIS context is limited by the computational issues emerging from the principal approach on which they are based – namely, pairwise comparisons of alternatives with respect to each criterion. For PROMETHEE, the number of comparisons equals $(m+1)(n+n^2)$, where m is the number of criteria, and n is the number of alternatives. For a GIS decision problem including ten criteria, and concerning a geographical area represented by a 200*200 raster where each of the 40 000 cells is processed as an unique alternative, it makes over 17 billion comparisons, which is obviously too computationally expensive (Malczewski & Rinner, 2015; Marinoni, 2006).

2.3.2.4 Analytic Hierarchy Process

Analytic Hierarchy Process is a widely used method for decision-making, developed by Thomas L. Saaty (Saaty, 1980). The method is defined in Saaty (2008) as *"... a theory of measurement through pairwise comparisons* [which] *relies on the judgements of experts to derive priority scales*" and described as a four-steps method. In step one, the problem and the type of knowledge required to solve it are defined. In step two, a decision problem is decomposed in a hierarchy with the overall goal at the top level, then objectives, criteria and alternatives. In step three, pairwise comparison matrices defining the relative importance (ranking) between the elements are constructed on each level. Finally, in step four, the final priorities of the alternatives are obtained by synthesis of priorities starting from the top level downwards. AHP relies on the fundamental scale for pairwise comparison (Saaty, 2008) presented in Table 6.

Table 6: AHP rating scale

Importance	**Definition**	**Explanation**
1	Equal importance	Two elements contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong importance	An activity is favored very strongly over another; its dominance is demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation

The priority scale is used to indicate how many times more important one element is compared with another. When comparing two elements, the dominated element obtains the reciprocal value of the favored element, and the obtained matrix is used to calculate the element weights. The weights of elements are calculated from the matrix containing the importance relation between each pair of elements. If the matrix is fully consistent, the weights can be obtained directly (see Table 7). If the comparison matrix is not consistent (see example in Table 8), the weights are calculated by the Eigenvalue method. Inconsistency is acceptable if the consistency ratio CR < 0.1. The consistency ratio is calculated as

$$CR = \frac{CI}{R_i}$$

where CI is consistency index for the matrix, calculated as

$$CI = \frac{\lambda_{(max)} - n}{n-1}$$

for n entries. R_i is the random consistency index, i.e. the consistency index of a randomly generated pairwise comparison matrix (Table 9), and $\lambda_{(max)}$ is the highest eigenvalue in the matrix.

Table 7: Elements A and B are equally important, A is two times more important than C, and three times less important than D; B is two times more important than C, and three times less important than D; C is six times less important than D. The matrix is consistent, and the weights can be calculated directly from the matrix.

	A	**B**	**C**	**D**	**Sum**	**Weight**
A	1	1	2	1/3	4.33	0.18
B	1	1	2	1/3	4.33	0.18
C	1/2	1/2	1	1/6	2.17	0.09
D	3	3	6	1	13	0.55
					23.83	1

Table 8: Elements A and B are equally important, A is two times more important than C, and three times less important than D; B is three times more important than C, and three times less important than D; C is four times less important than D. The matrix is not consistent, and the weights are calculated using the Eigenvalue method.

	A	**B**	**C**	**D**	**Sum**	**Weight**
A	1	1	2	1/3	4.33	0.19
B	1	1	3	1/3	5.33	0.21
C	1/2	1/3	1	1/4	2.08	0.09
D	3	3	4	1	11	0.51
					22.75	1

Table 9: Random inconsistency index for n = 1,…,9 proposed by Saaty (1980)

N	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The pairwise comparison matrix relies on subjective judgments of the decision-maker, and uncertainty that may have significant effect on the outcome is often associated with those judgments (Yang and Chen, 2004). Fuzzy AHP, i.e. AHP where the decision-maker's judgments are expressed in fuzzy numbers instead of crisp numbers (Laarhoven and Pedrycz, 1983), is often used in order to minimize the impact of uncertainty. Furthermore, fuzzifying AHP may moderate the rank reversal problem (Kordi and Brandt, 2011), i.e. the issue of the relative ranking of the criteria changing when criterion is added or deleted (Warren, 2004). Saaty himself, however, argued that judgments in AHP already are fuzzy, and that making them fuzzier can make the validity of the outcome worse (Saaty and Tran, 2007). Analytic Network Process (ANP) is another often used modification of AHP (Saaty, 1996). It aims to overcome the problems emanating from the underlying assumption of AHP that there is a dependency between elements of the hierarchical structure. Structuring the decision problem as a network consisting of clusters (components or levels) rather than a hierarchy allows for interaction and feedback both *within* clusters and *between* clusters (Malczewski and Rinner, 2015).

Notes on the use of AHP in GIS-MCDM

Being based on pairwise comparison of alternatives, AHP, just as the outranking methods, is not suitable for decision situations involving a large number of alternatives. However, AHP is the most often used method for exactly this kind of GIS-MCDM tasks, i.e. decision situations involving large raster-based datasets (Milutinovic et al., 2018). One of the most important features of the method, namely its hierarchical structure, is generally overlooked, and the method is in most cases limited to assigning the relative importance of criteria and deriving the criteria weights. But what does it actually mean that one criterion is more important than the other? If asked what is more important, health or wealth, most people would readily answer that health is definitely more important. However, if asked if they would pay ten million dollars for a pill that would make them never have a headache again, very few, if anyone, would answer that they would. It is just too much money for a relatively harmless condition. So can we say that, for those who would not pay for the pill, money is more important than health? Obviously not. Instead, we should question the rationality of comparing the importance of different objectives or criteria without considering the actual degree of variation among the consequences of the alternatives under consideration (Hammond et al., 1998; Keeney, 2013; Korhonen et al., 2013). With AHP, the comparison goes even further, as we even have to decide *how many times* more important one criterion is compared to another, without considering criteria value ranges. Let us use the same example as in Section 2.1.2 to demonstrate the inefficiency of this approach. The scenario and the information used in the example are repeated here, for readers' convenience.

John plans for a short vacation, and he needs to choose one among four available hotels. John is only interested in price, room size, and distance from city center. John decides that for him, price is two times more important than room size and three times more important than distance to city center, and room size is two times more important than distance to city center. The importance relations and obtained criteria weights are presented in Table 10.

Table 10: Assigned importance relations for the vacation example. Price is two times more important than room size, and three times more important than distance, and room size is twice as important as distance.

	Price	**Size**	**Distance**	**Weight**
Price ($)	1	2	3	0.53
Room size (m^2)	0.5	1	2	0.31
Distance (km)	0.33	0.5	1	0.16

The values of considered hotels in terms of the considered criteria are given in Table 11.

Table 11: The values in terms of price, room size and distance for hotels A, B, C and D in the vacation example.

	A	**B**	**C**	**D**
Price ($)	105	110	100	115
Room size (m^2)	14	18	16	26
Distance (km)	3.5	0.8	5.2	1.2

After normalizing the values in terms of different criteria to a common scale, we obtain values presented in Table 12.

Table 12: The scaled values for A, B, C and D in terms of price, room size and distance.

	A	**B**	**C**	**D**
Price ($)	0.67	0.33	1	0
Room size (m^2)	0	0.33	0.17	1
Distance (km)	0.39	1	0	0.9

The aggregated utility values for the alternatives are presented in Table 13.

Table 13: The aggregated utility values for hotels A, B, C and D, calculated for each hotel as the sum of products of criteria weights and scaled values of the alternative in terms of a given criterion.

	A	**B**	**C**	**D**
Price ($)	0.67*0.53	0.33*0.53	1*0.53	0*0.53
Room size (m^2)	0*0.31	0.33*0.31	0.17*0.31	1*0.31
Distance (km)	0.39*0.16	0.77*0.16	0*0.16	0.9*0.16
Utility	0.42	0.40	**0.58**	0.45

The alternative which you should choose, i.e. the alternative with the highest utility value, is alternative C. However, the most would agree that alternative D would be a better choice, as it is located 4 km closer to the city center than C, it is 10 m^2 larger than C, and it only costs 15$ more than C. Even alternative B would probably be a better choice. Now, if John had considered value ranges, he would have probably considered price to be far less important than size or distance, as the minimum price and the maximum price differ in only 15$, while the differences in terms of size and distance are much more relevant.

The remarks on the irrationality of assigning the importance to criteria without considering the actual alternatives can not be easily dismissed. One could argue that, for GIS-MCDM problems that involve large number of alternatives where AHP can not be applied as a complete method, assigning criteria weights would be better done using some weighting method which does consider criteria ranges, such as SWING weighting (Milutinovic, Ahonen-Jonnarth, and Seipel, 2019). However, AHP remains the *de facto* standard weighting method in GIS-MCDM.

2.4 Visualization and decision-making

This section covers visualization aspects relevant for multi-criteria decision-making. Section 2.4.1 contains a brief overview of some well known methods for visualization of multi-dimensional data. The issue of interaction is introduced in section 2.4.2, and the use of interactive visualization in geospatial decision-making is presented in section 2.4.3.

2.4.1 Visualization of multi-dimensional data

When applied to analysis, visualization usually involves manipulation of known data to find unknown relationships and answers (MacEachren and Kraak, 1997). That sets high demands on visual representation of multi-dimensional data, where relationships between different dimensions may easily remain hidden. Different multi-dimensional visualization techniques may be suitable for different tasks, depending on the type and the amount of data, and the number of dimensions. Keim and Kriegel (1996) classify visualizations of multi-dimensional data into six categories: *icon-based, hierarchical, graph-based, dynamic, pixel-oriented*, and *geometric projection.* Icon-based visualizations map data variables onto geometric (e.g. *star graphs*) and non-geometric (e.g. *Color Icons*) visual attributes (Nocke et al., 2005). While icon-based visualizations which use geometric mapping of visual attributes are primarily used to identify and compare data values, the second type allows for identification of trends and clusters in data (Nocke et al., 2005). However, icon-based visualizations are not suitable for visualization of large numbers of data items, and their capacity to visualize large number of dimensions is limited (Keim & Kriegel, 1996). Hierarchical methods are based on subdivision of the k-dimensional space and presenting the subspaces in a hierarchical fashion (Keim and Kriegel, 1996). These methods are primarily focused on visualization of multivariate functions (Keim & Kriegel, 1996). Graph-based techniques are based on the concept of presenting large graphs using query languages, abstraction techniques, and layout algorithms (Keim and Kriegel, 1996). In pixel based visualizations, the visual variables to express multiple attributes are colors defined by their perceptual dimensions hue, saturation, and lightness (Seipel and Lim, 2017). While these methods may not be the best choice for common multi-attribute choice tasks (Dimara, Bezerianos, and Dragicevic, 2018), they play a significant role in the geospatial context, where the number of data is usually very high. Dynamic methods (e.g. Ahlberg, Williamson, and

Shneiderman, 1992; Keim, Kriegel, and Seidl, 1994) use an interactive interface to dynamically query the database, visual representation of the database, and visual feedback of the search results. Geometric projection techniques aim to help the user to find interesting projections of data sets (Keim and Kriegel, 1996). Two of the most often used geometric projection techniques are *scatterplot matrices* and *parallel coordinates*. Scatterplots are often used method for representation of multidimensional data. However, the number of dimensions that can be represented by a scatterplot is rather limited. Even when employing spatial axes in three dimensions combined with other visual variables to represent additional data attributes, such as shape, color, or size, scatterplots still leave us with only a handful of dimensions that can be represented (Elmqvist, Dragicevic, and Fekete, 2008). Scatterplot matrices overcome this limitation. A scatterplot matrix decomposes the visualization of a multidimensional dataset into a 2D matrix layout that contains all pairwise comparisons between two variables in the dataset in form of 2D scatterplots (Figure 2). *Parallel coordinates* (Inselberg, 1985; Wegman, 1990) is another frequently used method for visualization and analysis of multivariate data. With parallel coordinates, each variable (attribute, criterion) is represented by an own axis, and the values are plotted as a series of lines connected across all axes (Figure 2). In Andrienko and Andrienko (2001) the authors applied the method on different types of data in order to test its suitability for different tasks. The list of tasks for which they found parallel coordinates suitable includes, among others, pairwise comparison of objects, comparison of value ranges of attributes (criteria), finding correlation between attributes and multi-criteria evaluation of alternatives.

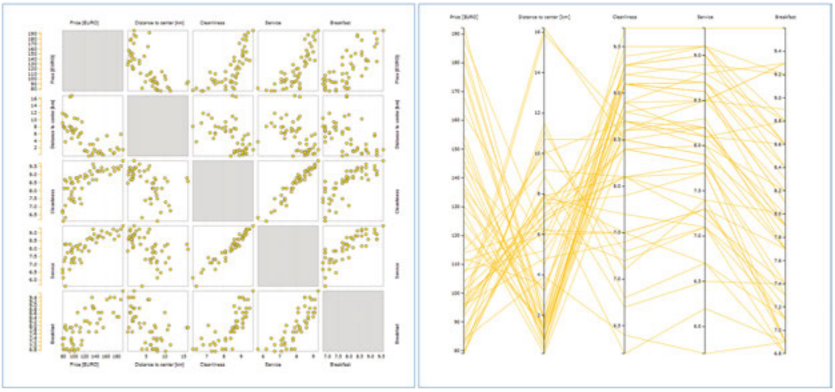

Figure 2: Scatterplot matrix (left) and parallel coordinates (right).

2.4.2 Interaction

The basic principle of interaction design was summarized in Shneiderman's *visual information seeking mantra*: overview first, zoom and filter, then details-on-demand (Shneiderman, 1996). Shneiderman coined the term *direct manipulation* for systems which offer continuous representation of the object of interest, physical actions instead of complex syntax, and rapid reversible operations with immediately visible impact on the object of interest

(Shneiderman, 1982, 1983). Interfaces based on the concept of direct manipulation should have the following properties (Shneiderman, 1982):

- Basic functionality is quickly learned by novices
- Experts can work rapidly, and define new functions and features
- Intermittent users can retain operational concept
- Error messages are seldom needed
- Results of users' actions are clearly shown, and users can easily change the direction if their actions are not leading towards their goal

Based partly on this concept, a number of different concepts, frameworks and guidelines concerning interaction design have emerged over the years. Keim et al. (2008) argued that interaction needs to be organized around the user's intent, rather than around the low-level interaction techniques provided by the system (Keim et al., 2008). Yi, Kang, Stasko, and Jacko (2007) proposed seven general categories of interaction techniques: select, explore, reconfigure, encode (alter the visual representation), abstract/elaborate, filter, and connect (highlight relationships between data items). Users' intent, as well as preferences and competence, are also important part of suggested guidelines for visualization recommendation systems suggested in Vartak, Huang, Siddiqui, Madden, and Parameswaran (2017). In an effort to tie together different interaction styles, Jacob et al. (2008) came up with the concept of *reality-based interaction*. While the authors consider the trend towards increasing reality based interaction a positive one, they point out that mimicking the real world should not be the sole objective. In order to make a useful interface, designers must find the balance between the power of their interface and its level of reality. The goal, however, should be to give up reality only in return for some other gains, such as expressive power, efficiency, versatility, ergonomics, accessibility, and practicality (Jacob et al., 2008).

2.4.3 Interactive visualization in GIS decision support systems

Interactive features of visualization frameworks integrated in geospatial decision support tools must meet high standards regarding efficiency and ease of use. Interface complexity, in combination with complexity of GIS datasets, often containing large amounts of high-dimensional data, may have a negative impact on decision-making, to the level where it influences decision outcomes even more than the decision problem complexity (Vincent et al., 2019). Simpler representation models may often lead to better results than more advanced cartographic models, as shown in Cheong et al. (2016). Similarly, Andrienko and Andrienko (2006) argued against the tendency to design generic systems that would cover the needs of many different users, which often results in complex systems which are hard to use. In recent years, there has indeed been a clear trend to develop task-specific decision support tools. A search[1] on Google Scholar for papers containing keywords "GIS decision support" in their title, published between 2014 and 2019, returned a list of 167 papers, reporting almost exclusively task-specific decision support systems. A review of the ten

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[1] Search performed on 03 February 2020

most cited papers from the list presenting decision support systems which include interactive visualizations highlights the two main points of this thesis. Seven out of ten presented support systems use some form of weighted summation for ranking of alternatives. Only the system presented in Rikalovic et al. (2018) uses a different approach, the adaptive neuro-fuzzy inference system (ANFIS). The system presented in Xia et al. (2014) uses AHP, probably combined with some aggregation method, although this is not clearly stated, and Kadiyala et al. (2015) fail to report on the used decision-making method. In terms of the use of visualization, all ten featured decision support systems deploy interactive visualization during the design phase of the decision process, and none of them makes use of interactive visualization during the choice phase (see Table 14).

Table 14: Use of interactive visualization in design phase and choice phase, respectively, in DSS presented in ten most cited papers reporting on visual decision support systems between 2014 and 2019.

DSS	**Visualization used**		**MCDM method**
	Design phase	Choice phase	
Stessens et al. (2017)	Yes	No	Weighted summation
Acutis et al. (2014)	Yes	No	Weighted summation
Mahmoud & Alazba (2015)	Yes	No	Weighted summation
Mondino et al. (2015)	Yes	No	Aggregation by ANN
Rikalovic et al. (2018)	Yes	No	Neuro-fuzzy (ANFIS)
Jayarathna et al. (2017)	Yes	No	Weighted summation
Kadiyala et al. (2015)	Yes	No	Not reported
Xia et al. (2014)	Yes	No	AHP (poorly reported)
Noorollahi et al. (2016)	Yes	No	Weighted summation
Latawiec et al. (2017)	Yes	No	Weighted summation

On this issue, V-Analytics is a rare exception among visual decision support tools. V-Analytics is a system for exploratory analysis of spatial and spatio-temporal data, evolved from Iris (Andrienko & Andrienko, 1997), Descartes (Andrienko & Andrienko, 1999), and later CommonGIS (Andrienko and Andrienko, 2003, 2004). It is a comprehensive visual analytics tool, designed in accordance with the concept of *sufficient minimum* which states that a system should be capable to recognize the minimum features and functions needed to analyze a specific data collection and simplify itself accordingly (Andrienko & Andrienko, 2006). It integrates a variety of visualization techniques, such as parallel coordinates, dot plots, frequency histograms, scatter plots and time graphs. The use of interactive visualization during the choice phase is achieved through the real-time update of the result map each time the decision-maker adjusts tolerance (Pareto set), criteria weights (WLC, OWA, Ideal point), or order weights (OWA). Notably, no weighting method is used for weight assignment. Instead, all considered criteria are assigned the same weight from the start. In the process, the weights can be adjusted explicitly one at the time, without option to select which criteria should be impacted by an adjustment.

Instead, every weight adjustment has impact on all criteria weights, which makes it difficult to assign desired weights.

Interactive maps, as means of exploration and support for decision-making, are a critical part of virtually every visual GIS decision support system today. The view that maps are aimed primarily for representation and communication, then dominant amongst cartographers, started to get challenged in the early nineties. MacEachren (1994) developed a concept of exploratory cartographic visualization, emphasizing *use* of visual displays. This concept was opposed to past communication-oriented view of maps as static media, the view which emphasized the extraction of specific information from maps. Instead, geo-info technologies which include maps should be oriented towards cognitive and decision-support functions (MacEachren and Kraak, 1997). In other words, maps should serve as aids for 'visual thinking', and this could be achieved through use of interactive techniques (Andrienko & Andrienko, 1999). The need for interactive cartographic representations that can effectively support spatiotemporal inference and decision-making increases with ever growing, rapidly changing data sets (Andrienko et al., 2014). Large data sets may require different approaches to visualization than to directly depict each record in a data set, approaches such as *i)* adding methods for aggregation prior to visual representation, *ii)* applying more sophisticated computational techniques, or *iii)* projecting data away from their geographic location, to more efficiently use the graphic space (Andrienko et al., 2010). It is of great importance that research on interactive cartography addresses these new challenges.

3 Methodology

Development of new methods and tools in the context of information systems is typically an iterative process of identifying problems, modelling, implementing and evaluating solutions. This methodological approach, deployed in the work presented in this thesis, is known as *design science research in information systems* (DSR, DSRIS). It results in purposeful IT artefacts, and knowledge and understanding of a design problem and its solution is built through building and application of an artefact (Hevner et al., 2004). In other words, system development is seen as a part of the research process, and we learn through the act of building (Kuechler & Vaishnavi, 2008). The design cycle, which constitutes the core of the DSRIS, consists of five steps, or phases (Figure 3): *awareness of problem*, *suggestion*, *development*, *evaluation*, and *conclusion* (Kuechler & Vaishnavi, 2008; Takeda et al., 1990).

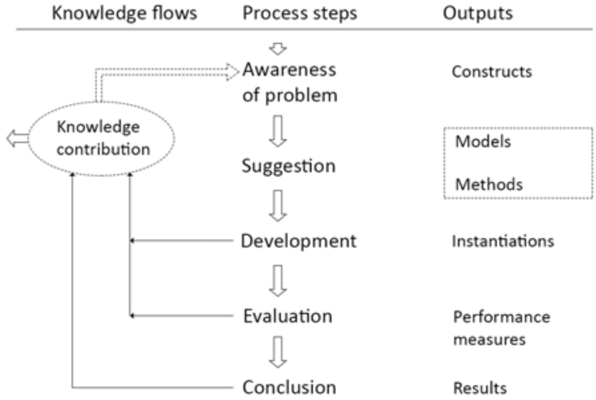


Figure 3: DSRIS model. Adapted from Kuechler & Vaishnavi (2008). Extended by research outputs defined in March & Smith (1995).

Depending on the nature of the research task, the first step, *awareness of problem*, may include literature studies, analysis of existing methods, experiments, or any other means of identifying a problem which is to be solved. In the *suggestion* phase, different approaches to the problem are suggested, and their feasibility is explored (Kuechler & Vaishnavi, 2008). Tentative directions for artefact generation are concretized through construction and iterative refinement in the *development* phase (Kuechler & Vaishnavi, 2008). The development phase and the *evaluation* phase are usually performed iteratively in a *generate/test* cycle (Hevner et al., 2004). Finally, in the *conclusion* phase, new knowledge is contributed to collective knowledge.

March & Smith (1995) define four types of research outputs from DSRIS research process: c*onstructs*, *models*, *methods*, and *instantiations*. *Constructs* constitute a conceptualization which defines the terms used when describing tasks, describes problems within the domain, and specifies their solutions. A *model* is a set of statements or propositions expressing relationships among constructs – a description, or a representation of how things are. A *method* is a set of steps used to perform a task, based on a set of underlying constructs. Finally, an *instantiation* is the realization of an artefact; it operationalizes and demonstrates the feasibility and effectiveness of the models and methods it contains.

The rest of this chapter contains a brief overview of the research methods employed in this thesis, which principally correspond to *awareness of problem* (Section 3.1), *suggestion* (Section 3.2), *development* (Section 3.3), and *evaluation* (Section 3.4).

3.1 Identification of research gaps

An in-depth study of the current research in the field of geospatial multi-criteria decision-making, in particular development of new and adaptations of existing methods, revealed that trade-off-based methods, such as even swaps, are hardly ever used in the GIC-MCDM context. Based on this insight, an extensive literature search was carried out for papers reporting on adaptations of the even swaps method and development of even swaps-based decision-making tools. A number of enhancements and adaptations of the even swaps method have indeed been proposed in the decision-making related literature (see Section 2.1.2), but just as the original method, they all operate in discrete choice models with a relatively small number of alternatives, which makes them unsuitable for GIS decision-making. Furthermore, the study of the current GIS-MCDM research also showed that findings of behavioral decision theories have hardly had any impact on the method development in GIS decision-making, as pointed out by Jankowski (2018). The first objective of this thesis aims to address these research gaps.

The second objective emanated from the comments on the use of interactive visualization in GIS-MCDM decision support tools (Andrienko & Andrienko, 2003). A review of a number of visual decision support systems showed that the use of interactive visualization in the choice phase of the decision-making process is still limited, partly due to the nature of deployed decision-making methods (see Section 2.4.3).

The third objective was formed based on literature studies of relevant work on the topic of evaluation of visual decision support tools and the impact of visualization on decision-making. Only a handful reported evaluations made an attempt to evaluate user performance (e.g. Andrienko et al., 2002; Bautista & Carenini, 2008). Even then, the focus was on usability, rather than the quality of choice. One of few studies concerned with the quality of choice is the study by Arciniegas et al. (2013). One obvious shortcoming of this study, however, is that the decision quality metrics were based upon the assumption of the existence of an objectively best choice. The situation was similar with studies evaluating the impact of visualization on decision-making. The paper by Dimara et al. (2018) was the only study we found which attempted to evaluate the impact of visual representation on the *quality* of decisions. They defined the quality of decisions as the consistency between the made choice and the self-reported preferences – a novel approach worth investigating further.

3.2 Development of methods and models

The even swaps method, with its straightforwardness and intuitiveness, is a given choice for addressing the first objective of this thesis, namely to develop methods for geospatial multi-criteria decision-making which would not be based on the assessment of the relative importance of criteria. However, as even swaps is based on the reduction of criteria by means of performing trade-offs between alternatives, the issue of applicability on large data sets needed to be addressed. In a scenario where no dominated alternatives are discarded during the whole decision process, the number of performed swaps c can be calculated as $c = (m - 1) * (n - 1)$, where m is the number of criteria and n is the number of alternatives. For a GIS decision problem including ten criteria, and concerning a geographical area represented by a 1000*1000 raster where each cell is processed as an unique alternative, the decision-maker would have to explicitly decide trade-offs and perform about 9 000 000 swaps, which is obviously too complex. In GISwaps, presented in paper I, this complexity is handled by automation of the swapping process. The method is built upon the new concept of *virtual alternatives*, i.e. alternatives that do not necessarily exist in reality, but are hypothetical alternatives that describe the outcome space. Adjustments performed by the decision maker on virtual alternatives are used to interpolate adjusted values for each actual alternative in the set. A different approach to utilize even swaps in quasi-continuous choice model was used in ESRDS, presented in paper IV. In the ESRDS model, complexity was handled through reduction of data sets, using the satisficing model as the basis for reduction (see Section 2.2). However, ESRDS does not fully adopt satisficing. Instead, it deploys a two-phase process that supports a behavior referred to in Malczewski and Rinner (2015) as *quasi-satisficing rationality*. The main content of this term is that, even if an individual behaves in accordance with satisficing principles of rationality, he/she still has some tendency towards maximization of utility (Malczewski and Ogryczak, 1996). The ESRDS model deploys a two phase process. In the first phase, the set of alternatives is reduced in a non-compensatory way, by iteratively adjusting thresholds of the relevant criteria. In the second phase, after the set of alternatives is reduced to a predefined manageable maximum, the even swaps method is used to select the alternative that best corresponds to the decision maker's preferences.

The development of GISwaps and ESRDS was driven not only by the need for geospatial decision tools that do not rely on the assessment of the relative importance of criteria, but also by the need to address the issue of limited use of interactive visualization in the choice phase of the decision process in the context of geospatial decision-making (Andrienko, Andrienko, and Gatalsky, 2003). GISwaps and ESRDS, with their intrinsic interactivity, support interactive visualization during this critical phase of a decision process. The core of visualization frameworks for both GISwaps and ESRDS consists of two linked views for representing alternatives in the attribute space and the geographical space, respectively, where each action in one view is mirrored in another, and the detail-on-demand feature is available in both views. As the potentially large number of considered alternatives remains constant in GISwaps during the whole decision process, a two-dimensional scatterplot is used to represent the alternatives in the attribute space. It visualizes three-dimensional data, where the third data dimension is visually expressed using color. While a scatterplot is an obvious choice when a large amount of data is to be visualized, it can only visualize a limited number of dimensions. In ESRDS, the number of alternatives is reduced in an iterative process, and the attribute space is represented by parallel coordinates. Unlike scatterplots, parallel coordinate plot can be used to visualize a layer of dimensions, but only a limited number of alternatives can be visualized before it becomes uninterpretable. For that reason, the plot is only made visible when the number of considered alternatives is equal to or smaller than the predefined upper limit. Both frameworks use interactive geomaps to visualize locations of alternatives in the geographical space. In addition to the attribute space unit and the geographical space unit, the proposed visualization frameworks contain one additional unit each. The GISwaps visualization framework contains a multi-line chart for visualization of trade-off value functions, i.e. visual representation of the scaling coefficients for trade-off values assigned to virtual alternatives. The ESRDS visualization framework contains a set of histograms and a pie chart in the threshold adjustment unit, to visualize the distribution of values for all considered criteria.

Both GISwaps and ESRDS visualization frameworks are designed in accordance with Shneiderman’s concept of direct manipulation (Shneiderman, 1983) and the basic principle of interaction design summarized in Shneiderman’s visual information seeking mantra: *overview first, zoom and filter, then details-on-demand* (Shneiderman, 1996). The frameworks are implemented in the test applications for decision support tools presented in this thesis: Visual GISwaps, based on GISwaps, and GISAnalyzer, based on ESRDS.

3.3 Implementation of models and methods

Visual GISwaps and GISAnalyzer were developed as stand-alone test applications for the purpose of demonstrating and validating the design of conceptual models presented in section 3.2., and evaluating their robustness in terms of ability to process large data sets. Visual GISwaps is a straight forward implementation of the GISwaps method and its visualization framework as presented in Section 3.2. Another test application implementing GISwaps, GISwaps Basic, was developed. GISwaps Basic does not include the visualization framework, and it was developed for the sole purpose of evaluating the impact of the interactive visualization in Visual GISwaps on decision-making. GISAnalyzer, apart from being an implementation of ESRDS and its visualization framework, implements also a weighted summation functionality, with either AHP or SWING weighting for assigning criteria weights, and WLC for aggregation of utility values. In addition, weighted summation using AHP and WLC can be run simultaneously with ESRDS, serving as a comparison method.

3.4 Evaluation

Evaluations of new models and methods are necessary in order to determine their contribution to the body of knowledge within the domain. However, evaluating decision-making models and methods is extremely difficult, as there is no ground truth. Decision tasks do not come with an objectively best alternative, or outcome, and different decision-makers will make different choices, depending on their preferences and knowledge. This is one of the main reasons why decision-making tools are usually evaluated through qualitative studies, using a process-tracing approach (Gratzl, Lex, Gehlenborg, Pfister, and Streit, 2013; Jankowski and Nyerges, 2001; Pajer et al., 2017), and focusing on process dynamics rather than on outcomes. The assessments are usually based on participants' behavior, opinions and perceptions, focusing on users' satisfaction and ease of use (Andrienko et al., 2003, 2002; Arciniegas, Janssen, and Omtzigt, 2011), usability in the context of human-computer interaction (Arciniegas et al., 2011; Jankowski, Andrienko, and Andrienko, 2001; Salter, Campbell, Journeay, and Sheppard, 2009), and users' perception of the usefulness of a tool. Quantitative methods are primarily used in comparative studies, and they rarely attempt to measure the actual quality of decisions, as there can be no absolutely reliable metrics for measuring the quality of a choice. Instead, commonly used measures include decision time, subjective ratings, choice satisfaction, or choice confidence. In evaluations carried out in this thesis, both quantitative and qualitative methods were employed in order to evaluate the impact of an interactive visualization framework integrated in a decision support tool (Section 3.4.1), and the potential impact of visual saliency on decision-making (Section 3.4.2).

3.4.1 Evaluation of the visualization framework for GISwaps

The evaluation of the visualization framework for GISwaps was based on two studies: an experimental user performance study, and a user experience study based on semi-structured interviews and observations. In both studies participants were working on the same hypothetical multi-criteria decision scenario. In both studies, two different stand-alone applications integrating the GISwaps method were used: Visual GISwaps, and GISwaps Basic, a simple form-based application that contains no graphical components other than elements necessary to perform even swaps, such as sliders and text fields. In order to reduce risks that the choice and the order of reference and response criteria influence the results (e.g. Koch, Eisend, and Petermann, 2009; Lahtinen and Hämäläinen, 2016), the decision path, i.e. the sequence of reference/response turns, as well as the number and the values of reference and response pivot-values, were preprogramed in the applications.

The user performance study was carried out with 30 student participants, each of whom had taken at least two GIS-related courses. Half of the participants worked on the assigned task using GISwaps Basic and the other half used Visual GISwaps. Both applications included a short questionnaire for participants to fill in after completing the task. For each participants, a log file was saved, containing all trade-off values set by the participant during the session, a timestamp for each swap turn, and the participant's answers to the questionnaire. The user experience study was carried out with five participants from different fields of expertise: two experts in the field of solar energy, two experts in decision, risk and policy analysis, and one GIS expert. Each session consisted of three parts. In the first part, participants were introduced to the GISwaps method. In the second part, participants worked on the decision task using GISwaps Basic, and in the third part, participants worked on the task using Visual GISwaps. During the second and the third part, participants were encouraged to comment while working on the task. After finishing the decision task, participants were asked a number of questions, aimed to give an insight into their perception of the efficacy and usefulness of the interactive visualization features. Data collected for each participant included audio recordings of the session, and written down observations.

3.4.2 Evaluation of the impact of saliency on decision-making

In the work presented in this thesis both scatterplots and parallel coordinates as means of visual representation of alternatives in the attribute space were used. It was noted that different visual representations are perceived differently by users, depending on their background and the field of expertise. Dimara et al. (2018) compared three visualization techniques: scatterplot matrices, parallel coordinates and tabular visualizations, and found that the quality of choice may differ depending on the used visual representation. As it has been shown that visual saliency influences our perception of visual content, a study presented in paper V included in this thesis was carried out in order to investigate if also visual saliency influences decision-making. An online experimental study was carried out to evaluate the impact of color saliency and size saliency on two different representations: scatterplot matrices and parallel coordinates. For each representations, three different implementations were used: without saliency, with color saliency, and with size saliency. The experiment was run on a crowd-sourcing platform, with no restrictions imposed regarding participants' background. The decision to run the experiment on a crowd-sourcing platform was based on recent studies which indicated that participants taking part in experiments carried out via crowd-sourcing platforms were just as attentive, or even more attentive, to the instructions than traditional subject pool samples (Goodman et al., 2013; Hauser & Schwarz, 2016; R. A. Klein et al., 2014). Participants were assigned the task of choosing one hotel among 50 available hotels in Berlin using parallel coordinates, and one hotel among 50 hotels available in London using scatterplot matrices. This type of scenarios was chosen to make sure that participants' choice is not influenced by their subject-specific knowledge, and that all participants can relate to the task equally. The participants were to make their choices based on their preferences on five criteria: price, distance to city center, cleanliness, service and breakfast. The number of criteria was kept low, as it was shown that increased complexity of decision tasks leads to decision-makers resorting to heuristics (Payne, 1976).

In this study, the approach first introduced in Dimara et al. (2018) was deployed, using the consistency between a participant's choice and his/her self-reported preferences as the indicative measure of quality of choice. Statistical analysis of results was carried out using estimations based on confidence intervals and effect sizes instead of commonly used null hypothesis significance testing, offering nuanced interpretations of results (see Cumming, 2014; Dragicevic, 2016).

4 Summary of papers, discussion and contributions

Papers included in this thesis cover three different areas, each of the areas being related to one of the objectives (Figure 4). *GIS-MCDM method development* is covered in papers I and IV. Both papers address research question 1, and paper IV also addresses research question 2. Two different methods are proposed, both utilizing *even swaps*. The method presented in paper I, GISwaps, is based on automation of *even swaps*. The method presented in paper IV, ESRDS, operates through reduction of the set of alternatives and processing the remaining alternatives with even swaps. *Interactive visualization development* was covered in papers II and IV. Research question 3 was addressed in both papers, where interactive visualization frameworks for GISwaps and ESRDS, respectively, were designed. Papers III and V cover *evaluation* issues. The study in paper III, undertaken to determine whether visual feedback has any impact on compensation values when working with GISwaps, and paper V, which investigates potential effects of visual saliency on decision quality, address research questions 4 and 5.

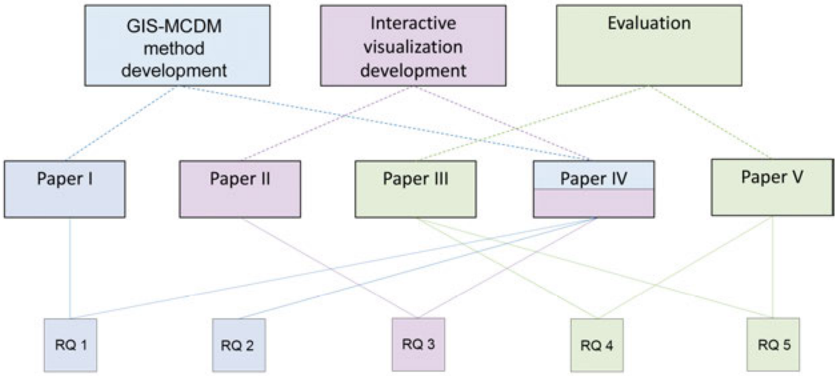


Figure 4: Schematic overview of the research presented in the thesis.

4.1 Paper I: GISwaps: A new method for decision making in continuous choice models based on even swaps

GISwaps, a method for GIS multi-criteria decision-making based on value trade-offs, is presented in this paper. The method is a generalization of even swaps, a well known trade-off method developed by Hammond et al. (1998). The core of the method is automation of the process of assigning compensation values in terms of the response criterion, in order to compensate for adjustments made in terms of the reference criterion. For this purpose, the new concept of *virtual alternatives* was introduced. Virtual alternatives are hypothetical alternatives, assigned pairs of pivot values in terms of the reference and the response criteria decided by the decision maker. For each virtual alternative, the decision maker assigns a compensation value in terms of the response criterion that will compensate for the maximum improvement in terms of the reference criterion. These compensation values are then used to interpolate new values in terms of the response criterion, which will compensate for maximum improvements in terms of the reference criterion, for all actual alternatives in the set. The method is described by the algorithm in Figure 5.

In geospatial decision-making, we usually want to obtain an ordered set of feasible alternatives for further analysis. For that reason, elimination of dominated alternatives is not employed in GISwaps, as it would leave us with a single best alternative. In addition, it is important to point out that in this context, a single alternative means a single raster cell, as each raster cell is processed as an unique alternative. Obviously, in practice, a raster cell as an alternative should be seen as merely an indicator of a possible solution. A feasible alternative would be an area represented by a number of connected raster cells, where the number of cells depends on the size of the area needed, as well as the resolution of the raster model.

The method was evaluated through a case study. The decision problem was to determine the best site location for a dam and reservoir for hydro-electrical power production on the Reventazón River in Costa Rica. Six basic relevant criteria were considered during the decision process: hydraulic head, water discharge, undulation, distance to forests, distance to agricultural areas, and distance to urban areas. Compensation values for the virtual alternatives used in the decision process were assigned by an expert in GIS-MCDM and hydrology. The results showed that the location pointed out as the best is the same location where the Reventazón Dam was actually built in 2016. While no conclusive statements about the efficacy of the method can be made on this result, it is nevertheless an indicator of its reliability.

In GIS-related decision problems it is often the case that the number of alternatives is quasi-continuous, only constrained by the limits of the used data representation model. The main contribution of this paper lies in the suggested algorithm for the automation of the trade-off-process. In that way, the concept of even swaps may be applied to any set of alternatives as long as it is discrete, i.e. as long as the number of alternatives is finite, which makes the method applicable to geospatial decision-making in quasi-continuous choice model. It provides efficient means for the decision maker to quantify his/her preferences considering the concrete values and differences between alternatives, rather than by means of the abstract concept of the relative importance of criteria. Another important property of the method is that it supports piecewise-linear value functions, which makes it more flexible than the commonly used approach of combining weighting and aggregation methods.

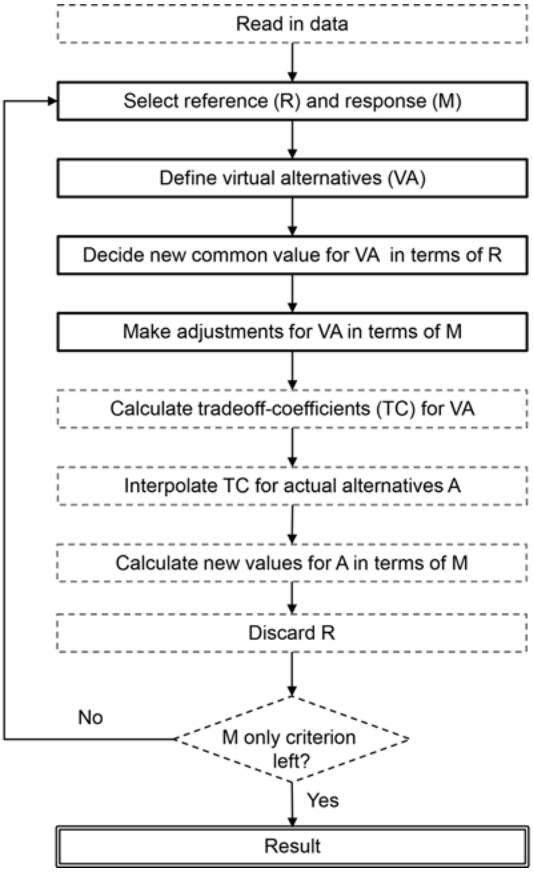


Figure 5: GISwaps algorithm. Steps in solid line rectangles are performed by the decision-maker, and steps in dotted line rectangles are performed by software.

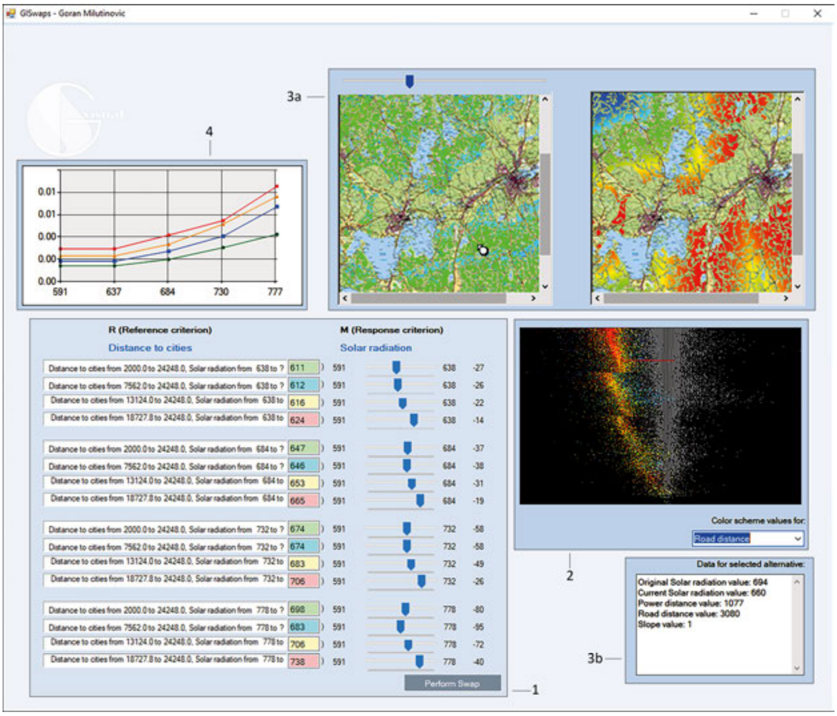
4.2 Paper II: Visual GISwaps – an interactive visualization framework for geospatial decision making

An interactive visual framework for GISwaps, designed to facilitate the decision maker during the choice phase of a decision process, is presented in this paper. It integrates fundamental visualization techniques, and consists of three conceptual units (Figure 6):

- Scatterplot for visualization of alternatives in the attribute space. The alternatives are plotted in a 2-dimensional scatterplot, with the value in terms of the *response* criterion on x-axis, and the value in terms of the *reference* criterion on y-axis. The scatterplot is updated each time the trade-off value of any of the virtual alternatives is changed. The plot gives the decision maker insight into the distribution of values of the alternatives with respect to the response criterion. It also reveals potential outliers that may have an impact on the reliability of the interpolated compensation values. Through extra information available on demand, it gives the decision maker an opportunity to get a closer look at alternatives of interest.

- Interactive maps for visualization of alternatives in the geographical space. The left map is color-coded using values in terms of the *response* criterion. The right map is a comparison map, color-coded using values in terms of the chosen comparison criterion, if any. If a point is marked in the scatterplot, the geographic position for all alternatives with the values in terms of *reference* and *response* as the marked point are shown in the left map. Detail-on-demand information about a specific alternative may be obtained by clicking on a marker. Being able to see the geographic location of a selected alternative may help the decision maker re-evaluate assigned compensation values, based on his/her preferences and knowledge.
- Multi-line chart for visualization of compensation coefficients for assigned virtual alternatives. The chart is updated each time the compensation value of any of the virtual alternatives is adjusted.

The main contribution of this paper is an interactive visualization that allows the decision maker to explore the consequences of trade-offs and costs accepted during the iterative decision process, both in terms of the abstract relation between different decision variables and in spatial context. The novelty of this visualization framework lies mainly in the context in which it operates, namely the choice phase of a decision process. As GISwaps is an interactive method that requires the decision maker to be active and to interact during the whole process, the visualization framework provides the possibility for the decision maker to see and analyze consequences of every adjustment.



R (Reference criterion)
Distance to cities

M (Response criterion)
Solar radiation

Distance to cities from 2000.0 to 24248.0, Solar radiation from 638 to ?	611	591		638	-27
Distance to cities from 7562.0 to 24248.0, Solar radiation from 638 to ?	612	591		638	-26
Distance to cities from 13124.0 to 24248.0, Solar radiation from 638 to	616	591		638	-22
Distance to cities from 18727.8 to 24248.0, Solar radiation from 638 to	624	591		638	-14
Distance to cities from 2000.0 to 24248.0, Solar radiation from 684 to ?	647	591		684	-37
Distance to cities from 7562.0 to 24248.0, Solar radiation from 684 to ?	646	591		684	-38
Distance to cities from 13124.0 to 24248.0, Solar radiation from 684 to	653	591		684	-31
Distance to cities from 18727.8 to 24248.0, Solar radiation from 684 to	665	591		684	-19
Distance to cities from 2000.0 to 24248.0, Solar radiation from 732 to ?	674	591		732	-58
Distance to cities from 7562.0 to 24248.0, Solar radiation from 732 to ?	674	591		732	-58
Distance to cities from 13124.0 to 24248.0, Solar radiation from 732 to	683	591		732	-49
Distance to cities from 18727.8 to 24248.0, Solar radiation from 732 to	706	591		732	-26
Distance to cities from 2000.0 to 24248.0, Solar radiation from 778 to ?	698	591		778	-80
Distance to cities from 7562.0 to 24248.0, Solar radiation from 778 to ?	683	591		778	-95
Distance to cities from 13124.0 to 24248.0, Solar radiation from 778 to	706	591		778	-72
Distance to cities from 18727.8 to 24248.0, Solar radiation from 778 to	738	591		778	-40

Color scheme values for: Road distance

Data for selected alternative:
Original Solar radiation value: 694
Current Solar radiation value: 660
Power distance value: 1077
Road distance value: 3080
Slope value: 1

Figure 6: Visual GISwaps main window consists of an adjustment panel (1) and the visualization framework consisting of three units: a scatterplot for visualization of alternatives in the attribute space (2), interactive maps for visualization of alternatives in the geographical space (3a) including a detail-on-demand feature (3b), and a multi-line chart for visualization of trade-off value functions (4).

4.3 Paper III: The impact of interactive visualization on trade-off-based geospatial decision-making

This paper presents the results of a user performance study and a user experience study carried out to evaluate the visualization framework introduced in paper II. The objective of the user performance study was to determine whether visual feedback has any impact on the magnitude of and variation in compensation values when making trade-offs in GISwaps. The user experience study was undertaken to gain insight into how different visualization techniques are perceived by users. The same decision scenario – finding the optimal location for a solar plant in the southern part of Gävleborg County, Sweden – was used in both studies. Factors to be taken into consideration included solar radiation, slope of the terrain, distance to urban areas, distance to power transmission lines, and distance to main roads.

The user performance study was designed as an experimental study with two groups of participants. Participants were recruited from different educational programs at the University of Gävle, and each participant had taken at least two GIS-related courses prior to the study. Each group consisted of fifteen participants. Participants in the first group used a basic GISwaps application, with no interactive visual features (GISwaps Basic), while participants in the second group used a GISwaps application with integrated visual framework presented in paper II (Visual GISwaps).

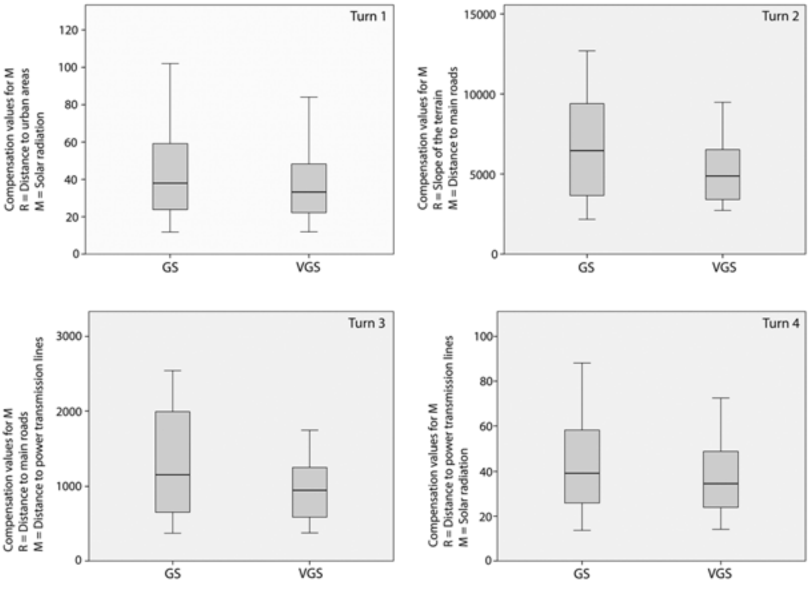


Figure 7: Box-plots showing the variation between the groups (GISwaps Basic and Visual GISwaps) in average trade-off values.

The main findings are that the participants using GISwaps Basic on average made trade-offs with more varying and less coherent compensation values than the participants using Visual GISwaps (Figure 7). Furthermore, the participants using GISwaps Basic were setting on average 20% larger compensation values than the participants using Visual GISwaps (Figure 8). This implies that participants using Visual GISwaps attached more importance to criteria used as response than to criteria used as reference. This indicates that visual feedback may have an impact on the *scale compatibility bias*, and on *loss aversion*, i.e. tendency to prefer avoiding losses to acquiring equivalent gains (Kahneman, Knetsch, and Thaler, 1991; Tversky and Kahneman, 1991). The application used by the participants in this study included also short questionnaires. The answers were used, together with the results of the user experience study, in the qualitative evaluation of the framework.

The user experience study was carried out with an expert group, consisting of five participants: two experts in the field of solar energy, two experts in decision, risk and policy analysis, and one GIS expert. The same decision scenario was used as in the user performance study, but this time, each participant worked first with GISwaps Basic, and then with Visual GISwaps. Data were obtained through observations and semi-structured interviews. The influence of the visualization framework was assessed positively by all participants in the expert group, and graded 3.33 of 5 on average by the participants in the non-expert group. One particularly interesting result was that, of the three visualization units in Visual GISwaps, the scatterplot unit was the least preferred by both expert group and student group. This was a surprising result, as the scatterplot was meant to be the central part of the visualization and the starting point of interaction. The unpopularity of the scatterplot unit may be due to the participants being unaccustomed to interpret scatterplots. Another explanation may be a lack of time, as the feedback from the other two units is immediate and easy to interpret, while interpreting scatterplot requires some learning.

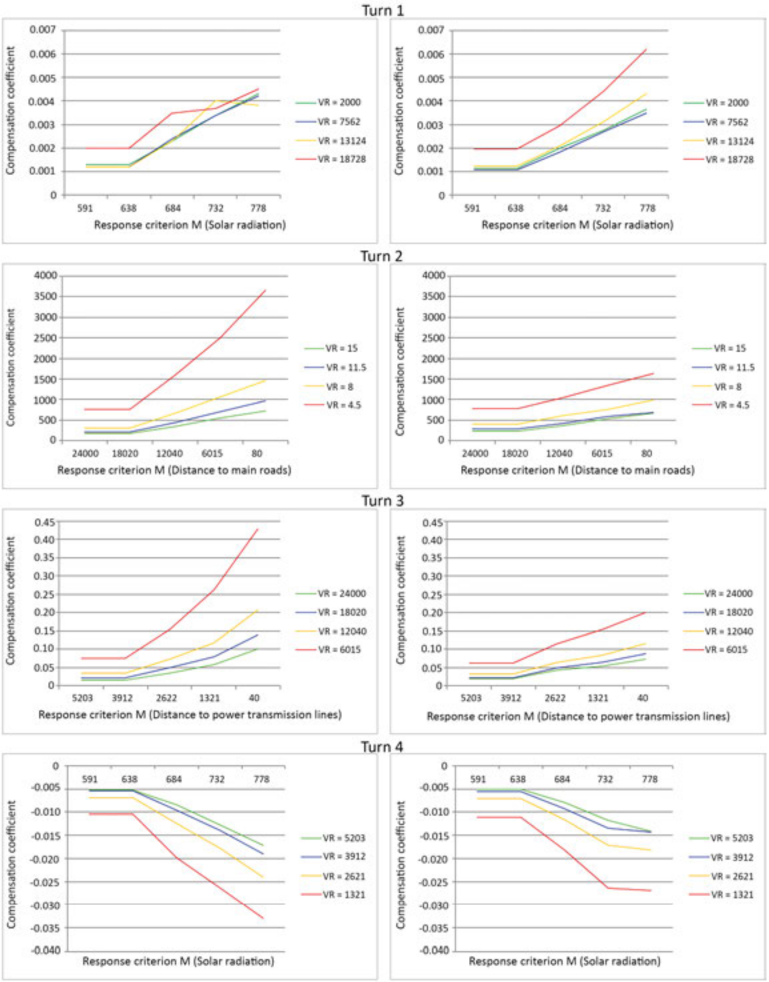


Figure 8: Diagrams show the difference between the groups (GISwaps Basic and Visual GISwaps) with regard to compensation variation.

The main contribution of this paper is the finding that interactive visualization does indeed influence the decision maker’s judgement in making trade-offs, both concerning magnitude and variation of compensation values. The impact on variation of compensation values can be considered positive, as the results show that visual feedback helps the decision maker make more coherent and more consistent trade-offs. The impact on the magnitude of compensation values can not be classified as either positive or negative, unless further studies are carried out to investigate apparent influence of visual feedback on the scale compatibility bias and the loss aversion bias.

4.4 Paper IV: Geospatial decision-making framework based on the concept of quasi-satisficing and even swaps

Multi-criteria decision-making methods are built upon the assumption that the deciding subject always tries to make the optimal choice. This model of rational behavior has been questioned by many critics, who instead adopt the concept of *bounded rationality*. According to this concept, our rationality is limited by our cognitive limitations, by the time available to make a decision, and by the incompleteness of available information. Rather than trying to make the optimal choice, we stop the decision process as soon as we find a solution that satisfies all the conditions and that we find sufficiently good. The decision-making framework introduced in this paper integrates a decision-making model based on combining this concept of *satisficing* with even swaps, and an interactive visualization with units and interaction paths compatible with the model. The proposed decision-making model, referred to as *quasi-satisficing,* is based on, but not limited to, the satisficing concept. It still allows the decision maker to choose any alternative from the set of the alternatives that satisfy all the conditions, but it also provides the option to apply even swaps upon the set of acceptable alternatives. Our model includes the following basic steps:

- Assign the minimum value (acceptability threshold) that an alternative must have in terms of each of the criteria. The set of acceptable alternatives includes all alternatives which conform to all acceptability thresholds.
- When the acceptability threshold for any criterion is increased, exclude from the set of acceptable alternatives all alternatives that do not conform to the new acceptability threshold. If the acceptability threshold is decreased, include in the set of acceptable alternatives all previously excluded alternatives which conform to the new acceptability threshold, as well as acceptability thresholds for the rest of the criteria.
- When the set of acceptable alternatives is reduced so that it can be handled by pairwise comparison of alternatives, select the best alternative using even swaps.

The process pipeline for the model is shown in Figure 9.

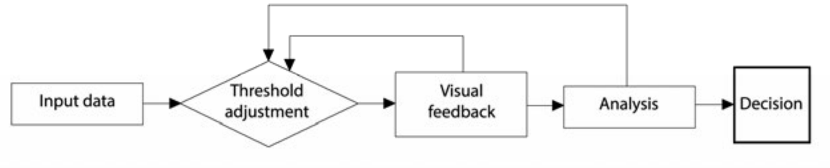
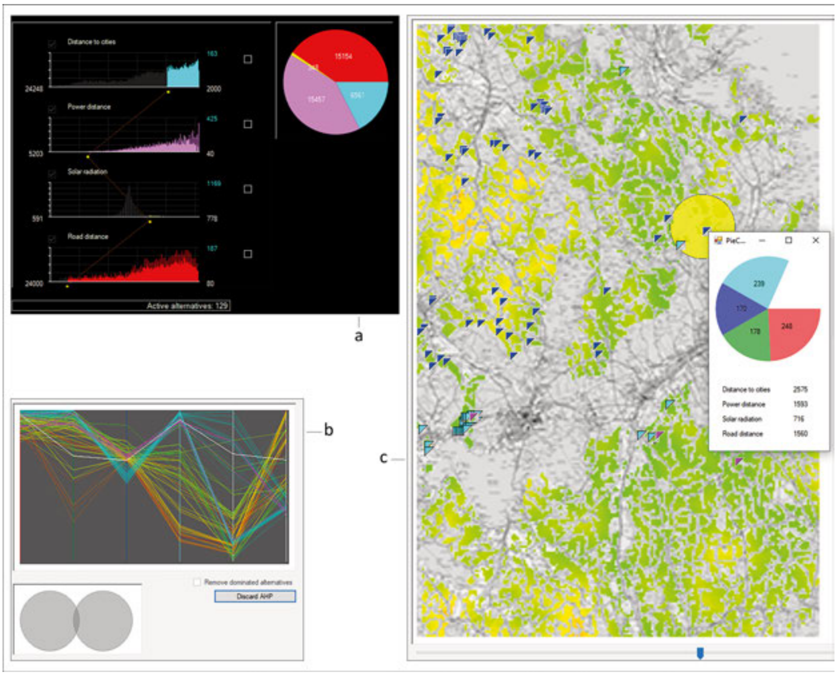


Figure 9: The process model for the framework. The core of the framework is the iterative threshold-adjustment process, supported by the interactive visualization framework.

The visualization framework integrated in the decision support system presented in this paper follows the principle that in any analytical process, the user has to be the ultimate authority in directing the analysis, and that the system must provide effective means of interaction that will facilitate the user in any specific task. It includes a *threshold adjustment unit* which uses histograms and a pie chart to visualize the distribution of values for all criteria, an *attribute space analysis unit* which uses parallel coordinates and a *Venn diagram* to visualize relations between acceptable alternatives in the attribute space, and a *geographical space analysis unit* which uses a geomap to visualize locations of acceptable alternatives in the geographical space, and a pie chart to provide the details of a selected alternative (Figure 10). The interaction path between the units is shown in Figure 11.



Active alternatives: 129

Distance to cities 2575
Power distance 1593
Solar radiation 716
Road distance 1560

Figure 10: GISAnalyzer main window consists of a threshold adjustment unit (a), an attribute space analysis unit (b), and a geographical space analysis unit (c).

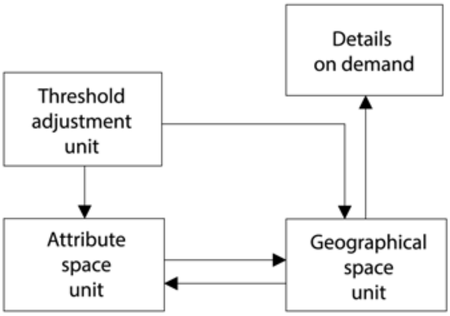


Figure 11: The interaction path between different units of the visualization framework implemented in GISAnalyzer.

The contribution of this paper is twofold. First, the presented decision-making model, which emanates from findings of behavioral decision-making theories, facilitates an iterative data reduction process, which makes it possible to use the even swaps method in its basic form in geospatial multi-criteria decision-making in quasi-continuous choice models. Second, the presented interactive visualization framework enables the use of the model in the geospatial context, providing visual feedback on the decision maker's every action throughout the decision process in both attribute and geographical space. This helps the decision maker to gain insight in the attribute dependencies and discover potential relations between the criteria that would otherwise remain hidden, and to analyze and compare the outcomes of different scenarios and decision paths.

4.5 Paper V: Does visual saliency affect decision-making?

Geospatial decision tasks usually include assessment of geo-referenced information, but explicit representations of geographic positions by use of maps are not necessarily best suited to perform such assessments. For instance, the assessment of relative position, i.e. the distance between geographically positioned information, is subject to bias in interactive visual analysis in map representations (Seipel, 2013). It is a known phenomenon that the estimation of lengths of lines is dependent on their orientation in the perceived image (Cormack and Cormack, 1974; Craven, 1993). Similarly, (Seipel, 2013) found that the accuracy of assessing relative distances between locations in a map is dependent on the angle between the imaginary lines between candidate pairs. Techniques from the field of information visualization, such as scatterplot matrix and parallel coordinates, offer alternatives for GIS-MCDM tasks when spatial reference is by label rather than coordinates and if exact comparisons of e.g. metric distance are needed. But how efficient are those techniques in the context of geospatial decision-making? In the study presented in paper V, the impact of visual saliency on the quality of decisions was investigated. The study investigates an MCDM problem where relative geographic distance is only one among several attributes where exact quantitative comparisons of distances is crucial. The alternatives available in the decision task are therefore presented in scatterplot matrix and parallel coordinates. The study investigates potential effects of visual saliency on the quality of decisions, where the quality of a decision is measured as the consistency between self-reported preferences and the made choice. In accordance with the effectiveness principle, criteria were visually accentuated, rather than alternatives. However, while the effectiveness principle suggest that decreasingly important attributes can be matched with decreasingly effective channels (Munzner, 2014), visual saliency was applied only to the criterion of highest importance for the participant.

The experiment was carried out online. The total of 153 participants submitted results. The decision task involved choosing the best hotel of fifty available hotels in London and Berlin, respectively. Each participant worked on the London-task using a scatterplot matrix, and parallel coordinates were used for the Berlin-task. The participants were divided into three groups, where the first group worked with visualizations without saliency, the second group worked with color saliency, and the third group worked with size saliency (see Figure 12).

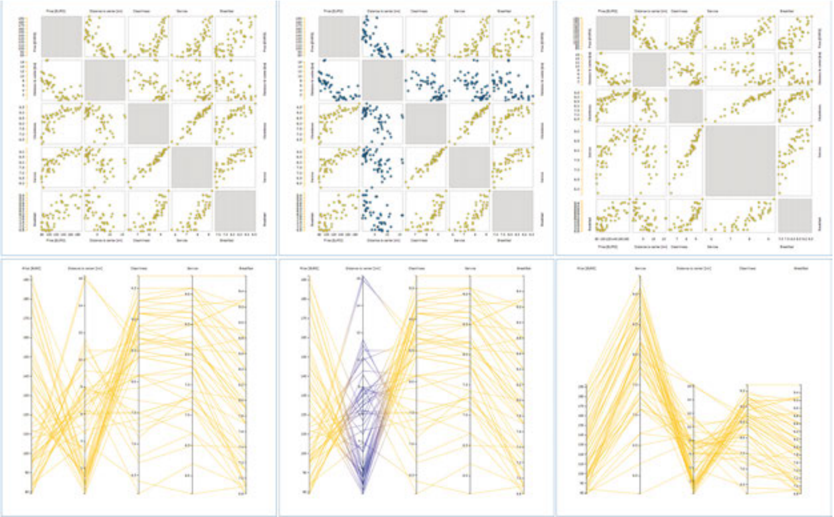


Figure 12: Visualizations used in the experiment. Upper row, from left to right: SPM with no saliency, SPM with color saliency, SPM with size saliency. Lower row, from left to right: PC with no saliency, PC with color saliency, PC with size saliency.

For PC, the results showed significant improvement of performance in terms of decision quality in the group working with color saliency, compared to the group working with the basic visualization with no saliency. However, no effect on the decision quality was observed in the group working with size saliency. For SPM, results showed no notable difference in the quality of choice between the saliency modes. We noted also that visual saliency, regardless of the visualization method, led users to choices which are in favor of the most preferred criterion. In terms of time, there was a weak indication that participants tend to spend more time when working with SPM with color saliency, compared to SPM with the other two saliency modes. No indication of difference was found for PC.

The main contribution of this paper is the finding that visual saliency can improve the quality of choice for certain combinations of saliency form and visualization methods. However, though the results are very encouraging, and we observed no adverse effects of using visual saliency in form of color or size, we should be cautious not to draw too far-reaching conclusions, as more work is needed on identifying reliable metrics of decision quality.

5 Conclusions and future work

This thesis emerged from the need to address two important GIS-MCDM issues. The first issue is the use of established decision-making methods in geospatial context. The most commonly used approach in geospatial decision-making, using weighted summation methods, is conceptually clear and intuitive. However, its efficiency and reliability is dependent not only on the applied weighting method, but even more so on the decision-maker's understanding of the method and its limits. The task of assigning relative importance to the criteria which need to be considered in a specific problem is inherently complex, and it demands high level of abstraction from the decision-maker in order to quantify his or her preferences. This tasks is even more abstract if the importance of criteria is to be decided without considering the values of the available alternatives in terms of the considered criteria. The second issue, closely related to the first, is the use of visualization in geospatial decision-making. While modern decision-support systems incorporate advanced interactive visualizations, these visualizations are mostly used in the initial phase of the decision process. In the choice-phase, i.e. when alternatives are evaluated and the choice is made, visualization is often limited to presenting the results. This issue is difficult to handle when a weighted summation method is applied. The role of the decision-maker is to prepare and enter the input data, and accept, or discard, the result. The "choice" is made in a split second, leaving the decision-maker no opportunity to follow the process and re-evaluate his or her preferences.

The first objective in this thesis addresses the issue of methods. This objective, to develop methods which will not rely on criteria weighting, is covered in papers I and IV. Both the method proposed in paper I and the model proposed in paper IV build upon the even swaps method, a well-known method based on value trade-offs. The model presented in paper IV, ESRDS, integrates even swaps in a framework designed on the premises of behavioral decision-making. The even swaps method in its original form is used to choose the most preferred alternatives from the set of alternatives reduced through an iterative process. The method presented in paper I, GISwaps, on the other hand, uses virtual alternatives as means of automatizing the even swap process, rather than having the decision-maker decide each trade-off him- or herself. The number of virtual alternatives, as well as the range of values they cover, is decided by the decision-maker, which makes the method flexible for fine-tuning. Both ESRDS and GISwaps can be applied to any decision problem under certainty, regardless of the number of alternatives, which makes them suitable for geospatial decision-making.

The second objective concerns the issue of interactive visualization in geospatial decision-making. The interactive visualization frameworks for GISwaps and ESRDS are presented in papers II and IV, respectively. They provide feedback for the decision-maker's every action throughout the choice phase of the decision process. The feedback is given both in the geographical space, using interactive maps, and in the attribute space, using visualization techniques such as scatterplots, line graphs, pie charts, diagrams, histograms and parallel coordinates. The GISwaps framework was evaluated and the positive impact of interactive visualization in the choice phase of the decision process was confirmed in the experimental study presented in paper III.

The third objective covers the issue of visualization evaluation, although not exclusively related to geospatial decision-making. The use of different visualization techniques and the role of visualization in the context of decision-making have been covered in a number of studies. One such study was carried out in paper III in this thesis, investigating the impact of interactive visualization on trade-off-based decision-making. However, when the work on this thesis begun, virtually no investigations of the impact of visualization techniques on the *quality* of decisions had been reported. The first study which considered this issue was the study by Dimara et al. (2018), in which the authors suggested the consistency between the self-reported preferences and the actual choice made by the decision-maker as the indicative of the quality of choice. The study presented in paper V uses the same approach to investigate the impact of visual saliency on decision-making. The results showed that the quality of decision outcomes differed not only depending on the mode of visual saliency used (or if no saliency was used), but also depending on the employed visualization technique (parallel coordinates and scatterplot matrices). While some combinations of saliency form and visualization method (parallel coordinates with color saliency) seem to be favorable in terms of gained decision quality, no adverse effects of using visual saliency in form of color or size were observed, neither in terms of reduced decision quality nor in terms of efficiency.

The GISwaps method presented in this thesis is based on an automation process which makes it possible to apply even swaps on geospatial decision problems. In the future, both the efficiency and the usability of the method should be analyzed more thoroughly. The approach used in paper V may be suitable to investigate how the method performs compared to some other methods in terms of the quality of decisions. Regarding the efficiency of the method, it would be worth investigating if it could be improved by using a continuous utility value function instead of piecewise-linear. Also ESRDS, as well as its visualization framework, needs to be evaluated for efficiency and usability in the context of geospatial decision-making. Furthermore, it would be interesting to investigate how an alternative visualization framework based on the findings presented in paper V would compare to the current visualization framework.

There is a number of issues related to value trade-offs which may have impact on the GISwaps method. Phenomena such as *trade-off contrast*, *loss aversion*, *scale compatibility* and *path dependence* have all been shown to have impact on how we make trade-offs (see paper I, Section 4). In a future work, the impact of those biases on the GISwaps method should be investigated.

The issue of evaluation of decision-support methods is a very complex one, due to the fact that the outcome is ultimately dependent on the decision-maker's preferences, expectations and knowledge. The fact that decision tasks by definition do not come with an objectively best alternative makes comparative evaluations of decision support tools and methods difficult, as there are no objective, reliable metrics for measuring their efficiency. The approach suggested in Dimara et al. (2018), adopted in paper V, is a good start. However, more work needs to be done on providing guidelines for assessment of decision quality. This includes both subjective metrics, i.e. how the decision-makers' preferences are expressed, as well as objective metrics, i.e. how the decision-makers' expressed preferences are translated to reliable measurable values.

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… and this is where my thesis ends. That feeling of closure and fulfillment that I was hoping for is strangely absent. The short-lived sense of achievement has already vanished, dissolved in the realization that I've barely scratched the surface. It is not a pleasant feeling, but I guess it is this feeling of hopeful frustration that pushes us to do more, to learn more, and I have no choice but to embrace it.

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Papers

Associated papers have been removed in the electronic version of this thesis.

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