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An improved Genetic Algorithm for spatial optimization of multi-objective and multi-site land use allocation

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ABSTRACT

As a result of multiple land use types, spatial heterogeneity, and conflicts of interest among multiple participants, multi-site land use allocation becomes a complex and significant optimization issue. We propose an improved Genetic Algorithm (GA) to deal with multi-site land use allocation, in which maximum economic benefit, maximum ecological benefit, maximum suitability, and maximum compactness were formulated as optimal objectives; and residential space demand and some regulatory knowledge were set as constraints. A Goal Programming model with a reference point form was used to manage trade-offs among multiple objectives. In order to improve the efficiency of the common GA applied to multi-site land use allocation, two crossover steps and two mutation operations were designed. This paper presents an application of the improved GA to the Regional District of Central Okanagan in Canada. Results showed that the proposed GA exhibited good robustness and could generate any optimal land use scenario according to stakeholders' preferred objectives, thus having the potential to provide interactive technical support for land use planning.

1. Introduction

Land use planning with the multiple macro-scale objectives of economic development, improvement of human well-being, and environmental conservation is an important policy instrument to achieve sustainable development goals. Generally, land use planning may be divided into two associated parts, of which the first is to generate alternative land use scenarios and the second is to assimilate public feedback and decide on a final land use allocation scheme. The core concrete work of land use planning is the first part, which is to allocate land use types to different spatial units having characteristics related to their geographical locations, with the purpose of seeking the best land use layout. Land resource allocation is thus a spatial optimization problem, where the planner tries to reconcile multiple conflicting interests as rationally and transparently as possible by manipulating the quantities and locations of land uses (Carsjens & van der Knaap, 2002).

In this paper, we deal with multi-site land use allocation (MLUA), referring to the problem of allocating more than one land use type to different spatial units, which is challenging as it not only deals with trade-offs among multiple objectives but must also conciliate the competition of different land uses for the same spatial unit (Aerts et al., 2003). When allocation decisions are made, there may be conflicting responses from multiple stakeholders, who have different land-use preferences for a limited land resource (Berke & Kaiser, 2006; Bojórquez-Tapia et al., 1994). Every spatial unit has a different fitness for a given land use type, meaning that some spatial units may be more appropriate for a particular land use because of site characteristics or other factors. Ideally, to maximize societal, economic, and ecological benefits, all of these factors should be taken into account (Eastman, Jin, & Kyem, 1995). Furthermore, the problem exhibits spatial dependency, and an additional planning objective may be to keep land use types connected, contiguous, or compact (Stewart, Janssen, & van Herwijnen, 2004). The reason for this is that the way a spatial unit is used has an effect on the future attributes of its neighbouring units, e.g., if a parcel is planned as a residence, its neighbours may be designated as commercial, residential, park, or transportation land use types, aiming to reduce the arrangement cost of public facilities and to improve community accessibility. Dealing with these spatial considerations, along with other economic and social constraints, to ensure that a community develops in a way that promotes well being, reduces transportation costs, and maintains ecosystem services is one of the key challenges faced by urban land use planners.

Land use change, however, is one of the single most important human drivers of environmental degradation on local, regional, and global scales (Foley et al., 2005). Appropriate and efficient land use planning is therefore one of the key ways to achieve sustainable development. There is an urgent need for effective tools to assist planners in determining the optimal allocation of future land use, taking into consideration various spatial and geographical constraints as well as community development goals. Computational approaches to land use

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allocation can help to resolve this problem, by generating a range of possible solutions that meet defined constraints and objectives.

Various tools and methods have been developed to resolve land use allocation. Some attention has been paid to optimization of land use structure, i.e., just optimizing the allocation of land use quantity; however the hypothesis of these approaches is that all cells are homogeneous across space, which is obviously not the case in a real situation (Liang & Yanfang, 2002; Sadeghi, Jalili, & Nikkami, 2009). For spatial optimization, a hierarchical optimization method for MLUA was presented in early works (Campbell et al., 1992; Carver, 1991), however it only considered the criterion of site suitability and neglected spatial target demands. As well, the efficiency and effectiveness of this approach is not ideal. Later, linear programming (LP) was applied to find solutions for MLUA (Cocks & Baird, 1989; Ligmann-Zielinska, Church, & Jankowski, 2008; Meyer, Lescot, & Laplana, 2009), but there are two distinct limitations to this approach: one is that it can't completely take into account spatial objectives whose values vary nonlinearly with cells' attribute values; the other is its helplessness in handling regions with more than 50×50 cells because of numerous variables and constraints (Aerts et al., 2003). Recently, more attention has been paid to applying heuristic algorithms to resolve land use allocation issues. Eastman, for example, proposed an Iterative Relaxation (IR) approach (Eastman, Jin, & Kyem, 1995), but it is unlikely to generate good solutions when spatial characteristics are of great importance (Brookes, 1997b). Brookes put forward a heuristics with a Genetic Algorithm (GA) for single site allocation and multi-patch design. However, the heuristic algorithm neglected competition of land uses for spatial locations, and requiring cells of the same land use to be contiguous may be a limitation of this approach (Brookes, 1997a, 2001). Matthews explored two chromosome representations of GA for rural spatial land use allocation and identified the strengths and weaknesses of each representation (Matthews, 2001).

On the whole, four main heuristics have been used to find optimized alternatives for MLUA. The most widely used is GA, which is a type of heuristic algorithm based on the mechanics of natural selection to search for a global optimum. GA has been proven effective in MLUA problems (Cao et al., 2012; Day et al., 1999; Feng & Lin, 1999; Liu, He et al., 2014; Liu et al., 2015), especially in large and complex search spaces (Goldberg, 1989). The second is the Simulated Annealing (SA) algorithm, which was first applied to solve MLUA by Aerts & Heuvelink (2002), and has been compared with other spatial allocation methods on effectiveness (Aerts et al., 2005; Santé-Riveira et al., 2008). In addition, a knowledge-informed Pareto SA was developed specifically to tackle multi-objective allocation problems by Duh & Brown (2007). The third heuristic is Particle Swarm Optimization (PSO), which was successfully used for MLUA by Liu (Liu, Liu et al., 2012), and subsequently a hybrid PSO was used to improve the convergence speed by Liu (Liu, Ou et al., 2013). The fourth is the Ant Colony Optimization (ACO) method, which involves seeking optimized alternatives by imitating ant colonies' food-search behaviour. ACO was improved to conduct MLUA and it has been demonstrated that its efficiency and effectiveness are both better than GA and SA (Li, He, & Liu, 2009; Liu, Li et al., 2012; Liu, Tang et al., 2014).

Each of the methods described above has limitations that restrict its ability to effectively solve MLUA problems. Although SA uses a temperature parameter to control the acceptance probability of solutions, thus avoiding local optimization traps, it was verified as having no advantage over GA approach by Aerts et al. (2005), and Liu, Li et al. (2012). We also compared the efficiency of SA and GA on the MLUA issue, the results of which are included as a supplement to this manuscript. The PSO method includes the general PSO and hybrid PSO. The general PSO may be unrealistic for MLUA problems due to the unsolved location renewal mechanism for multiple dimensions of particles (Ma, He, & Yu, 2010); and the hybrid PSO is in essence the same as GA, having crossover and mutation as evolutionary operations; the dimension of particles represents area proportions of landscapes, requiring that there be constant land use proportions set as constraints prior to spatial allocation (Liu, Ou et al., 2013). For ACO used to solve MLUA, ant type is determined by land use type, and every cell is an ant; the essence of ACO is to modify the conversion probability of cells with a feedback value of optimized objective from the previous loop, which in fact is an evolutionary operation to improve alternative performance. This method was shown to be a little more efficient than GA for MLUA (Liu, Li et al., 2012), however it probably cannot be used for typical, multi-objective optimization since it is not clear which objective's value should be selected as feedback to adjust the cell conversion probability in an evolutionary process, and multiple objectives are always in contradiction to each other. As a whole, GA for MLUA has two advantages: the first is that solutions are searched for via an evolutionary process, not completely depending on iterative selection, and thus providing a very efficient method of convergence towards the ideal solution. The second is that it can generate a non-dominated set for further analysis to reveal optimal solutions for a range of cases. For these reasons, we chose to use GA applied for MLUA in our study.

In addition to searching for optimal alternatives, another crucial aspect of MLUA is the technique used for multi-criteria decision making. Three approaches are commonly used. The first is the simple weight sum method, where each normalization objective value is given a weight, and then the weights are accumulated as a final pursuant objective (Aerts et al., 2003). The second is to seek the non-dominated set as an acceptable alternative, using the principle of the Pareto Optimum (Xiao, Armstrong, & Bennett, 2002; Xiao, Bennett, & Armstrong, 2007). The last is an application of Goal Programming (GP), in which a reference point is used for comparison of solutions. In this case, GP is used to pursue the solution with a minimum distance to a reference alternative, which can be adjusted by stakeholders based on their preferences for different objectives (Stewart, Janssen, & van Herwijnen, 2004). The first method with linear form could lead to highly biased solutions (Stewart, 1993, 1996), in which the comprehensive objective value may be perfect but some sub-objective values are poorly satisfied. Such solutions are obviously unacceptable for meeting the multi-objective (i.e., ecological, social and economic) requirements of sustainability. The Pareto Optimum method guarantees all sub-objective values of a selected solution are better than previous solutions, effectively averting the biased solution circumstance. There are, however, still two limitations, the first being that the increase in the number of objectives makes it difficult, as well as meaningless, to search for a non-dominated set. The other limitation is the inability to find an optimized solution that meets stakeholders' preferences for the multiple objectives.

Lastly, the data format (grid or vector) is also an important issue for MLUA problems. When in vector format, diverse approaches can be used to calculate a spatial objective, both computational efficiency and accuracy may be improved, and generally the number of spatial units can be decreased as compared to gridded data (Stewart & Janssen, 2014). However, there is a severe drawback to using the vector data format for MLUA, which is related to the cursory resolution of the spatial unit. For example, a large vector object that could be divided into many cells in a grid can only have one land use when working in vector format. When working in raster format, however, this same object could be assigned one land use for each cell. The use of vector format thus limits the flexibility of optimized allocation results for land use planning. For this reason, although the huge number of cells reduces operation efficiency, we will conduct MLUA using grid formatted data in this study.

Although some publications have focused on MLUA with heuristics tools, most of these studies have neglected to include objectives in their analysis; also government regulation on regional land use is rarely considered, which may seriously influence the final result of MLUA. In addition, recent heuristics applications have mainly focused on small regions with no empirical studies of MLUA on relatively large regions. Thus, there is still a great deal of development to be done before MLUA can meet the requirements of an interactive land use planning