Intl. Trans. in Op. Res. 12 (2005) 203–213

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

A mathematical model for zoning of protected natural areas

A. Verdiell[a,b], M. Sabatini[a,c], M. C. Maciel[a,b] and R. M. Rodriguez Iglesias[a,c]

[a]*Universidad Nacional del Sur, Bahía Blanca, Argentina,*
[b]*Departamento de Matemática, Argentina,*
[c]*CONICET, Departamento de Agronomía, Argentina*
E-mails: averdiel@criba.edu.ar [Verdiell]; sabatini@criba.edu.ar [Sabatini]; immaciel@criba.edu.ar [Maciel]; cerodri@criba.edu.ar [Rodriguez Iglesias]

Received October 2003; received in revised form September 2004; accepted October 2004

Abstract

When formulated in mathematical terms, the problem of zoning a protected natural area subject to both box and spatial constraints results in a combinatorial optimization problem belonging to the NP-hard class. This fact and the usual dimension of the problem (regularly in the tens of thousands order) suggest the need to apply a heuristic approach. In this contribution we describe a quantitative method for zoning protected natural areas based on a simulated annealing algorithm. Building upon previous work by Bos (1993), we introduce three main innovations (a quadratic function of distance between land units, a non-symmetric matrix of compatibilities among uses, and a spatial connection constraint) that make the approach applicable for ecological purposes. When applied to solving small-size simulated problems, the results were indistinguishable from those obtained via an exact, enumerative method. A coarse-scale zoning of Talampaya National Park (Argentina) rendered maps remarkably similar to those produced by subject area experts using a non-quantitative consensus-seeking approach. Results are encouraging and show particular potential for the periodical update of zoning of protected natural areas. Such a capability is crucial for application in developing countries where both human and financial resources are usually scarce but still critical for updating zoning and management plans.

Keywords: protected areas; zoning; combinatorial optimization; quadratic assignment problem; simulated annealing; heuristics

Introduction

Social and scientific interest in the protection of natural areas has been developed over the past 100 years. Since the creation of the first national park in 1872, thousands of protected natural areas have been established worldwide. Protected areas were initially established for the enjoyment of scenery, tourism, and recreation (Nelson, 1991; Sabatini and Rodriguez Iglesias, 2001). Additional objectives (e.g. conservation of species and ecosystem diversity, preservation of ecological processes, promotion of scientific activities, limited resource exploitation) were developed over time. Inevitably, a variety of objectives and alternative land uses generated a complex landscape of interests. As expected, opposing interests lead to conflicts (Cendrero et al., 1993; IUCN, 1993; McNeely, 1994; Sabatini and Rodriguez Iglesias, 2001).

Zoning, that is the process of assigning land units to specific uses, is a useful alternative for conflict mitigation. Researchers and managers frequently emphasize the value of zoning for conflict abatement in the management of protected areas (Miller, 1980; Haas et al., 1987; Salinas Chavez and Casas Cid, 1992; Cendrero et al., 1993).

Until now, zoning methods applied to protected natural areas are mostly qualitative, rely heavily on the involvement of subject experts, and are highly demanding of human effort and financial resources. As a consequence, zoning usually fulfills a descriptive rather than a prescriptive function. This is particularly true for developing countries where natural areas are usually run under stringent financial constraints (Sabatini and Rodriguez Iglesias, 2001).

Prescriptive zoning plays a pivotal role in driving decisions and, ideally, it should be periodically reviewed and updated. The objective of this contribution is to develop a quantitative tool for the prescriptive zoning of protected natural areas, with capabilities for rapid review and update on demand. We formulate a mathematical model incorporating most of the features related to zoning of protected natural areas and propose a method for solving the problem. Our work builds upon the forest zoning approach developed by Bos (1993). We describe major modifications that make such an approach applicable to ecological purposes. Simulated and real-life examples are solved and discussed.

Mathematical formulation of the problem

In order to formulate a quantitative method for solving the zoning problem, the protected natural area, the area for short, is represented by a rectangular grid divided into parcels of land or cells and the demands of different social groups are translated or represented by uses, for instance natural conservation, stationary and dispersed recreation, research, and so on.

In fact, the assignment of each land unit to a specific use will depend on the agreement between the land attributes, namely physical, ecological, and the characteristics that define the aptitude for certain uses such as water availability, proximity to roads, and so on, all embedded into the context of constraints imposed by the managers. This process of zoning is modeled as a combinatorial optimization problem with constraints.

Let us define the objective function and the constraints.

Assume that the grid has $m \times r$ cells; each one can be identified by a pair (i, j) or by a positive number $(i-1)r+j$.

In this work, the distance between cells g and h is considered as the Euclidean distance in $\mathbb{R}^2$ and denoted by $d(g, h)$.

We define:

$n = m \times r$: the number of cells in the grid;
s: the number of uses;
A_{gu}: the aptitude of the cell g assigned to the use u. $A = (A_{gu}) \in \mathbb{R}^{n \times s}$;
P_u: the preference given to the use u. $P = (P_u) \in \mathbb{R}^s$.

Since for each cell a use has to be assigned, the decision variables are:

$$X_{gu} = \begin{cases} 1 & \text{if use } u \text{ is assigned to the cell } g, \\ 0 & \text{otherwise.} \end{cases}$$

$X = (X_{gu}) \in \mathbb{R}^{n \times s}$.

C_{uv}: the measure of the compatibility between uses u and v. $C = (C_{uv}) \in \mathbb{R}^{n \times s}$.

If g, h are two cells, we define:

$$D_{gh} = \begin{cases} \frac{1}{d(g,h)^2} & \text{if } g \neq h, \\ 0 & \text{otherwise.} \end{cases}$$

Finally, let $M \geqslant 0$ be a weighting parameter.

The objective function is defined as follows:

$$f(X) = \sum_{g=1}^{n} \sum_{u=1}^{s} A_{gu} P_u X_{gu} + M \sum_{g,h=1}^{n} \sum_{u,v=1}^{s} C_{uv} D_{gh} X_{gu} X_{hv} \tag{1}$$

and the goal is to solve the following problem:

$$\begin{array}{ll} \max & f(X) \\ X \in \Omega & \end{array} \tag{2}$$

where Ω is the set of constraints.

The linear term in (1) represents the contribution of each cell's aptitude towards the general goal, when weighted according to preferences for different uses. The contribution of the quadratic part is a function of the compatibility among uses and the distance between cells assigned to the same or a different use. The coefficient M provides a convenient numerical knob for fine-tuning relative contributions of aptitude-use agreement versus spatial configuration. Both terms represent highly relevant issues in the zoning problem as applied to protected natural areas.

If the aptitude of a cell g for a determined use u were the sole criterion for assignment, then a global maximum should be reached by allocating each cell to the use for which it has the highest aptitude value A_{gu}. In order to give priority to one use over another, the P_u weighting factor is incorporated.

One of the main problems that managers have to face is how the assignment of a use to a piece of land is affected by the uses to which adjacent cells were previously assigned. This is because both compatibility and conflict among uses have to be taken into account when allocating cells in a spatial context. In the objective function, compatibility among uses is explicitly considered through the C_{uv} coefficient. If uses u and v are compatible (e.g. strict preservation and scientific research) C_{uv} should be greater than zero; otherwise (e.g. recreation and conservation) C_{uv} should be given some negative value. It is worth mentioning that compatibility among uses is not usually a symmetric relation for protected natural areas. Recreation will probably be affected in a very negative way by logging activity nearby but the opposite is not necessarily true. Thus, in contrast to Bos (1993), the C matrix in our proposal is, in general, a non-symmetric matrix.

From a zoning perspective it is desirable that cells allocated to conflicting uses be located further apart than cells assigned to compatible ones. In accordance, compatibility coefficients in (1) are multiplied by the inverse of the squared Euclidean distance between cells. This has the effect of clustering cells allocated to compatible uses, a desirable property from a land management point of view. In Bos (1993), proposal distance is modeled as a linear effect that has the undesirable consequence of not exhausting the influence of neighboring cells quickly enough to produce clustering.

Since use allocation within a natural area is usually influenced by the characteristics of the surrounding area, the zoning model explicitly incorporates a neighborhood of the protected area into the grid. Cells in the surrounding area are pre-assigned to fixed uses (e.g. agriculture, city limits, lake) but they may still exert an influence on the allocation of cells to uses within the natural area via the C and D matrices.

Constraints depend on planning needs. In this work we consider two types of constraints. The first type are box constraints and they appear when minimum and/or maximum numbers of cells must be assigned to a use in accordance with planning decisions (e.g. minimum area required for camping).

If $u_{\min}$ and $u_{\max}$, represent, respectively, the minimum and maximum number of cells that can be assigned to use u, the set Ω is defined by the assignments that satisfy:

$$\begin{aligned} &u_{\min} \leqslant \sum_{g=1}^{n} X_{gu} \leqslant u_{\max}, \quad 1 \leqslant u \leqslant s, \\ &X_{gu} \in \{0, 1\}, \quad 1 \leqslant u \leqslant s,\ 1 \leqslant g \leqslant n. \end{aligned} \tag{3}$$

The second type of constraint considered relates to the connection among cells assigned to a given use. This kind of constraint is motivated by characteristic needs of protected natural areas such as required corridors from nesting to feeding areas, continuity in recreational circuits, etc. Corridors favor structural continuity and are key, indispensable landscape elements in protected natural areas.

For this purpose the following sets are defined:

$$V = \{u \in \mathbb{N},\ 1 \leqslant u \leqslant s : \text{the use } u \text{ requires connection}\}$$

$$W = \{i \in \mathbb{N}, 1 \leqslant i \leqslant n : \text{and cell } i \text{ is not in the surrounding area}\}.$$

For each $i \in W$, let

$$I_i = \{j \in W : i \neq j \text{ and cells } i,\ j \text{ are adjacent}\}.$$

Then, the set Ω is defined by (3) and the assignment satisfying

$$\sum_{j \in I_i} X_{jg} \geqslant 1, \quad \text{if } X_{ig} = 1,\ i \in W,\ g \in V. \tag{4}$$

As formulated, the proposed zoning model is a combinatorial problem of quadratic assignment belonging to the NP-hard class (Nemhauser and Wolsey, 1988). The solution of this kind of problem by exact methods is computationally feasible only for small problems (Bruenegger et al. 1996). Even when mapped on a scale of hectares, protected natural areas are composed of at least tens and not uncommonly tens of thousands of land units to be assigned. Thus, it is virtually impossible to compute exact solutions via exact methods. Heuristics (Silver et al. 1980) offer a possible alternative and we use the well-known simulated annealing paradigm to solve the zoning problem, which has a record of good results for quadratic assignment problems (Burkard, 1984; Burkard and Rendl, 1984; Connolly, 1990; Bos, 1993).

The framework of the algorithm

For the sake of completeness, we include our algorithm based on the simulated annealing method.

Algorithm

Given T_i, T_f the initial and final values of the control parameter, S the initial assignment, $f(S)$ the objective function value, *iter* the number of times that the inner iteration is repeated keeping the control parameter value.

Set change $\leftarrow$ *true*
Repeat Step 1 to 3 **until** change = true or $T_i > T_f$
Step 1: Set change $\leftarrow$ false

Step 2: **Repeat** iter times
  2.1 Compute S' and evaluate the change in the objective function value
    $\Delta = f(S) - f(S')$.
  2.2 Decide if S' is accepted
    If $\Delta < 0$ go to 2.3
    else
      generate a random variable $x \in (0, 1)$
      If $x < e^{-\Delta/T_i}$ go to 2.3
      else
        go to 2.1
      endif
    endif
  2.3 Accept S' and update the information:

$$S \leftarrow S', f(S) \leftarrow f(S'), \textit{change} \leftarrow \textit{true}$$

Step 3: Decrease T_i.

The main characteristics of the algorithm are:

- The basic procedure consists of a loop with a random change generator that modifies the objective function value. It begins with a starting solution S that can be randomly assigned and a starting objective function value: $f(S)$. The assignment S' is chosen and the corresponding change $\Delta = f(S) - f(S')$ is evaluated; if Δ is less than zero, the assignation is accepted and S' becomes the new configuration S. Otherwise it is treated probabilistically.
- Because of the adopted procedure for choosing S', the probability of accepting worse solutions is not monotonically decreasing since if T_i decreases constantly, Δ may compensate it, providing a probability $e^{-\Delta/T_i}$ greater than some previous value of the parameter. Therefore T_f must be chosen small enough in each problem in order to ensure that there are no worse acceptable solutions at any moment in the simulation.
- The quadratic objective function to optimize is not necessarily convex, and so we cannot guarantee the global maximizer. We are dealing with sub-optimal solutions (Nemhauser and Wolsey, 1988).

- The good performance of the algorithm depends on the neighborhood structure. It is established as follows: given an assignment $S \in \mathbb{R}^{r \times s}$, let us considerer a feasible $S' \in \mathbb{R}^{r \times s}$ obtained from S satisfying one of the following properties:

  (1) interchanging rows: $S' = P(i,j)S$ where $P(i,j)$ is the permutation matrix obtained from the identity matrix interchanging the rows i and j.
  (2) interchanging two elements: if $S_{iu} = 1$ and $S_{iv} = 0$ then $S'_{iu} = 0$ and $S'_{iv} = 1$.

  The set $\mathcal{N}(S) = \{S' \in \mathbb{R}^{r \times s}$, S' satisfies (1) or (2)$\}$ is said to be a neighborhood of S. At each iteration of the algorithm, given the current assignment S, a new one is chosen at random in $\mathcal{N}(S)$.

- An important issue in the algorithm is the choice of a cooling schedule: the simulated annealing strategy proposes to decrease the control parameter, T, known as temperature. There are several schedules: the ones proposed by Lundy (Lundy and Mees, 1986), Aarts (Aarts and van Laarhoven, 1985), and the geometric schedule (Kirkpatrik et al., 1983). In this work we use the geometric schedule, which consists of decreasing the value of the parameter T_i at the end of each loop according to the rule: $T_i = \alpha \times T_i$, for some $\alpha < 1$.

Implementation details

In this section a specific implementation of the algorithm is described. A Fortran code was written using Visual Fortran 6.0 in a PC environment (Pentium IV, 512 Mb of RAM). Specific characteristics of the implementation are given below:

- The initial assignment S, and the parameter value T_i are determined by trial and error and depend on each specific problem.
- T_f is defined as $T_f = T_i/n^3$, in order to satisfy a condition of sufficient decrease of the control parameter.
- A feasible solution to the problem is stored as an array of size n, in which the i-th component value identifies the use assigned to the i-th cell.
- The choice of *iter* influences the quality of the solution. We set it as $O(n^2)$ following the suggestion of Burkard (1984).
- The value of α used to decrease the temperature is taken equal to 0.8.

Numerical experiments

The solutions obtained via the algorithm described were compared with those obtained by using an enumerative method for small-size problems (Table 1) and by applying a qualitative method for a real-world problem as described below.

Even though the examples shown in Table 1 are not zoning problems because of their dimensions, exact methods can be applied only in this kind of problem because of the NP-hardness.

The weight parameter M was taken equal to 2 in the first two examples and 0.5 in the last one. The value $u_{\min}$ was always chosen equal to 1 and $u_{\max}$ was taken equal to 16, 25, and 36, respectively.

The cardinality of the feasibility set, $|\Omega|$, is shown in the second column of Table 1.

It is important to emphasize that, in all the cases, the solutions $X \in \mathbb{R}^{n \times 2}$ obtained by using both methods are the same. The difference between the optimal value of the function occurs

Table 1
Comparison between the enumerative and heuristic methods

Problem dimension	$\lvert\Omega\rvert$	Value of the objective function		Relative error
		Enumerative method	Heuristic method	
16	2^{16}	85.5635140115	85.5635143046	3.424993053917e − 009
25	2^{25}	7.39244241018e+002	7.392444270215e+002	3.949573010130e − 008
36	2^{36}	1429.4095424455	1429.409549262	1.350881265313e − 007

Table 2
The new proposal and the Hadley, Rendl, and Wolkowicz (HRW) bound

Dimension	Objective function value	HRW	Relative error
9	360.769	354.003	0.0191
16	50	49.03	0.0198
144	142154.44	150172.42	0.0534
196	1079.7805	1056.2112	0.0223
256	1516.5703	1465.5989	0.0348

because in the heuristic method the objective function value was computed once and updated according to the rule $f(S') = f(S) – \Delta$, and in the exact method it was computed as in (1).

As mentioned above, the real problems that motivate this work involve $r \times s$ matrices with $r \gg s$. In spite of this fact, in order to show that the function values obtained are in the range of the bounds computed by the well-known algorithm proposed by Hadley et al. (1992), a set of problems with $r = s$ was tested. In these problems A and C are symmetric matrices with entries drawn at random from 1 to $2 \times r$ and D results from its definition. The values obtained are shown in Table 2. The meaning of the columns is as follows: first comes the dimension of the problem, and then we provide the objective function obtained from a feasible arbitrary solution. The third column shows the Hadley, Rendl, and Wolkowicz's bound and finally the relative error between values of columns 2 and 3.

A real-world application: Talampaya National Park (Argentina)

Talampaya National Park was created in 1997. Located in Northwestern Argentina, its 215,000 ha were declared a World Heritage Site by UNESCO in 2000. Its main conservation assets are an extremely rich fossil record, geological resources, archeological cave paintings, and a bushy ecosystem containing numerous endangered species (Dellafiore and Sylvester, 2000).

Current zoning of Talampaya was produced using a non-quantitative method by Dellafiore and Sylvester (2000). A quantitative alternative zoning using the method described in this paper was performed at different scales (Sabatini, 2003). Here we report results obtained when Talampaya and its surroundings were represented by using a grid of 900 cells: 278 to be assigned and 622 corresponding to the neighboring area.

Four different uses were considered: two of them, extensive recreation and strict preservation, to be assigned to Talampaya Park and the other two ones corresponding to the neighboring areas, Ischigualasto Provincial Park and private properties. Ischigualasto Park protects rich fossil records and geological resources; private lands are dedicated to extensive ranching use (raising livestock, mainly cattle and goats). These uses are meaningful for zones to be assigned within the boundaries of Talampaya National Park in the light of management and ecological purposes. For instance, it is more convenient for the strict preservation zone to be closer to the Ischigualasto Park than to the extensive ranching zone. This influence of the surrounding area is explicitly considered through the compatibility coefficients among uses as shown in Table 3.

Land aptitude map files were assembled from information on land aptitude and recreation potential provided by Dellafiore and Sylvester (2000), Fig. 1. The rest of the data required to run the implementation of the quantitative method (e.g., compatibility constants, weighting parameters, connection requirements) were approximated from the criteria applied in the qualitative method (Table 3).

The quantitative method produced results quite similar to the current zoning of the park (Fig. 2). The main differences occurred in the south-east of the reserve, which is a badland area with no preservation value (Fig. 2); its current allocation to strict preservation was motivated by an arbitrary interest in reaching some upper bound in total land area under strict preservation (F. Sylvester, private communication). Key zoning features for protected natural areas are close local agreement between land aptitude and land use, spatial continuity of uses, and compactness of certain areas. As shown by comparing spatial configurations in Fig. 3a and b, the use of a squared rather than linear distance term produced a better local matching between land aptitude and land use for strict preservation. A similar effect is observed when non-symmetric

Table 3
The Talampaya parameters definition

Parameters of objective function	Data
Land aptitude	See Fig. 1
Use preference	Strict preservation: 0.75
	Extensive recreation: 0.25
Weighting parameter	0.075
Compatibility use	Between uses to be assigned:
	Strict preservation–strict preservation: 2
	Strict preservation–extensive recreation: −2
	Extensive recreation–extensive recreation: 0
	Extensive recreation–strict preservation: 2
	Between uses to be assigned and uses of the surrounding area:
	Strict preservation–Ischigualasto Provincial Park: 2
	Strict preservation–extensive ranching: −1
	Extensive recreation–Ischigualasto Provincial Park: 1
	Extensive recreation–extensive ranching: −1
Connection constraint	Strict preservation: yes
	Extensive recreation: no
Number of cells constraint	Minimum–Maximum
	Strict preservation: 70, 170
	Extensive recreation: 1, 300

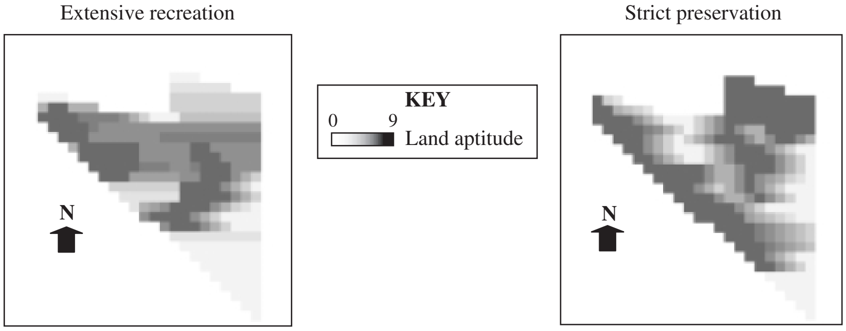


Fig. 1. Talampaya land-use aptitude and its surrounding area.

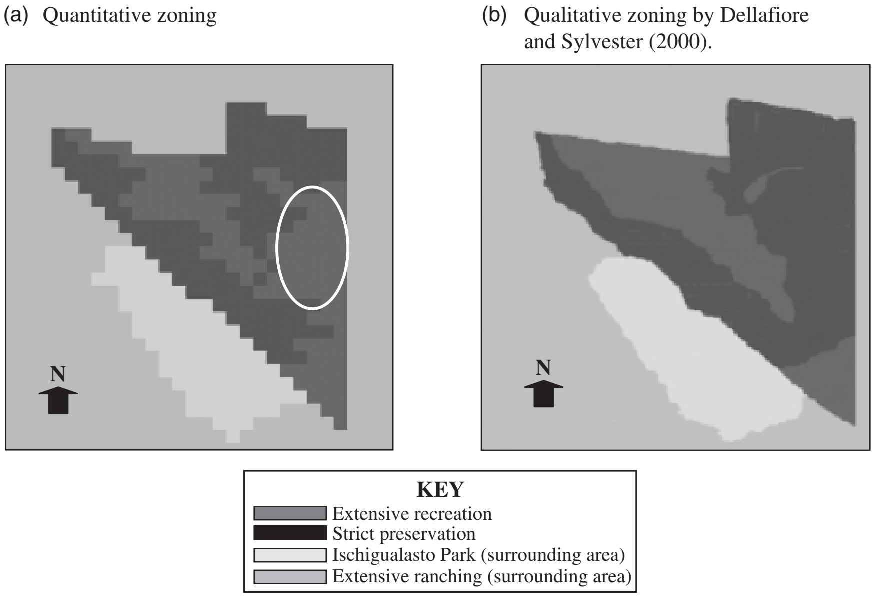
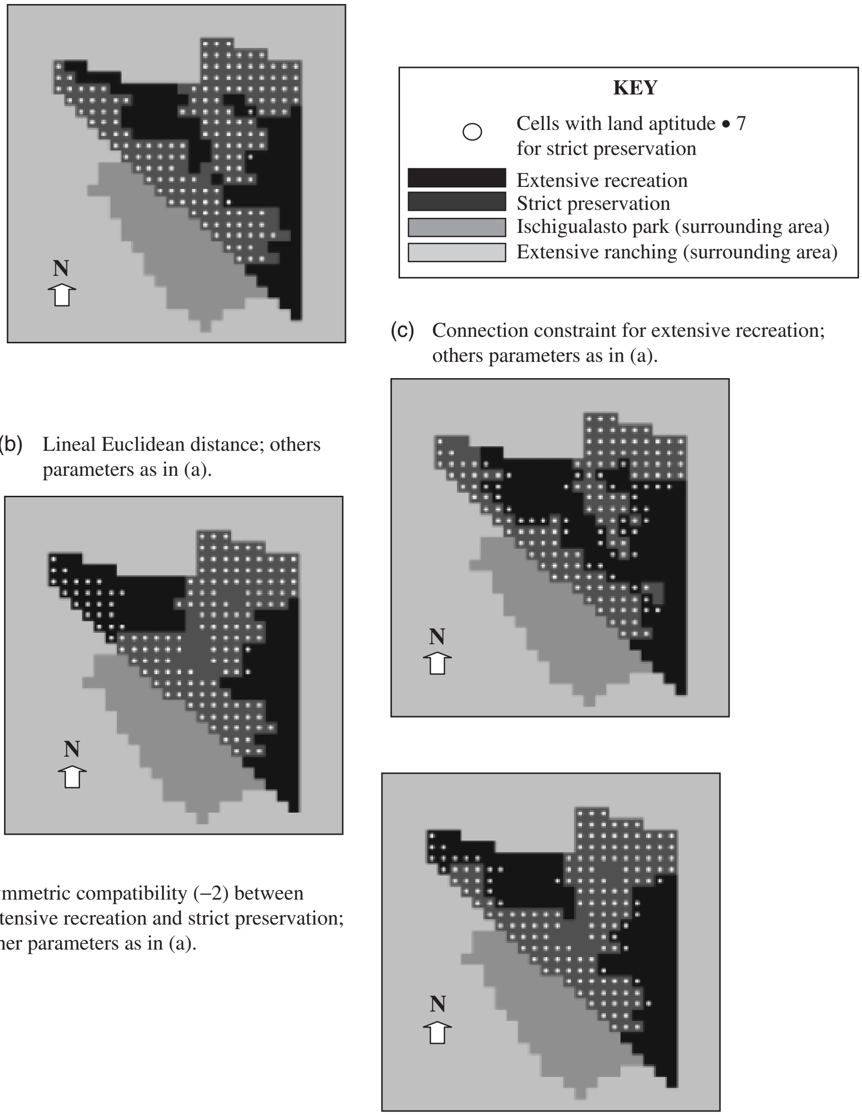


Fig. 2. Comparison maps between Talampaya zoning (quantitative method) and present zoning (non-quantitative method).

compatibility relations are allowed (compare Fig. 3a and d). On the other hand, the formation of land ‘corridors’ is noticeable when a connection constraint is applied (compare Fig. 3a and c).

Concluding remarks

Our quantitative zoning model allows for the consideration of both land aptitude and possible spatial interactions. Obviously, representation of reality is simplified; not every possible criterion for use aptitude would be easily coded for inclusion in the model. There is still ample room for the work of subject experts in defining possible uses, aptitude, compatibilities among uses, spatial constraints, etc. What the model guarantees, however, is that, given a complete input set for a target area, it will produce alternative zoning plans by modifying key input terms such as



(a) Squared Euclidean distance, connection constraint for the strict preservation use and non-symmetric compatibility between uses (extensive recreation-strict preservation = 2, strict preservation-extensive recreation = –2); others parameters in Table 3.

(b) Lineal Euclidean distance; others parameters as in (a).

(c) Connection constraint for extensive recreation; others parameters as in (a).

(d) Symmetric compatibility (–2) between extensive recreation and strict preservation; other parameters as in (a).

Fig. 3. Alternative zoning of Talampaya National Park obtained under different assumptions for key parameters.

weighting coefficients (P, M) and constraints. The choice of parameters will depend on the experience and ability of the group providing expert knowledge data.

The proposed heuristic algorithm is efficient in producing near-optimum values for the objective function. All solutions obtained satisfy the required constraints. Prescriptive zoning, however, will usually still require several re-runs of the procedure until one or more solutions satisfying subject experts and managers are obtained.

An important advantage of the quantitative approach is that periodical adjustments to the zoning plan could be performed in a fast and economic way once an initial zoning version is completed with the assistance of subject experts.

Acknowledgements

The authors gratefully acknowledge the suggestions and comments of the referees. This work was supported by the Universidad Nacional del Sur, Project 24/L057 and CONICET PIP 02156.

References

Aarts, E., van Laarhoven, P., 1985. Statistical cooling: a general approach to combinatorial optimization problems. *Philips Journal of Research*, 40, 193–226.

Bos, J., 1993. Zoning in forest management: a quadratic assignment problem solved by simulated annealing. *Journal of Environmental Management*, 37, 127–145.

Bruenegger, A., Clausen, J., Marzetta, A., Perregaard, M., 1996. Joining forces in solving large-scales quadratic assignement problems in parallel. *Technical Report TR96-23*, Department of Computer Science, University of Copenhagen, Denmark.

Burkard, R., 1984. Quadratic assignment problems. *European Journal of Operational Research*, 15, 283–289.

Burkard, R., Rendl, F., 1984. A thermodynamically motivated simulation procedure for combinatorial optimization problems. *European Journal of Operational Research*, 17, 169–174.

Cendrero, A., de Teran, J.D., Gonzalez, D., Masciti, V., Rotondaro, R., Tecchi, R., 1993. Environmental diagnosis for planning and management in the High Andean Region: the biosphere reserve of Pozuelos, Argentina. *Environmental Management*, 17, 683–703.

Connolly, D., 1990. An improved annealing scheme for the QAP. *European Journal of Operational Research*, 46, 93–100.

Dellafiore, C., Sylvester, F., 2000. Zonificación Parque Nacional de Talampaya. *Technical Report*, Administración de Parques Nacionales, Buenos Aires, Argentina.

Haas, G., Driver, B., Brown, P., Lucas, R., 1987. Wilderness management zoning. *Journal of Forestry*, 85, 16–21.

Hadley, S., Rendl, F., Wolkowicz, H., 1992. A new lower bound via projection for the quadratic assignment problem. *Mathematics of Operational Research*, 17, 3, 727–739.

IUCN 1993. Managing tourism in protected areas. *National Park Journal*, 37, 13–14.

Kirkpatrik, S., Gellat, C., Vecchi, M., 1983. Optimization by simulated annealing. *Science*, 220, 671–680.

Lundy, M., Mees, A., 1986. Convergence of an annealing algorithm. *Mathematical Programming*, 34, 111–124.

McNeely, J., 1994. Protected areas for the 21st century: working to provide benefits to society. *Biodiversity and Conservation*, 3, 309–405.

Miller, K., 1980. *Planificación de parques nacionales para el ecodesarrollo en Latinoamérica*. FEPMA, Madrid, España.

Nelson, J., 1991. Beyonds parks and protected areas: from public and private stewardship to landscape planning and management. *Environments*, 21, 23–34.

Nemhauser, G., Wolsey, L., 1988. *Integer and Combinatorial Optimization*. Wiley-Interscience, New York.

Sabatini, M., 2003. *Zonificación de áreas protegidas: marco conceptual y desarrollo metodológico cualitativo para su ejecución*. Master's Thesis, Departamento de Agronomía, Universidad Nacional del Sur, Bahía Blanca, Argentina.

Sabatini, M., Rodriguez Iglesias, R., 2001. A global context for the evolution and current status of protected areas in Argentina. *Natural Areas Journal*, 21, 274–281.

Salinas Chavez, E., Casas Cid, O., 1992. La zonificación funcional y la planificación turística en Areas Protegidas. *Flora, fauna y áreas silvestres*, 14, 10–12.

Silver, E., Vidal, R., de Werra, D., 1980. A tutorial on heuristic methods. *European Journal of Operational Research*, 5, 153–162.