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Multiobjective decision support for land-use planning

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Abstract. The overall objective of this paper is to show how a formal decision support method can be used effectively to support a land-use planning problem. Central to our approach is a heuristic algorithm based on a goal-programming/reference-point approach. The algorithm is tested on a small region in the Netherlands. To demonstrate the potential use of the algorithm, a planning problem is defined for this region. An interactive session with a land-use planner is then simulated, to show how feedback from the planner is used to generate a plan in a number of rounds. It is concluded that the approach has potential for the support of land-use problems especially in the first rounds of policy design as long as maps are used to interface between planner and algorithm. It is also shown that computational problems still hinder the achievement of realistic detail in the representation of the plan area.

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 (eg Aerts, 2002; Aerts and Heuvelink, 2002; Carver et al, 2001; Pettit, 2005; White and Engelen, 2000). A decision support system (DSS) can be defined as an instrument for finding (sets of) alternative solutions for a decision problem. In terms of spatial planing, a DSS should be ale to support the finding of optimal spatial distributions of land use. Since such a DSS often uses GIS functionality, is it referred as a spatial DSS (SDSS) (Carver, 1991).

An SDSS may also contain multicriteria analysis (MCA) techniques that enable users to evaluate available alternative solutions against each other (eg Carver, 1991; Janssen, 1992; Janssen and Rietveld, 1990; Pereira and Duckstein, 1993; van Herwijnen, 1999). However, MCA typically requires that land-use alternatives be defined beforehand. This problem can be tackled using land-use growth models (eg Clarke et al, 1997; Lau and Kam, 2005; Oxley et al, 2004; White et al, 1997), 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 (eg Aerts et al, 2003; Cova and Church, 2000; Williams and Revelle, 1996). The 'optimal' solutions for each of a number of different preference structures then generate a finite set of alternatives that may be evaluated by other MCA techniques (eg Stewart and Scott, 1995).

The type of land-use allocation problems dealt with in this paper involve specification of a single activity to each parcel of land and thus have a fundamentally combinatorial nature. Such problems are often highly nonlinear, and involve large amounts of data and widely divergent objectives (Densham and Rushton, 1992). Although attempts have been made to structure such problems in a form suitable for solution by linear programming techniques, the combinatorial and/or nonlinear characteristics of the problem have led to heuristic MOOT gaining attention as suitable design techniques within an SDSS (eg Aerts et al, 2005; Stewart et al, 2004). These are fast and capable of handling large datasets, such as those present in much of the current spatial planing processes. Studies on the application of heuristic algorithms are relatively conceptual and little methodological research exists as to how to use design techniques in actual planning processes, including making reference to the potential of the techniques for using them in a multistakeholder setting.

The complexity, and indeed the multiobjective nature, of land-use planning problems has been recognized from as early as the 1970s. Barber (1976) and Arad and Berechman (1978) discuss land-use design in terms of the units of different activities that may be allocated to each zone or site in a region, and consider also interactions between regions. Both stress the importance of dealing explicitly with conflicting objectives in such planning, and Barber reports an application of one of the earliest interactive algorithms for solving multiobjective optimization problems (ie that of Geoffrion et al, 1972). Neither of these papers deal with spatial attributes such as compactness or connectedness, however.

Hopkins (1977) describes an assignment model of land-use planning (such that each zone is allocated only to one land use), as in our formulation. This model includes a quadratic assignment term to represent interactions between land uses in different sites, which is a possible extension to be considered for implementation in our model. Hopkins does not, however, deal explicitly with multiple objectives or with spatial attributes.

This paper is a follow-up of a more technical paper that includes a full description of the algorithm and numerical experiences with its implementation (Stewart et al, 2004). It describes a step-by-step application of such a heuristic design technique, based on this genetic algorithm approach and specifically developed for use in a prototype SDSS. The present paper is more planning oriented and aims at issues linked to implementation and application.

The approach followed in this paper addresses the following requirements for the application of the design technique:

(1) The SDSS should be able to handle differing priorities by multiple stakeholders. Involvement of stakeholders also requires interactive use of the algorithm: stakeholders provide feedback on solutions generated and make adjustments to these solutions. This means that the SDSS must be able to generate a comprehensive range of relevant solutions.

(2) The SDSS should facilitate multiple objectives defined in a spatial context, such as spatial relationships across land uses in adjacent areas, in the sense that attribute values associated with one unit may be dependent on activities in neighbouring units (eg Murray and Church, 1995).

(3) The SDSS should be able to handle a large amount of data while maintaining good communication between the SDSS and the end users.

(4) The SDSS must be able to accommodate rapid adjustments to land-use plans developed by the stakeholders in interactive sessions with the SDSS. This requires short response times from the algorithm, at least during earlier stages of evaluation.

In section 2 we start by summarizing the mathematical formulation for the land-use planning problem as developed in Stewart et al (2004) following a goal-programming/reference-point methodology. In section 3 this mathematical formulation is applied to an SDSS model that describes a land-use planning problem in a region of The Netherlands called the Jisperveld. In section 4 the operational use of the SDSS is demonstrated by applying the heuristic algorithm in a stepwise approach to a set of land-use plans for the Jisperveld. We conclude finally with a forward look to improving the prototype SDSS for the decision context in which the SDSS will ultimately be used, and which remaining research questions such implementation will require.

2 Multicriteria formulation

In this section we provide a brief outline of the model developed in Stewart et al (2004), describing the formal problem formulation in mathematical terms, the MOOT model (generalized goal programming) and the numerical solution of this model by means of a genetic algorithm approach.

The region of interest is represented by a two-dimensional grid of cells, arranged into R rows and C columns. A specific land use, say U_{rc} (from a set of K possible land uses), needs then to be associated with each cell (r, c). For algorithmic purposes, it is useful to define *binary decision variables* χ_{rck}, such that $\chi_{rck} = 1$ if land use k is allocated to cell (r, c), and $\chi_{rck} = 0$ otherwise. Mathematically, then, the problem is to select binary values for each of the RCK decision variables, so as best to achieve the decision maker's objectives, subject to a variety of constraints. Clearly the first constraint is to ensure that one and only one land use is allocated to each cell—that is:

$$\sum_{k=1}^{K} \chi_{rck} = 1, \qquad \text{for } r = 1, \ldots, R; \; c = 1, \ldots, C \, . \tag{1}$$

The total number of cells allocated to a particular land use is given by $N_k = \sum_{r=1}^{R} \sum_{c=1}^{C} \chi_{rck}$. There may usually be direct restrictions on N_k, which may be expressed in the form:

$$\lambda_k \leqslant N_k \leqslant \mu_k \, . \tag{2}$$

Note that a full list of variables used in the paper is provided in the appendix.

Other constraints may include minimum sizes of clusters of a single land use, and restrictions on which land uses may be allowed in specific cells. The model differentiates between two types of objectives, namely simple *additive objectives*, which associate costs or benefits with the allocation of any particular land use to a specific cell, and are then cumulated additively across all cells; and *spatial objectives* which indicate the extent to which the different land uses are connected, contiguous, or fragmented across the region.

By definition, additive objectives may be expressed in the form:

$$f_p(\boldsymbol{u}) = \sum_{r=1}^{R} \sum_{c=1}^{C} \sum_{k=1}^{K} a_{rckp} x_{rck} \, , \tag{3}$$

for $p = 1, \ldots, P$ (the number of additive objectives), and where $\boldsymbol{u}$ denotes the specific land-use map described by the χ_{rck}. For the purposes of describing the algorithm used, we shall in this section treat all of these additive objectives as costs to be minimized. There is no loss in generality in doing so; if any of these objectives are in fact benefits to be maximized (as occurs in our later case study), then the signs of the coefficients may be reversed (to treat benefits in effect as negative costs). It can easily be seen that the ultimate aggregate scalarizing function which is to be minimized [equation (5), below] is invariant to reversal of the signs of the a_{rckp} coefficients.

Spatial objectives require greater care in definition. Aerts et al (2005), for example, describe three distinct measures on the 'compactness' of areas allocated to each land use. In Stewart et al (2004) it was argued that a flexible tool for describing spatial objectives could be based on identifying all land-use '*clusters*'—that is, sets of contiguous cells having the same land use. Three cluster-based objectives were then proposed as follows:

(1) Minimize the number of clusters for each land use, say C_k: this measures the degree of fragmentation of land use, and minimization of C_k for each k tends to ensure that areas of the same land use are maximally connected.

(2) Maximize the relative magnitude of the largest cluster for each land use, say L_k: if multiple clusters are formed (ie $C_k > 1$), it is often better to have one relatively large cluster, with all others much smaller, than for all clusters to be of a similar (moderate) size.

(3) Maximize the compactness of each land use k, denoted by R_k, defined as the average across all clusters of the ratio of the number of perimeter cells to the total number of cells in the cluster: square or circular clusters have lower R_k than long thread-like clusters, which are argued to be more difficult to manage. A referee to an earlier version of the present paper has pointed out by counterexample that it would be better to base the compactness measure on the perimeter itself (the sum of unconnected edges), rather than on the number of perimeter cells. This revised definition will be incorporated into future versions of the software. However, for purposes of the present paper (to demonstrate the effectiveness of the decision support approach), the current definition of R_k was retained.

These cluster-based objectives are highly nonlinear, and in fact cannot be expressed in closed mathematical form as functions of the χ_{rck}. Nevertheless, they are relatively easy to compute numerically for any given set of χ_{rck} values.

We have thus identified three spatial objectives for each land use, expressed as functions of the land-use map $\boldsymbol{u}$, say $\mathrm{g}_{kq}(\boldsymbol{u})$, defined implicitly through a clustering algorithm rather than in closed algebraic form. Once again, for illustrative purposes, we shall suppose that all the $\mathrm{g}_{kq}(\boldsymbol{u})$ are defined such that minimization of each is desirable, so that formally we would need to define $\mathrm{g}_{k2}(\boldsymbol{u})$ by $-L_k$.

The problem is thus represented as a multiobjective optimization problem with $P+KQ$ minimizing objectives. A temptation at this stage is simply to combine the objectives into a single weighted additive function of the form:

$$\sum_{p=1}^{P} w_p \mathrm{f}_p(\boldsymbol{u}) + \sum_{k=1}^{K}\sum_{q=1}^{3} w_{kq}\mathrm{g}_{kq}(\boldsymbol{u}) \ . \tag{4}$$

However, the additive form in equation (4) [unless the functions f_p and g_{kq} have been structured as 'value functions' satisfying some very special properties (eg Belton and Stewart, 2002, section 4.2), can lead to highly biased results with a tendency to extremes (some objectives being very well satisfied, while others perform very poorly] rather than balanced compromises (Stewart, 1993; 1996). It is true that sufficient systematic experimentation with different weights in equation (4) can identify all nondominated solutions to a convex multiobjective optimization problem (eg Miettinen, 1999, section 3.1), but the problems we have described are not, in general, convex, while such systematic experimentation would in any case be computationally expensive for implementation in the proposed SDSS.

In order to seek better compromises, the DSS described here is based on the reference-point (generalized goal-programming) methodology (Wierzbicki, 1999). Technical details are described in full by Stewart et al (2004), but, in summary, the approach involves the following key features.

- An *ideal value* (I_p or I_{kq}) is specified for each objective, indicating the smallest possible value that can practically be taken on by the objective functions $\mathrm{f}_p(\boldsymbol{u})$ or $\mathrm{g}_{kq}(\boldsymbol{u})$, respectively (recalling the assumption that objectives are to be minimized). In some cases the ideal can be directly computed, but in some cases it needs to be heuristically assessed.
- A *goal value* ($\gamma_p > I_p$ or $\gamma_{kq} > I_{kq}$) is specified for each objective, indicating a level of performance that can be categorized as satisfactory. These goals are the primary means by which preferences of the decision maker are modelled. In the current implementation of the DSS, the goals are not specified explicitly by the user of the system; they are initialized at an intermediate level between ideal and worst-case levels, and are then adjusted up or down internally in the system as the user changes nominal *priority levels*.
- The system generates the land-use map which approximates as closely as possible the specified goal values by minimizing the following aggregate ('scalarizing') function, subject to the constraints indicated earlier:

$$\sigma(\boldsymbol{u}) = \sum_{p=1}^{P} \left[\frac{\mathrm{f}_p(\boldsymbol{u}) - I_p}{\gamma_p - I_p} \right]^4 + \sum_{k=1}^{K} \sum_{q=1}^{3} \left[\frac{\mathrm{g}_{kq}(\boldsymbol{u}) - I_{kq}}{\gamma_{kq} - I_{kq}} \right]^4 . \tag{5}$$

For performance better than the goal level—that is, $\mathrm{f}_k(\boldsymbol{u}) < \gamma_k$ or $\mathrm{g}_{kq}(\boldsymbol{u}) < \gamma_{kq}$, the corresponding terms in equation (5) contribute essentially no penalty. As performance violates the stated goal, the corresponding penalty term grows rapidly and at an ever-increasing rate. As a result, minimization of the scalarizing function $\sigma(\boldsymbol{u})$ avoids outcomes in which very poor performance occurs even for only one or two objectives, and thus tends to generate balanced compromises.

The resulting 'optimal' land use does depend on the goals which have been specified. The user of the DSS exercises control over the relative importance attached to each objective simply by allocating higher or lower priorities on a scale of 0 to 1 for each, which then result in adjusted goal levels. Further refinements of the model are planned to allow more user-friendly inputs of these priorities.

Some of the constraints (such as bounds on N_k or minimum cluster sizes) tend to be quite fuzzy in practice, and are in fact also dealt with as 'goals' in the same way as in the case of the objectives, with deviations from these goals incorporated as additional terms in equation (5).

Minimization of equation (5) involves a difficult nonlinear combinatorial optimization problem. An approach to the solution of such problems, which has become widely used in recent years, is that of a *genetic algorithm* (eg Fonseca and Fleming, 1995; Jaskiewicz, 2002; Mirrazavi et al, 2001). The central features of the genetic-algorithm approach are the following:

(1) random generation of a large number of possible solutions (land-use maps) which are placed in a 'population';

(2) implementation of 'crossovers' between pairs of randomly selected members of the population to produce 'child' solutions, each of which shares part of the characteristics from each of its 'parents';

(3) introduction of small random mutations to each new child solution before it is added to the population;

(4) systematic elimination of the least fit members of the population (on the basis of their scalarizing function values) at each generation.

General-purpose genetic algorithms do exist, but there appear to be substantial advantages in developing a special-purpose genetic algorithm for the land-use problem, exploiting many of its special characteristics. It is this special-purpose algorithm which is described in Stewart et al (2004), and which is used for the results reported in the present paper.

3 Formulation of the decision problem

Land-use planning in the Jisperveld is selected to experiment with the model and algorithm. The Jisperveld is part of the largest connected brackish peat meadow area of Western Europe. It is situated in the northwest of the Netherlands and measures 2000 ha, of which 800 ha belong to a nature organisation. The whole area is criss-crossed with water, which gives it its special character (see figure 1). The high natural value of the area is caused by the presence of rare meadow birds, such as black-tailed godwit, common redshank, and lark, and by the existence of special vegetation like sundew, peat heather, and various types of orchid.

For the purpose of the present numerical studies, a 400 ha region was selected. Figure 2(a) shows the aerial picture of the area and figure 2(b) the land-use map. The land-use maps identify as many as thirty-three distinct land-use types for this area. For computational reasons the land-use map has been simplified to a 20 cell $\times$ 20 cell representation [figure 2(c)], and the number of land-use types has been reduced to nine [figure 2(d)].

As part of a large development plan, a combined recreation and nature plan is developed for this reason. For this plan three additive attributes were identified, corresponding to the objectives: (1) maximization of the natural value of the area, (2) maximization of the recreational value of the area, (3) minimization of the cost

Figure 1. [In color online, see http://dx.doi.org/10.1068/b33071/] Aerial photograph of the Jisperveld.

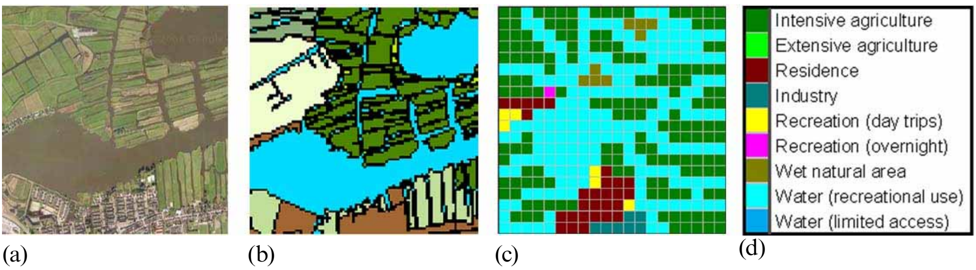


Figure 2. [In color online.] (a) Satellite image, (b) land-use map, (c) simplified land-use map, and (d) legend of the simplified land-use map.

of changing land use. In addition, all three of the spatial objectives defined in section 2 were considered relevant to the current case study. This results in six objectives:
(1) maximize the natural value of the area,
(2) maximize the recreational value of the area,
(3) minimize the cost of the changing land use,
(4) minimize fragmentation,
(5) maximize the largest cluster,
(6) maximize compactness.

The spatial objectives minimization of fragmentation, and maximization of the largest cluster, and compactness are defined in section 2. The *natural* value is measured by a simple additive attribute [equation (6)]. The total natural value is calculated in two steps. First the type of land use for each grid cell is determined, and a value is attached to the grid according to its land use. Second, the value of all 400 grids are aggregated.

$$\mathrm{f}_{\text{nature}}(\boldsymbol{u}) = \sum_{r=1}^{20}\sum_{c=1}^{20}\sum_{k=1}^{9} a_{rck(\text{nature})}\,\chi_{rck} \quad . \tag{6}$$

The value assigned to nature for each land-use type k is $a_{rck(\text{nature})}$. This value can be constant (equal for all r and c) or can be dependent on the location of a grid cell. The values used for nature are shown in the first data column of table 1.

It can be seen in this table that, if the land-use type is industry, the value for nature is 1, irrespective of location. The table also shows that the value for nature of land-use type 'extensive agriculture' is represented as a map [figure 3(a)]. This means that this value is dependent on the location of extensive agriculture. The value map used

Table 1. Values for nature and recreation per land-use type.

Land-use type (k)	Nature value $[a_{rck(\text{nature})}]$ range: [1, 10]	Recreation value $[a_{rck(\text{recreation})}]$ range: [1, 10]
1 intensive agriculture	4	6
2 extensive agriculture	map figure 3(a)	map figure 3(a)
3 residence	3	3
4 industry	1	1
5 recreation (day trips)	5	map figure 3(b)
6 recreation (overnight)	5	map figure 3(c)
7 wet natural area	map figure 3(a)	7
8 water (recreational use)	7	map figure 3(b)
9 water (limited access)	map figure 3(a)	1

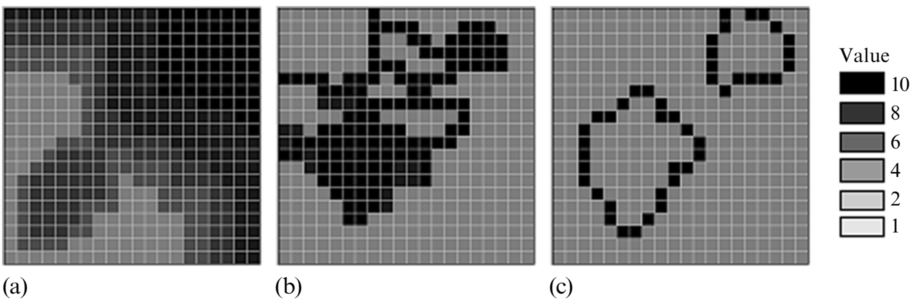


Figure 3. Value maps for nature (a) and recreation (a, b, c) (see table 1).

depends to a large extent on the value for meadow birds. The variation in value reflects the distance from disturbance such as industry and residence. The same map is used for the land uses 'wet natural area' and 'water (limited access)'.

The *recreation* objective [equation (7)] is defined similarly to the nature objective [equation (6)]. The values $a_{rck(\mathrm{recreation})}$ indicate the recreation values for land-use types k. Again, these values can be defined as a constant or as a map (table 1 and figure 3). In the case of nonspatial valuation the values $a_{rck(\mathrm{recreation})}$ are equal for all r and c. The list of constant recreation values is given in the second data column of table 1.

$$\mathrm{f}_{\mathrm{recreation}}(\boldsymbol{u}) = \sum_{r=1}^{20}\sum_{c=1}^{20}\sum_{k=1}^{9} a_{rck(\mathrm{recreation})}\chi_{rck} \quad . \tag{7}$$

The assumptions in respect of attribute measures such as 'natural' and 'recreational' values are that these are elicited in such a way as to be defined on at least an interval scale (eg Wolman, 2006), such that additive aggregation across the region is legitimate. Unaided value assessments may indeed run the risk of violating this assumption (as argued by Wolman). The risk can, in our experience be moderated by guiding users, through reference to analogies with which they are familiar, such as school grades and/or thermometer scales (see, for example, the discussion in section 5.2 of Belton and Stewart, 2002).

The cost is defined as the total cost of converting the current situation into a new situation. For each pair of land uses l and k, d_{lk} represents the cost of changing land use from type l into k (table 2). Thus, for any cell (r, c), the cost of allocating a land use k to this cell—that is, $a_{rck(\mathrm{cost})}$—is then simply d_{lk}, where l is the current land use in cell (r, c). Conversion costs for all grids are aggregated to arrive at the total costs.

$$\mathrm{f}_{\mathrm{cost}}(\boldsymbol{u}) = \sum_{r=1}^{20}\sum_{c=1}^{20}\sum_{k=1}^{9} a_{rck(\mathrm{cost})}\chi_{rck} \quad . \tag{8}$$

The conversion costs presented in table 2 are based on the changes in land value that result from a conversion from one land-use type to the other and on the cost of measures linked to the conversion. The price of agricultural grassland in the area for the year 2005 is used as a starting point (www.boerderij.nl). In addition, management costs and costs of moving soil in case of conversion to water were included. Management can be constant for a certain land use but also be location dependent—for example, as a result of different levels of access. Some conversions are excluded (indicated with an x). In the content of this planning process it is, for example, not feasible to consider demolishing houses or dismantling industry for agriculture, recreation, or water.

Table 2. Positive and negative revenues of conversion from land use l to k (d_{lk}) in 1000 €/ha land-use type (x indicates infeasible conversions).

Land-use type	1	2	3	4	5	6	7	8	9
1 intensive agriculture	–	−75	150	150	−225	0	−150	−300	−300
2 extensive agriculture	75	–	150	150	−150	75	−75	−225	−225
3 residence	x	x	–	x	−10 000	−10 000	x	x	x
4 industry	x	x	x	–	−10 000	−10 000	x	x	x
5 recreation (day trips)	150	75	3	300	–	150	0	−150	−150
6 recreation (overnight)	0	−75	150	150	−150	–	−150	−300	−230
7 wet natural area	x	75	225	225	−75	150	–	−75	−75
8 water (recreational use)	100	100	x	x	x	x	0	–	15
9 water (limited access)	100	100	x	x	x	x	0	0	–

Constraints can be set for the area to be allocated to each land-use type. Figure 4 shows, for each land-use type, the existing area in the current situation and the minimum and maximum area sizes specified as constraints. Note that intensive agriculture covers 157 ha but is constrained to 150 ha, thereby forcing a change. Extensive agriculture, on the contrary, does not occur in the original map but has to cover at least 20 ha in the new design.

Areas can be fixed to a certain land-use type. This creates the opportunity to predefine land use in certain grids, which allows the user to exclude changes that are impossible or unacceptable to the user. In this example, residential areas, industrial areas, and wet natural areas are fixed (figure 5). Note that this type of constraint limits the searching area for new plans and therefore speeds up the optimization process.

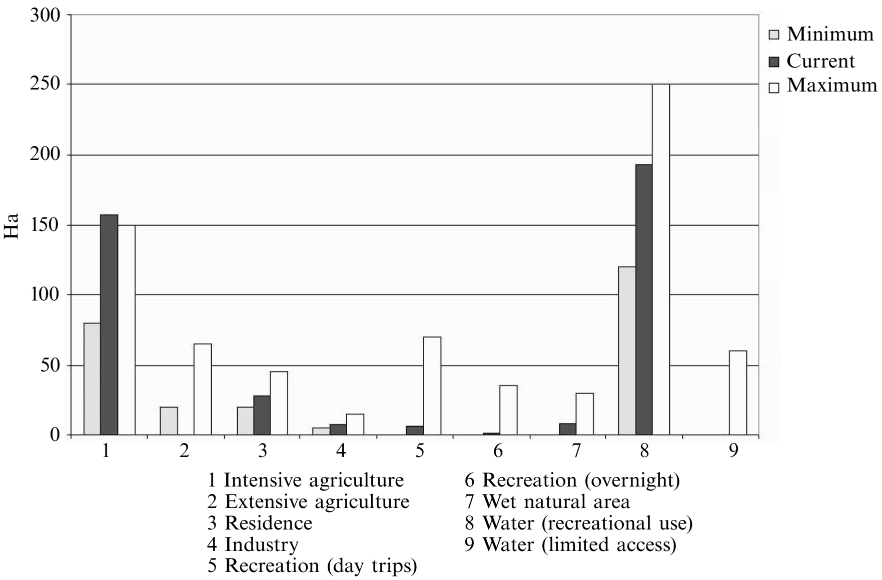


Figure 4. Minimum, current, and maximum size per land-use type.

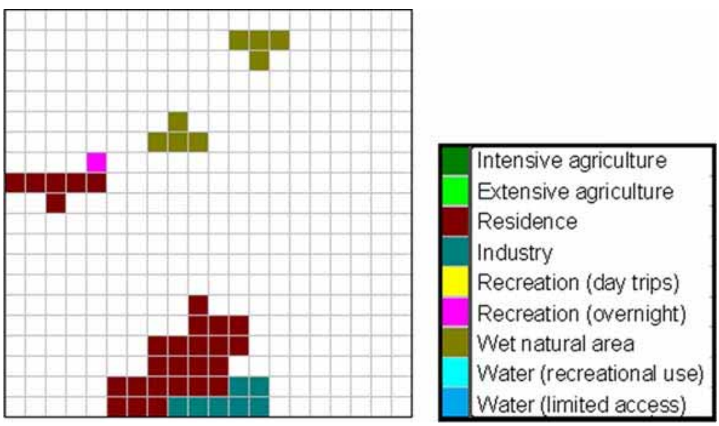


Figure 5. [In color online.] Fixed land-use types.

4 Design of land-use plans

An interface is built around the algorithm, in order to facilitate interaction with the planner. The interface is based on feedback provided by the planner in a planning session. A typical interactive session includes a number of rounds. At the start of each round a land-use plan is presented to the planner. The planner is asked to provide feedback on this plan. The algorithm uses this feedback to generate a new version of the land-use plan, which is presented to the planner at the start of the next round. The session ends when the planner is satisfied with the result. It is assumed that the planner sharpens his or her priorities in response to the plans presented.

In each round the planner can adjust (1) weights of the six policy objectives, (2) minimum and maximum areas of the nine land-use types, and (3) cells that the planner wants to stay the same in the next round. An example of an interactive session is presented in this section. The session starts with the current land-use map and reaches an acceptable solution in eight rounds.

The interface of the optimization algorithm is presented in figure 6. This figure shows the current map (left) and the first land-use plan (right). To generate this plan equal priority is given to all objectives.

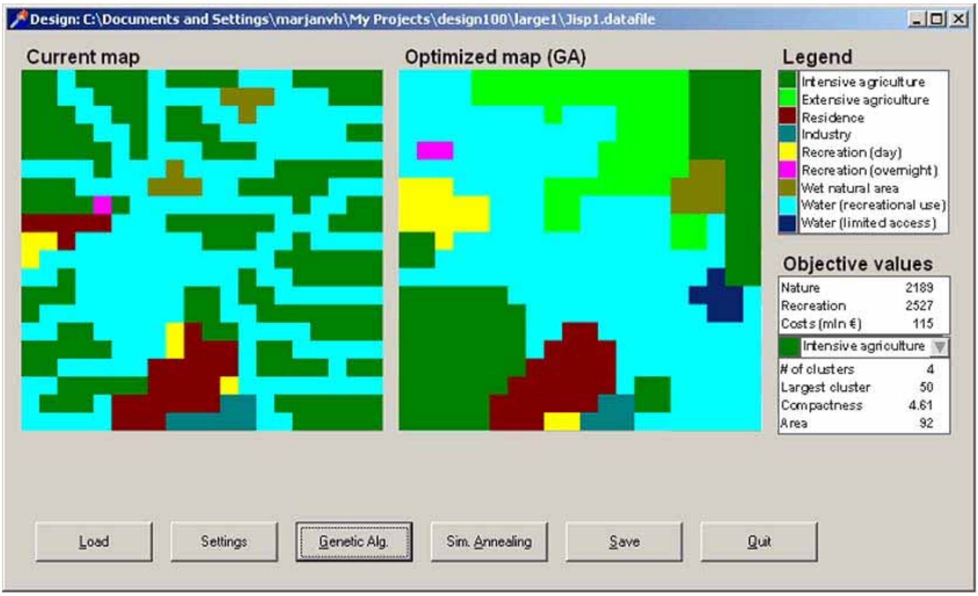


Figure 6. [In color online.] The design interface with the current map and results of the first round.

The difference between the current situation and the results of round 1 are large. Land use in a large number of grid cells has changed. The effects on the policy objectives are summarized to the right. The large change in land use results in a very high conversion cost of 115 million euros.

All input values are shown in table 3. The first three rows show the priorities of the additive objectives. These priorities are linked to the distance between the worst (nadir) and best (ideal) possible results, given the specified constraints. A value of 0.5 indicates that the goal is set halfway between these extremes. The second section includes priorities for spatial objectives, which are for each type of land use separately. The priorities range from 0 (no need for improvement) to +++ (strong need for improvement). The next nine rows show the minimum and maximum area required

Table 3. Input values round 1 – 8. Where only one value is given for the minimum – maximum areas it represents the fixed value used for that round.

	Round							
	1	2	3	4	5	6	7	8
Priorities (*additive objectives*)								
Nature (0 – 1)	0.5	0.5	0.7	0.7	0.7	0.7	0.7	0.7
Recreation (0 – 1)	0.5	0.5	0.3	0.3	0.3	0.3	0.3	0.3
Costs (0 – 1)	0.5	0.7	0.7	0.7	0.7	0.5	0.5	0.7
Priorities (*spatial objectives*)								
Number of clusters intensive agriculture	+ +	+ +	0	0	+ + +	+ + +	+ + +	+ +
Number of clusters wet natural area	+ +	+ +	0	+ + +	+ + +	+ + +	+ + +	+ +
Number of clusters water limited access	+ +	+ +	0	+ + +	+ + +	+ + +	+ + +	+ +
Largest cluster wet natural area	+ +	+ +	0	0	0	0	0	+ +
Compactness intensive agriculture	+ +	+ +	0	0	+ + +	+ + +	+ + +	+ +
All others	+ +	+ +	0	0	0	0	0	0
Minimum or maximum area of land use								
1 intensive agriculture (ha)	80 – 150	80 – 150	80 – 150	80 – 150	106	106	106	106
2 extensive agriculture (ha)	20 – 65	20 – 65	20 – 65	20 – 65	20 – 65	20 – 65	20 – 65	20 – 65
3 residence (ha)	20 – 45	20 – 45	20 – 45	20 – 45	20 – 45	20 – 45	20 – 45	20 – 45
4 industry (ha)	5 – 15	5 – 15	5 – 15	5 – 15	5 – 15	5 – 15	5 – 15	5 – 15
5 recreation (day) (ha)	0 – 70	0 – 70	0 – 70	0 – 70	0 – 70	0 – 70	0 – 70	0 – 70
6 recreation (overnight) (ha)	0 – 35	0 – 35	0 – 35	0 – 35	0 – 35	0 – 35	0 – 35	0 – 35
7 wet natural area (ha)	0 – 30	0 – 30	0 – 30	14 – 30	14 – 30	14 – 30	14 – 30	14 – 30
8 water (recreational) (ha)	120 – 150	120 – 150	120 – 150	120 – 150	120 – 150	120 – 150	120 – 150	120 – 150
9 water (limited access) (ha)	0 – 60	0 – 60	0 – 60	28 – 60	28 – 60	28 – 60	28 – 60	28 – 60
Fixed land use	none	figure 5	figure 5	figure 5	figure 5	figure 5	figure 5	figure 5
Conversion costs (agriculture to water)	table 2	table 2	table 2	table 2	table 2	table 2	+ €100 000	not allowed

Table 4. Results for the current situation (round 0) and rounds 1–8.

	Round								
	0	1	2	3	4	5	6	7	8
Additive objectives									
Nature (400–4000) [a]	1766	2189	1928	2098	2087	2037	2146	2173	1960
Recreation (400–4000)	2580	2527	2558	2514	2423	2358	2358	2410	2383
Costs (million €)	0	115	13	12	13	20	25	27	12
Spatial objectives									
Number of clusters intensive agriculture	19	4	8	11	10	1	4	4	9
Number of clusters wet natural area	2	1	2	2	1	1	1	1	1
Number of clusters water limited use	0	1	1	3	1	2	1	3	3
Largest cluster wet natural area	4	8	5	10	25	23	21	27	31
Compactness intensive agriculture (9.4–4.0) [b]	5.42	4.61	4.98	5.04	5.28	4.83	4.68	4.50	4.90
Area per land-use type									
Intensive agriculture (ha)	157	92	130	103	98	107	105	105	108
Extensive agriculture (ha)	0	58	50	52	33	48	51	51	43
Residence (ha)	28	26	34	29	35	28	28	28	32
Industry (ha)	7	5	5	8	8	8	7	7	7
Recreation (day) (ha)	6	16	3	5	5	21	5	5	6
Recreation (overnight) (ha)	1	2	3	11	8	9	2	8	9
Wet natural area (ha)	8	8	9	14	25	23	21	27	31
Water (recreational) (ha)	193	187	153	150	157	120	142	125	121
Water (limited access) (ha)	0	6	11	28	31	36	39	44	31

[a] The minimum value of a cell for nature is 1 and the maximum value is 10. Since the size of the area is 400 ha, this results in a range of 400–4000.

[b] The value of this attribute ranges from 9.4 (worst) to 4.0 (best). Please note that for this attribute a lower value is better than a higher value.

for each type of land use (the constraints). Note that these values can be higher or lower than the current situation. For example, a minimum value of 20 ha is set for extensive agriculture, although there is currently no extensive agriculture in the area. Finally, no land uses are fixed in round 1 and the costs of conversion are as specified in table 2.

The input values for round 1 are shown in the first column in table 3. The results of round 1 are shown in the second column of table 4. This table shows that, compared with the current situation (round 0), nature has improved, but recreation shows a small decline The spatial objectives have improved substantially. Table 4 also shows how much land is allocated in each type of land use.

The complete interactive session with the land-use planner is shown in table 5. At the start of each round a map is presented to the planner, together with the numerical values included in table 4. The planner provides feedback, which results in the input values for the next round (table 3). This results in a new map, which is the starting point for the next round. The map presented to the planner in round 1 is the current land-use map. Eight rounds of feedback are necessary to produce a map that is satisfactory to the planner. This map is shown in the last row of table 5.

Table 5. [In color online.] Interactive design of a land-use plan in eight rounds. See table 1 for the key to the land uses denoted in the map.

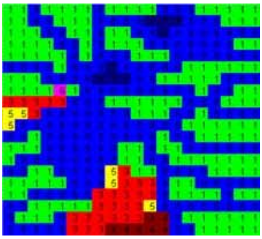
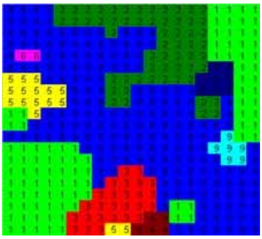
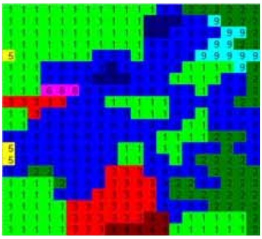
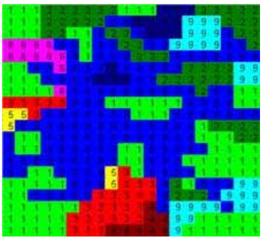
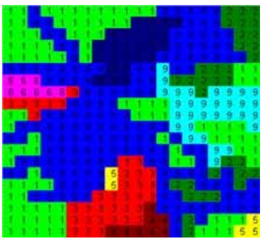
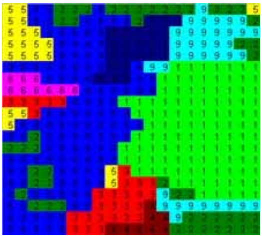
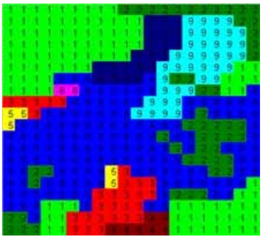
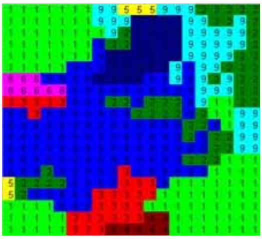
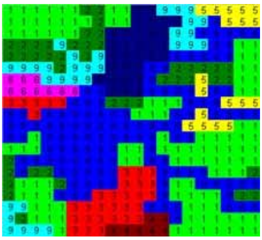
Map presented	Feedback
1 	The current land-use map shows a highly fragmented area without extensive agriculture (land use 2) and wet natural area (land use 7). The planner specifies a minimum size for extensive agriculture and decides to see what happens if all objectives are given equal weight.
2 	The input map for round 2 differs enormously from the current land-use map. Large areas of extensive agriculture (land use 2) and a small patch of wet natural area (land use 7) have been created. Fragmentation is now low. However, the large changes in land use come at a cost of 115 million euros (table 4). The planner decides that the plan is too expensive and increases the priority for costs.
3 	The overall value for nature is low (see table 4), mainly because nature is located at unfavourable locations. The costs are now at an acceptable level. The planner decides to run the model again with a higher weight for nature.
4 	Although the value of nature has increased in this map (table 4), the various clusters of wet natural area (land use 7) and water limited access (land use 9) are not connected. This is not good for maintaining sustainable populations of water animals. The planner decides to increase the weights of the number of clusters of wet natural area and water limited access and decides to set minimum areas for these land uses.
5 	The map that results from round 4 is a farmer's nightmare. There are many small and irregular patches of agricultural land (land uses 1 and 2) that, in some cases, can be reached only by boat. To improve connectedness and compactness the weight of the number of clusters and the weight of compactness of intensive agriculture are increased. The total size of the agricultural area is fixed at the level of round 4.

Table 5 (continued)

Map presented	Feedback
6 	Connectedness of intensive agricultural (land use 1) has improved to the maximum: only one cluster is left. Also, compactness has improved. The planner decides to fix the area allocated to intensive agriculture and lower the weight for costs.
7 	The planner is worried that, due to new regulations linked to the Water Framework Directive, the cost of soil removed will increase. The conversion cost of agriculture to water is increased by 100 000 €/ha.
8 	The planner compares this map with the current situation and is worried that the characteristic pattern of the area of patches of land surrounded by water (see figure 1) is lost. The planner decides to block changes from agriculture land to water.
9 	The planner compares the result with the current map (map 1). The general impression of the two maps is similar. The natural value and spatial characteristics are substantially improved and the costs are acceptable. The planner is satisfied with the result and the interactive session is ended.

5 Conclusions

The overall objective of this paper has been to define and evaluate a spatial decision support system (SDSS) process for land-use planning. In this SDSS, decision-maker preferences are modelled in terms of a goal-programming/reference point approach, which lends itself to implementation in an interactive manner. In order to evaluate the proposed process, it was applied to a real land-use planning problem in the Netherlands, but with a simulated study of an interactive session with a planner.

The SDSS process can be evaluated on the basis of (1) feasibility of the interactive approach to establishing planning priorities; (2) relevance of the spatial objectives used; and (3) system response times.

5.1 Interactive establishment of priorities

The simulated session demonstrated how policy goals and priorities can be specified indirectly in terms of simple sets of constraints and visual assessment of maps. Users may not be able to specify such goals or priorities a priori, but the process summarized in table 5 illustrates how examination of the output maps and tables can lead ultimately to a plan that satisfactorily achieves the implied goals. In this process these implied goals or priorities do in fact become explicit as part of the interactive process, leaving a clear audit trail of value judgments.

5.2 Relevance of the spatial objectives

The current design of the SDSS recognizes three distinct types of spatial objectives— the number of clusters, the relative magnitude of the largest cluster, and a measure of compactness. The simulated session demonstrated the ease with which visual patterns observed in the maps can be interpreted in terms of these three objectives, leading to determination of the direction in which the current land-use plan should be modified in order better to fulfill goals. These objectives can be assessed separately for different land uses, with the possibility of associating different levels of importance of the spatial objectives for different land uses.

Of particular importance is the demonstration that qualitative and spatial objectives can be included in an SDSS, even if not representable in terms of explicit mathematical formulae. Aspects such as visual attractiveness or historical context of the plan can be left to the expert judgment of those using the interactive form of SDSS illustrated above (eg Janssen and Uran, 2003; Uran and Janssen, 2003).

5.3 Response times

The examples presented above are based on a 20×20 grid representation. At this resolution level, the running time of the optimization step for one set of priorities averages about 48 seconds (on an Intel Pentium 1.86 GHz processor), which is adequate for the level of interaction envisaged here (in which evaluation of the resulting map might take many minutes of contemplation or discussion). Preliminary computational experience suggests that this running time increases proportional to approximately the 2.7th power of the number of cells (ie a doubling of the numbers of rows and columns would increase computational time by a factor of approximately $4^{2.7} = 42$).

Figure 7 shows the same area as used in our example, but presented on a 142×142 grid (ie approximately 20 000 cells, or a fifty-fold increase). This level of resolution would seem to be desirable in order to obtain a realistic representation of the area for purposes of interaction. Other regions may in fact be of greater area extent,

Figure 7. [In color online.] A 142×142 grid representation of the Jisperveld.

thus requiring even larger numbers of cells. These requirements present the greatest challenge to the ongoing algorithmic research. The fifty-fold increase with the current software would imply a computation time of more than twelve hours per interaction and this we aim to reduce to a few minutes at most.

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Appendix: list of variables

r	cell row index for $r = 1, \ldots, R$;
c	cell column index for $c = 1, \ldots, C$;
k	land-use index for $k = 1, \ldots, K$;
p	additive objective index for $p = 1, \ldots, P$;
q	spatial objective index for $q = 1, \ldots, Q$;
U_{rc}	specific land use for cell (r, c);
$\boldsymbol{u}$	vector representation of land-use allocation for all cells; (ie U_{rc} for all r and c);
χ_{rck}	binary decision variable indicating whether cell (r, c) is allocated to land use k (i.e. $\chi_{rck} = 1$ if $U_{rc} = k$, and is 0 otherwise);
N_k	total number of cells to be allocated to land use k;
λ_k	minimum number of cells to be allocated to land use k;
μ_k	maximum number of cells to be allocated to land use k;
$\mathrm{f}_p(\boldsymbol{u})$, $\mathrm{g}_{kq}(\boldsymbol{u})$	formal representation additive and spatial objectives respectively;
a_{rckp}	objective function coefficient for additive objective p;
C_k	numbers of clusters for land use k;
L_k	relative magnitude of the largest cluster for land use k;
R_k	compactness of land use k;
I_p, I_{kq}	ideal values for additive and spatial objectives respectively;
γ_p, γ_{kq}	goal values for additive and spatial objectives respectively;
d_{lk}	cost of changing land-use type 1 into k.