Computers, Environment and Urban Systems 45 (2014) 101–113

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

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

An exploratory approach to spatial decision support

Piotr Jankowski [a,b,*], Grant Fraley [a], Edzer Pebesma [c]

[a] Department of Geography, San Diego State University, San Diego, USA
[b] Institute of Geoecology and Geoinformation, Adam Mickiewicz University, Poznan, Poland
[c] Institute for Geoinformatics, The University of Münster, Germany

A R T I C L E I N F O

Article history:
Received 24 March 2013
Received in revised form 17 February 2014
Accepted 18 February 2014
Available online 13 March 2014

Keywords:
Spatial decision support systems
Spatial optimization
Multi-objective genetic algorithms
Multiple criteria decision analysis

A B S T R A C T

The paper presents a decision support approach to solving problems characterized by spatially-explicit decision variables, multiple objectives, and preferences for ancillary decision criteria. The approach offers a three-step workflow, in which Pareto non-dominated solutions to a multi-objective decision problem are generated with a spatially adaptive genetic algorithm, objective value trade-offs are examined in an interactive graphics environment, and the selected solution alternatives are evaluated on the bases of ancillary multiple criteria. The three-step workflow is demonstrated on the example of a selection problem involving alternative configurations of sensors for radioactivity monitoring in a trans-border region including the state of Lower Saxony in Germany and the Netherlands. The presented approach promotes the search for diverse, non-dominated solution alternatives by coupling a fuzzy logic system with spatially adaptive genetic operators. The three-step workflow offers a comprehensive approach to spatial decision support starting with diverse option generation, through exploration of decision objective trade-offs, to multiple criteria evaluation of the selected non-dominated decision alternatives.

1. Introduction

Spatial Decision Support Systems (SDSS) has been an important subfield of GIScience, with contributions to many other fields including agriculture, business, civil engineering, environmental and resource management, health care, transportation, and urban planning. Sugumaran and DeGroote (2011) identified 447 publications on the subject of SDSS published since 1986 with more than a half appearing after 2003. A concept of decision support, followed in a number of these publications, derives from a well-known three-stage model of decision making proposed by Simon (1960), and focuses on stages 2 (design) and 3 (choice). Design, in the decision making context, involves search for decision options (alternatives) characterized by attributes, and bounded by constraints owing to the internal/external requirements. Choice is an evaluative step, in which the *designed* decision options are systematically evaluated on the bases of common evaluation criteria. This conceptualization of decision making has shaped the meaning of *decision support* as an analytic process involving search for feasible decision options followed by their systematic evaluation.

In GIScience, the concept of *spatial decision support* extends beyond the above notion by focusing on geographical characteristics and spatial (topological) relationships guiding the search for and evaluation of decision options. At an operational level, two approaches to spatial decision support have emerged over the last three decades: (1) a multiple criteria evaluation approach, and (2) a spatial optimization-based approach. The former, facilitated by spatial analysis operations and a *Boolean* combination of spatial and attribute queries performed typically in a GIS, has been used in search for locations satisfying suitability criteria. In order to discriminate among suitable locations, various multiple criteria evaluation techniques have been proposed and integrated with GIS (Malczewski, 2006). Search for decision alternatives representing suitable locations has been also the focus of the spatial optimization-based approach (Tong & Murray, 2012). Both approaches offer different strategies for structuring a decision problem, searching for, and evaluating its solutions. Over the past twenty years some efforts have been made at integrating GIS-based multiple criteria evaluation with spatial optimization in order to create versatile spatial decision support systems (Bojorquez-Tapia, Diaz-Mondragon, & Ezcurra, 2001; Cromley, 1994; Cromley & Hanink, 1999; Cromley & Hanink, 2003; Kao & Lin, 1996; Sinha and Silavisesrith, 2012; Coutinho-Rodrigues, Simao, & Antunes, 2011; Wang, Lee, Peng, & Wu, 2013). Yet, integrating both approaches has received little attention relative to the overall research on SDSS. A potential benefit of integrating

* Corresponding author at: Department of Geography, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182-4493, USA. Tel.: +1 619 594 0640; fax: +1 619 594 4938.
E-mail address: pjankows@mail.sdsu.edu (P. Jankowski).

http://dx.doi.org/10.1016/j.compenvurbsys.2014.02.008
0198-9715/© 2014 Elsevier Ltd. All rights reserved.

GIS-based multiple criteria evaluation with spatial optimization includes leveraging combinatorial search capabilities of the latter with scoring functions of the former, and in effect providing a systematic approach to first generating, and then evaluating non-dominated decision alternatives. Another potential benefit includes a possibility of expanding a model of decision situation by including its ancillary characteristics, represented by evaluation criteria, that otherwise might be difficult to incorporate in a spatial optimization model.

This paper contributes to research on integrating the two important methodological areas of SDSS by presenting an integrative spatial decision support approach for generating, exploring, and evaluating decision alternatives comprised of discrete, point-based location. The approach is comprised of a three-step workflow, in which a spatially adaptive, multiple objective genetic algorithm generates Pareto non-dominated solutions. Then, an interactive trade-off exploration technique is deployed to narrow down a potentially large number of non-dominated solutions to a few choices. This is followed by multiple-criteria evaluation of the selected solutions using ancillary spatial criteria. An application of the workflow is demonstrated on the example of hazard management, in which a decision task involves selecting a geographic configuration of environmental sensors for radioactivity monitoring in a trans-border region of Lower Saxony in Germany and the Netherlands. The remainder of the paper is structured as follows. A brief discussion of heuristic optimization methods for generating decision alternatives is presented in section two. This is followed by an overview of the tri-step workflow for generating, exploring, and evaluating Pareto-efficient decision alternatives. An application of the workflow for optimizing the geographical configuration of radioactivity sensors is presented in section four. The paper closes with the discussion of the application example and with general comments on a broader applicability of the presented approach.

2. Multi-objective optimization and genetic algorithms

Geographical decision problems involving multiple objectives, such as facility site location and vehicle routing, are commonly solved with optimization methods (Church & Murray, 2009; Church & et al., 2003; Malczewski, 2006; ReVelle & Eiselt, 2005; Tong & Murray, 2012). Optimization methods for multi-objective problems typically involve transforming a spatial problem into a single linear objective function by weighting and summing each objective based on decision maker preferences (Cohon, 1978; Gal, Stewart, & Hanne, 1999) This, however, requires a priori specification of weights representing preferences for decision objectives. There are other methods of solving multi-objective problems requiring either a priori specification of preferences or a posteriori selection by a decision maker from a set of non-dominated solutions. Examples of the former are lexicographic method and goal programming (Cohon, 1978) while an example of the latter is the Normal Boundary Intersection (NBI) method (Das and Dennis, 1998).

In addition to preference specification, the complexity of optimization algorithms arises from a computationally expensive search for a global optimum. Consequently, exact solution methods such as Linear Programming (LP) are not practical for solving large size, NP-hard spatial optimization problems such as 0–1 integer programming problems (Aerts & et al., 2003; ReVelle & Eiselt, 2005). Heuristic algorithms, including: tabu search (Murray & Church, 1995; Rosing, ReVelle, & Rosing-Vogelaar, 1979), simulated annealing (Aerts & Heuvelink, 2002; Duh & Brown, 2007; Murray & Church, 1996; van Groenigen, Siderius, & Stein, 1999), and evolutionary algorithms (Cao et al., 2011; Hosage & Goodchild, 1986; Xiao & Armstrong, 2006; Zhang & Armstrong, 2008), have been employed to overcome these limitations and generate feasible solutions in a variety of NP-hard search and optimization problems. Because evolutionary algorithms, including their subset called genetic algorithms (GA), have been developed to effectively handle multiple-objectives and find non-dominated solutions even in large optimization problems (Coello, 1999), they are a viable method for generating feasible decision options in spatial problems with quantifiable decision objectives.

GA have been applied in solving a variety of geographic problems such as: landscape design (Roberts, Hall, & Calamai, 2011), crime hot-spot analysis (Wu & Grubesic, 2010), locating utility corridors (Zhang & Armstrong, 2008), forest management (Ducheyne, De Wulf, & De Baets, 2006), map labeling and cartographic generalization (van Dijk, Thierens, & de Berg, 2002), choropleth map classification (Armstrong, Xiao, & Bennett, 2003), facility location (Jaramillo, Bhadury, & Batta, 2002) site suitability analysis (Zhou & Civco, 1996), and environmental management policy making (Bennett, Wade, & Armstrong, 1999; Bennett, Xiao, & Armstrong, 2004). GA operate with a population of potential solutions, and typically generate multiple non-dominated solution alternatives as a result. Multiple decision alternatives are particularly desirable when stakeholders' preferences are uncertain and examining trade-offs among non-dominated decision alternatives can provide additional information about their impacts (Ligmann-Zielinska, Church, & Jankowski, 2008). GA formulations incorporating multiple objective functions (Multiple Objective GA or MOGA in short) explicitly represent multiple objectives in a problem formulation, as opposed to commonly used scalar function approaches based on LP, which transform multi-objective problems into a single-objective scalarized function.

The general heuristic of a genetic algorithm can be applied to a wide range of problems; however, efficiency of an algorithm can be increased when problem specific knowledge is incorporated (Vrugt & Robinson, 2007). In hazard scenarios, for example, a speed up in computation time can result in a valuable decrease in decision-making time. Xiao (2008) presents a framework to exploit spatial structure in GAs, but cautions to avoid approaches that are too specific to individual problems. Incorporating spatial structure in GA can result in a set of solutions that are diverse in their geographic arrangement, which is desirable from the standpoint of providing decision makers with diverse decision options (Bennett et al., 2004; Ligmann-Zielinska et al., 2008). Tong, Murray, and Xiao (2009) introduced in their single objective genetic algorithm a crossover operation that is specific to facility location problems and incorporates the geographic arrangement of facilities to promote dispersion. In the category of spatial decision problems involving an arrangement of point-based locations, decision options are desired to have either clustering of point locations in space or dispersion of point locations throughout space (Tong et al., 2009). Cao et al. (2011) proposed a single parent crossover operator, for land use allocation problem, based on a randomly selected clump of cells fitting in a 3×3 cell window. The crossover operation is accomplished by randomly selecting the locations and the shape of the crossover clumps and swapping their cell values. Cao et al. (2011) claimed a 2-dimensional single parent crossover operator lead to faster solution convergence in land use allocation problems than a traditional single-point or multi-point crossover between two parents (chromosomes).

Another technique promoting diverse solutions, called *fuzzy adaptation* (Tarokh, 2008), examines the population throughout execution of the algorithm and adjusts operator probabilities using a fuzzy sets approach. Jaramillo et al. (2002) used variable operator probabilities in their genetic algorithm; however, the approach was not based on problem specific knowledge and produced small gains in objective performance in the solution set. The approach