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# A multiobjective GIS-based land use planning algorithm

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ABSTRACT

This paper purposes an enhanced land use optimization model for land-use planning with a new spatial component. This component uses a simple representation of the proximity of related land uses to each other as a function of distances between parcel centroids. A special purpose genetic algorithm is developed for solving the resultant optimization problems for both the direct (additive) objectives and the indirect (spatial) objective. The context relates to interactive decision support for land use planning in which the data are stored in a vector-based GIS, and the requirement was to integrate the multiobjective optimization with the GIS structure. The present work thus extends earlier work by the authors which used a grid (raster) structure. The model is based on a reference point approach in which both additive and spatial goals can be specified. Numerical testing of the algorithm, and experimentation with possible user inputs, are described in the context of a real case study from a region of The Netherlands. It is shown that the simplified spatial proximity measure and the associated algorithm produce consistent results in which the spatial distribution of activities are essentially the same as with more complex modeling of spatial goals, achievable in the particular case study with little loss in terms of the additive objectives.

## 1. Introduction

During the last decade a large number of spatial decision support systems have been developed to assist decision makers in the field of resource allocation and, in particular, spatial planning issues (Geertman & Stillwell, 2009). When alternatives or objectives are spatial, data are needed on the geographical locations of alternatives, spatial formulations of objectives and data on the spatial pattern of criterion values. This requires a combination of multicriteria methods with a geographical information system (GIS) (Arciniegas, Janssen, & Omtzigt, 2011; Malczewski, 2010). This combination is referred to as a spatial decision support system (SDSS) (Carver, 1991). GIS is used to produce thematic maps and to perform spatial operations. Multicriteria methods are used to translate these maps into value maps, optimal or compromise maps and to rank spatial alternatives (Arciniegas, Janssen, & Rietveld, 2013; Alexander et al., 2012; Janssen, Arciniegas, & Verhoeven, 2013).

Spatial multicriteria analysis (MCA) typically starts with a set of land-use alternatives that is defined beforehand. This set of alternatives can be defined using the inputs from experts such as spatial planners or landscape architects (Arciniegas & Janssen, 2012), land-use models, (e.g. Lau & Kam, 2005; Oxley, McIntosh, Mulligan, Winder, & Engelen, 2004), or by applying design methods based on multiobjective optimization techniques (MOOT). Such design techniques generate an 'optimal' solution for a specific preference structure from a large or possibly infinite set of alternatives, where the set of alternatives to choose from is implicitly defined through constraints and exogenous influences. In other words, the optimal solution is created or 'designed' by the SDSS using techniques based on tools such as multiobjective linear programming (Aerts, Eisinger, Heuvelink, & Stewart, 2003; Cova & Church, 2000). As a special case of design methods, interactive optimization offers solutions to the planner in a number of steps where, after each step, the planner can change the conditions for optimization (Janssen, van Herwijnen, Stewart, & Aerts, 2008; Stewart, Janssen, & van Herwijnen, 2004). Using optimization to generate the optimal solution requires that all objectives can be described in mathematical terms and incorporated in the optimization model.

Geographical information systems make use of two types of data: spatial data and attribute data (Longley, Goodchild, Maguire, & Rhind, 2005). The spatial data describe location and shape of spatial entities; the attributes are the properties of these

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spatial entities. In using GIS as input to an optimization model, the decision units are related to spatial entities, in the sense that choices have to be made for land uses at every spatial location. An attribute table includes both the decision variables, e.g. types of land use, together with any attribute values which need to be included in the objective function(s). Spatial data in a GIS are typically arranged using one of two models: vector or raster. Entities in vector format are represented by strings of coordinates (points). Two points can be connected to form a line segment, while sequences of lines can be connected to each other, terminating back at the starting point to form a polygon (parcel or area). Attribute data are stored for each polygon (which can be of varying sizes). Data in a raster model are stored in a two-dimensional matrix of uniform cells on a regular grid. Depending on the model used, each polygon or grid cell is assumed to have homogeneous properties.

By their nature raster data are substantially easier to include in mathematical representations of the world for purposes of optimization. As a result most GIS-based applications of MOOT use grid-based data as their input. Using a grid based representation of a planning region, Stewart et al. (2004) and Janssen et al. (2008) showed that it was possible to formulate a spatial planning problem in mathematical terms and apply MOOT to generate optimal solutions interactively. Unfortunately, they also had to conclude that using a grid size which would realistically describe the planning region leads to unrealistically long computation times, as a result of the large number of decision variables. This prevented use in a fully interactive setting where short response times are essential. Other examples of grid-based applications can be found in Cao, Huang, Wang, and Lin (2011), Ligmann-Zielinska, Church, and Jankowski (2008), and Santé-Riveira, Boullon-Magan, Crecente-Maseda, and Miranda-Barriós (2008).

Looking at Fig. 1 it is immediately clear that moving to a vector based representation will lead to a more efficient representation of the problem. The vector presentation (Fig. 1(b)) shows the border of the spatial decision unit (e.g. a parcel) with type of land use as its decision variable. The raster representation of the same spatial unit requires a large number of cells with an equally large number of decision variables bound together by the constraint that the land use for all grid cells must be the same. Although it is clear that a vector representation leads to a more efficient representation of the problem, it is also clear that the switch from grid to raster creates new complications. In a raster each grid cell has the same shape and size, borders on exactly four other grid cells and has four borders of equal length. In a vector format each polygon can have any shape and size, and have any number of borders of various lengths.

Closely related land use optimization problems based on a GIS link include Matthews, Sibbald, and Craw (1999), who do not however consider the spatial objectives which we shall later discuss, Demetriou, See, and Stillwell (2013), who examine partitioning of a region into distinct land uses, and Porta et al. (2013) which is perhaps most closely allied to our problem, but with some differences we shall highlight later.

Janssen et al. (2008) differentiate between two types of objectives, namely simple additive objectives, which associate costs and/or benefits with the allocation of any particular land use to a specific cell, which are then cumulated additively across all cells; and spatial objectives which indicate the extent to which the different land uses are contiguous (i.e., the extent to which activities are or are not fragmented across the region). The shift from a grid to vector based representation do not create great difficulties for the additive objectives. The differences in area size of the decision units can easily be accommodated using area size as a weighting factor in calculating overall performance. The shift from raster to vector is not so easily implemented for the spatial objectives, as we shall discuss in the next section.

The present paper describes a genetic algorithm that can be used to generate land use plans that maximize both additive and spatial objectives in a vector based GIS environment. The algorithm will be applied as part of a series of collaborative planning workshops to support a land use allocation problem in a peat-meadow polder in The Netherlands. Results from the algorithm will be used to generate a number of land use plans that can serve as reference plans at the start of these workshops.

This article is organized as follows. In the next section, alternative formulations of the land use planning problem are discussed, giving rise in general to a non-linear combinatorial optimization problem. In Section 3 we describe a practical case study providing background for the type of situation in which our algorithms would be applied. Algorithmic methods for solving the non-linear problem are described in Section 4, including reference to a simplified linear formulation excluding spatial objectives. The specially designed genetic algorithm (GA) for the full optimization step is then defined in some detail, and numerical testing of this GA is reported in Section 5. Finally, in Section 6, some experimental runs for the case study are described.

## 2. Mathematical formulation

Suppose that the total region is represented by $I$ parcels of land, labeled $i = 1, \ldots, I$. In a raster-based GIS, these would be rectangles of uniform size, but for a vector-based GIS each parcel would be represented by "polygons" of unique size and shape. The underlying assumption is that parcels are defined to a level of size and resolution such that a single land use would need to be assigned to each parcel. Parcels for which land uses are fixed (e.g. streams, roads, etc.) can either be omitted from the data base, or the land use assignment can be pre-specified as a hard constraint. (Our model implementation allows the user both options.) This may be a restriction in other application contexts than our own, where division of a polygon into more than one land use may be desired.

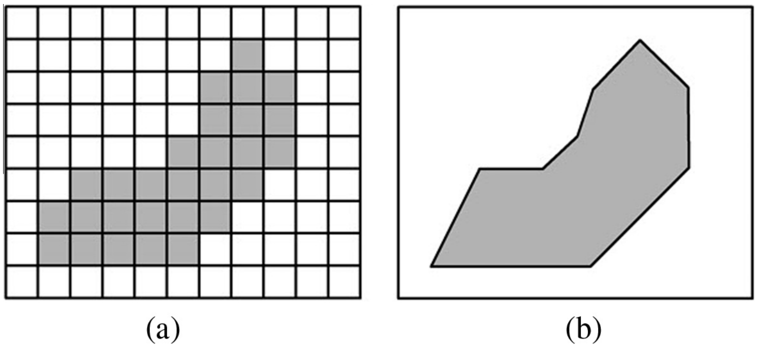

**Fig. 1.** Raster (a) and vector (b) data representation.