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An improved simulated annealing algorithm for interactive multi-objective land resource spatial allocation

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ABSTRACT

The primary work of formulating land use planning is to pursuit an optimized land use pattern to guide human activities for land utilization effectively. However, due to numerous spatial units and multiple land use types, as well as the spatial heterogeneity and incompatible objectives, land resource spatial optimization (LRSA) becomes a challenging issue. Currently, relevant research focuses on the exploitation of methods to enhance the efficiency of LRSA to meet the interactive demand of plan making. This paper designed a new simulated annealing (SA) algorithm for LRSA and provided an interactive platform to determine the ideal land use pattern in terms of stakeholder preferences on conflicted objectives. First, a general optimization model with three parts, including objectives, constraints and the multi-objective decision making technique, was presented. Second, for SA with crossed combinations of three cooling functions and four types of solution renewal jump steps, 12 SA sub-models were proposed, of which efficiency was compared. Lastly Jiangdu County in China was used as a case study. The following conclusions were reached: our excavation made SA efficiency for LRSA increased by about 35%, and the sub-model with logistic curve as cooling function and jump step was a gradually decreasing parameter was the most effective model; the proposed approach could obtain an ideal solution on any location of the frontier according to stakeholder preferences for conflicted objectives, thereby providing a useful interactive tool to reach an agreeable scheme transparently.

1. Introduction

Recent land use change primarily caused by rapid urbanization has given rise to a series of problems, including the encroachment of arable land, a reduction in biodiversity, environmental pollution, and a modified hydrological cycle, which creates challenges for global food safety and the ecological environment, thereby resulting in development with poor sustainability (Foley et al., 2005; Liu et al., 2014a; Scholz, 2007; Song et al., 2002). Land is an important factor of production, and it is essential for human development and the ecological environment. Thus, the allocation of land to various departments determines the structure and function of socioeconomic system. Land allocation is increasingly becoming a useful management tool to achieve sustainable development (Cao et al., 2012; Liu et al., 2013). In reality, land resource spatial allocation (LRSA) is the core of land use planning which is typically divided into two associated parts: the first is to generate land resource allocation alternatives with integrated models; based on this, the second is to assimilate public engagement to determine an agreeable plan (Janssen et al., 2008). Therefore, to effectively enhance land use planning of promoting sustainability, LRSA is studied to advise policy makers on the quantity and location of land resource allocation for different socioeconomic departments, which fundamentally determines the level of sustainability. Essentially, LRSA is a spatial optimization problem, where planners attempt to reconcile multiple conflicting interests as rationally and transparently as possible by manipulating the quantity and locations of different land use types (Carsjens and van der Knaap, 2002). However, because of the following characteristics, it becomes a rather complex optimization issue.

The first is the massive spatial units and various land use types, which means planners have to determine the land use type of every spatial unit, e.g., 100×100 cells with n land use types will have astronomical $n^{100*100}$ possibilities, which is called NP-hard problem in the operational research field, and there are currently no good methods to solve it accurately. Compared to allocation of only one land use type, the allocation of multiple landscapes requires the management of their occupation competition for spatial units, which drastically increases the complexity. Second, LRSA is a typical multi-objective optimization, including not only economic and ecological benefits but also a spatial objective, which refers to the spatial distribution of land use patterns, such as compactness, adjacency and coherence. Thus, measuring the

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spatial objective and reconciling the conflicts of various objectives are significant challenges. Third, heterogeneous space increases the complexity of LRSA. Due to differences of geographical locations, spatial cells even with the same land use type, will have different economic and ecological benefits, which is the primary reason for adopting spatial optimization rather than quantity optimization. Thus, we need to calculate each cell value of the suggested objectives with different landscapes. Fourth, temporal dimension must be considered. Typically, the LRSA object for land use planning is not at present, but in the future. Hence, influential factors of future land use should be forecasted spatially to help determine the land use types of the spatial units, which undoubtedly brings many challenges. Therefore, although LRSA is the essence of spatial planning which is employed to guide human activities to achieve sustainability, it is difficult to resolve because it is a typical NP-hard problem with incompatible objectives and non-linear spatial peculiarity, as well as spatial heterogeneity.

Various methods were previously applied to LRSA, which were generally classified as traditional programming, i.e., linear and non-linear programming (Aerts et al., 2003; Campbell et al., 1992; Cocks and Baird, 1989; Ligmann-Zielinska et al., 2008; Meyer et al., 2009; Zhang et al., 2015) and a heuristic approach. There are two disadvantages for traditional programming: first, it cannot completely account for nonlinear spatial objective values, and it always simplifies the spatial objective formulation. Second, it is unable to handle a region with cells exceeding 50×50 due to the numerous variables and constraints, and the solution time of traditional programming has disadvantages compared to heuristics (Aerts et al., 2003). Although Ligmann-Zielinska et al., 2008 used traditional programming model to calculate the spatial allocation for 73,396 cells, later Zhang et al., 2015 used the same model to calculate for 1244×944 cells, and utilized the paralleled branch and bound algorithm to search for an exact optimal solution using a super computer. However, they assumed the space is homogenous, which we think did not capture the essence of LRSA due to the neglect of spatial heterogeneity; thus, they significantly simplified this issue. There is currently no significant evidence that traditional programming could manage LRSA properly in large regions.

Therefore, current researchers tend to use heuristics applications to resolve this situation. Overall, five primary heuristics methods have been used to search for an optimized alternative for LRSA: simulated annealing (SA) algorithm, genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO) and other heuristics. The traditional GA modified on crossover and mutation operations was widely used for LRSA (Cao et al., 2011, 2012; Feng and Lin, 1999; Haque and Asami, 2014; Kundu, 2009; Stewart et al., 2004). Theoretically, that is completely feasible, however, when cell numbers are larger than 100×100 the runtime is too long. To shorten the runtime, a spatially explicit GA model was proposed (Holzkämper and Seppelt, 2007; Liu et al., 2015) where only cells on the spatial boundaries of different landscapes were allowed to evolve; in addition, different paralleled GA paradigms were designed to enhance optimizing efficiency (Porta et al., 2013). SA is the second most popular heuristic method for LRSA (Aerts and Heuvelink, 2002; Duh and Brown, 2007; Eldrandaly, 2010; Liu et al., 2012c; Santé-Riveira et al., 2008), which uses randomly selected clusters that are altered to create a new solution during the evolutionary mechanism searching for the ideal alternative, and it was always comparable to GA on efficiency (Aerts et al., 2005). PSO primarily includes general PSO and hybrid PSO. For general PSO, due to the unsolved location renewal mechanism of multi-dimensional particles, it may be unrealistic for spatial allocation application (Ma et al., 2010). For hybrid PSO, it is essentially the same as GA, having crossover and mutation as evolutionary operations. However, for PSO, the particle dimensions represent the areas of different landscapes, requiring a constant area constraint for each landscape before spatial allocation (Liu et al., 2012b, 2013; Wang et al., 2012). Therefore, it could not determine the optimized solution solely based on the occupation competition for cells using spatial characteristics. When ACO is used for spatial allocation, ant type is determined using land use type, and each cell is an ant; the essence of ACO is to modify the cells' conversion probability of next iteration with feedback values of the optimized objective from last loop, which is an evolutionary operation of improving alternative performance and was proved to be more efficient compared to GA and SA (Liu et al., 2012a, 2014b). However, we think it cannot be used for typical multi-objective optimization, because there are always several conflicting objectives and it is not clear which objective's should be selected as feedback to adjust the conversion probability in the evolutionary process. For example, if economic objective is chosen as feedback, then the final solution is economic-biased, and if the ecological objective is the feedback, then the final solution is ecology-biased. Other heuristics application for LRSA including artificial bee colony (ABC) (Yang et al., 2015), artificial immune system (AIS) (Huang et al., 2013), tabu search (TS) (Mohammadi et al., 2016), however we find the evolutionary operation of these heuristics are just like crossover and mutation of GA, or just like the Hop-Skip-Jump technique firstly proposed by Brill et al. (1982).

Multi-objective decision making is important for LRSA, as different stakeholders have different requirements on land utilization, and an informed scheme can only be obtained if the advantages and disadvantages of the alternatives are carefully considered to make the decision process transparent and clear (Linkov et al., 2006), which is necessary for land use planning formulation. Thus, LRSA methods should have the ability to manage trade-offs among multiple objectives and to measure these trade-offs. According to the literatures, there are three practices for multi-objective decision making. The most common is the simple weight sum method where each objective is given a weight with which multiple objectives are summed up linearly as the final optimization criteria (Aerts et al., 2003). The second is the Pareto Optimum method that seeks the non-dominated set as the final solution (Polasky et al., 2008; Xiao et al., 2002, 2007). The third is the Goal Programming model where a reference point is used to generate the desired solution (Stewart et al., 2004). The first approach always leads to highly biased solutions and cannot find solutions on the frontier. The second and third approaches both find solutions on the frontier, and their difference (Fig. 1) is that the second determines a non-dominated set which is a group of solutions on the frontier, while Goal Programming only determines one solution on the frontier every time. According to the convex character, the nearest distance from the reference point to dashed area is the distance to its boundary, therefore, the solution solved by Goal Programming is also on the frontier. In this paper, Goal Programming is chosen because it can generate a non-inferior solution with regards to stakeholder preferences denoted by the reference point.

Data type (vector or grid) can impact the efficiency of LRSA modeling to some extent, and due to generally having relatively fewer spatial units and the advantage of measuring spatial objectives, vector format optimization is thought to be more efficient. However, the practical regulation demand of land use planning should be considered: if plot is regulated as the basic land use unit and is not allowed to be divided into small parcels, vector format will be chosen; otherwise grid format is the better selection. Due to intense demand pressure, land resource is more inclined to have fragmented utilization, e.g., sometimes plots need to be divided to satisfy different stakeholder claims. Therefore, vector format optimization may provide limited significance for land use management. From previous available studies, we also found grid format allocation to be the primary practice, and few references used vector format (Liu et al., 2012c; Porta et al., 2013; Stewart and Janssen, 2014). In short, the final purpose of LRSA is to develop a planning decision support system which requires an acceptable runtime for generating alternatives. Currently, with computer hardware improvements, the paralleled algorithm is the future trend (Porta et al., 2013; Zhang et al., 2015). However, we should first determine which heuristics to be employed as meta-heuristics for the parallel design, since it impacts optimizing efficiency fundamentally.

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