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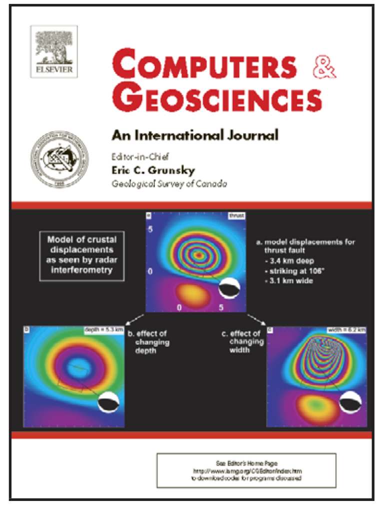

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Algorithm based on simulated annealing for land use allocation

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Abstract

This article describes the use of simulated annealing for allocation of land units to a set of possible uses on, the basis of their suitability for those uses, and the compactness of the total areas allotted to the same use or kind of use, which are fixed *a priori*. The results obtained for the Terra Chá district of Galicia (N.W. Spain) using different objective weighting schemes are compared with each other and with those obtained for this district under the same area constraints, using hierarchical optimization, ideal point analysis, and multi-objective land allocation (MOLA) to maximize average use suitability. Inclusion of compactness in the simulated annealing objective function avoids the highly disperse allocations typical of optimizations that ignore this subobjective.

Key words: multicriterion land allocation, land uses, MOLA, hierarchical optimization, ideal point analysis.

1. Introduction

Rural land use allocation is becoming increasingly complex due to the emergence of new uses, the growing multifunctionality of rural areas, and the pressures put on these areas by urban and industrial expansion. In these circumstances, land use allocation must try to reconcile multiple conflicting interests as rationally and transparently as possible (Carsjens and Van der Knaap 2002), which among other things, involves evaluating land units not only with regard to their suitability for competing uses but also in regard to such factors as contiguity among units assigned to the same use, and the compactness of the single-use land masses so created (Aerts *et al.* 2003; Nalle *et al.* 2002).

Most land use allocation techniques consider only one use at a time; see, for example, Carver (1991), Malczewski (1996) and Pereira and Duckstein (1993). Studies distributing land simultaneously among several mutually incompatible uses include those of Aerts and Heuvelink (2002), Aerts *et al.* (2003), Martínez-Falero *et al.* (1998) and Stewart *et al.* (2004); see also Cromley and Hanink (2003). The computational burden on computer programs for land use allocation, which makes exact optimization methods such as integer programming infeasible when there are more than two or three thousand land units to be allocated (Aerts *et al.* 2003), is increased by simultaneous consideration of multiple possible uses. It is, therefore, necessary to turn to heuristic algorithms capable of achieving near-best solutions in a reasonable time (Matthews 2001). In particular, good results have been obtained using stochastic methods such as the simulated annealing technique (SA) originally due to Kirkpatrick *et al.* (1983) (Aerts *et al.* 2003; Alier *et al.* 1996; Boyland *et al.* 2004; Nalle *et al.* 2002); an additional advantage of such methods is the possibility of using nonlinear objective functions with essentially no increment in computational complexity (Tarp and Helles 1995). Studies in which SA has been applied to land use allocation include work by

Martínez-Falero *et al.* (1998), who allocated ten agricultural activities using an objective function that took six considerations into account (profit, land-use transformation cost, social costs, environmental impact, total land area, and continuity); Aerts and Heuvelink (2002), who minimized development costs while maximizing spatial compactness; Sharma and Lees (2004), who compared SA with the IDRISI multi-objective land allocation facility MOLA; and Duh and Brown (2007), who endowed their SA program with mechanisms by which auxiliary knowledge could be used to increase search efficiency.

In the work described in this paper, we applied SA to the problem of distributing given total areas of 13 crops or covers among the 182,168 cells with a size of $100\,\mathrm{m} \times 100\,\mathrm{m}$ which make up the district of Terra Chá (Galicia, N.W. Spain). We employed an objective function that took into account the suitability of each land unit for each use, the compactness of the total area assigned to each use, and the compactness of the total area assigned to each group of similar uses. We ran the algorithm with several different sets of weights applied to these three objectives, and we compared the corresponding results with each other and with those obtained when average suitability alone was maximized using hierarchical optimization (Campbell *et al.* 1992; Carver 1991; Mendoza 1997), ideal point analysis (Barredo 1996) and MOLA (Eastman *et al.* 1998).

In Section 2 below, we describe the SA algorithm in terms allowing its generalization to problems other than the specific case of Terra Chá; in Section 3, we provide details of the application of SA and the other methods to Terra Chá in this study; and, in Section 4, we compare the various sets of results obtained. Section 5 concludes.

2. The general problem and the simulated annealing algorithm

Our problem is to distribute I square land units, each of unit area, among N different uses under the constraint that the total number allocated to each use n is the given number I_n, with $\Sigma_n I_n = I$. Also given are the suitability A_{in} of each land unit i for each use, and, optionally, a set of use weights w_n that allow preferences among uses to be taken into account as well as the suitability of the land unit for those uses (see Section 2.2). We aim to obtain solutions addressing three objectives, individually or jointly: maximization of the overall *w*-weighted suitability of the land units for the uses allocated to them; maximization of the compactness (and hence minimization of the fragmentation) of the total area assigned to any particular use; and maximization of the compactness of the total area assigned to any particular group of uses, as defined by the problem solver (for example, use groups for the case of Terra Chá are defined in Section 3).

The simulated annealing algorithm, as its name suggests, emulates the behaviour of a thermodynamic system that, as the result of configurational changes subject to the Boltzmann probability distribution, finally adopts its least-energy configuration as its temperature is gradually reduced to absolute zero (Metropolis *et al.* 1953). When applied in non-thermodynamic contexts, energy is replaced by the objective function to be minimized or maximized, and temperature by an arbitrary parameter T that is used to control the thoroughness of the search for the optimum. The basic procedure is as follows: 1) Given the current configuration of the system being optimized, a trial configuration is generated by a method that includes some element of chance. 2) The value of the objective function for the trial configuration, E_t, is compared with the value of the objective function for the current configuration, E_c. If E_t is better than E_c, the trial configuration is adopted as the current configuration for the next iteration of the procedure. If E_t is worse than E_c, the trial configuration is adopted as the next current configuration according to the Boltzmann probability distribution; that is to say, only with probability $e^{-(Et - Ec)/T}$ (if E is to be minimized) or $e^{-(Ec - Et)/T}$ (if E is to be maximized). 3) For each value of T, the system is allowed to explore configuration space in this way for a number of iterations (or a number of iterations resulting in a change of configuration) that, in principle, should be sufficient to ensure that, with very high probability, E values are within a range that is so good that worse E values are being accepted at a lower average rate than better E values, so that the average value of E keeps improving. The value of T is then reduced (so that better E values are again favoured through a heavier filtering in the Metropolis condition) and the loop starts again. 4) The algorithm terminates upon satisfaction of some appropriate stop condition such as a pre-established number of temperature reductions.

For the present application, the whole procedure is summarized in Fig. 1. In what follows, we describe in greater detail its main components: the generation of trial solutions, the objective function, and the annealing schedule.

<Figure 1 about here>

2.1. Generation of land use configurations

At the beginning of the procedure a configuration is generated that satisfies the constraint on the total area of land allotted to each land use. In order to ensure satisfaction of this constraint by successive trial configurations, these latter are generated by simply exchanging the land use allocations of a randomly selected pair of land units. This procedure furthermore facilitates calculation of the value of the objective function for the trial configuration, which will differ from the value for the current configuration by a quantity that can be determined by consideration of only the land units affected by the proposed change in configuration.

2.2. The objective function

As noted above, the objective function E combines three distinct subobjectives: maximization of overall w-weighted land suitability (function S), maximization of the compactness of the total area assigned to any particular use (function UC), and maximization of the compactness of the total area assigned to any particular group of uses (function GC). These subobjectives are combined linearly:

$$E(S,UC,GC) = \alpha_1 S + \alpha_2 UC + \alpha_3 GC$$

where the coefficients α_j are chosen by the problem solver, subject to the condition $\Sigma_j\, \alpha_j = 1$, so as to control the relative importance of satisfying the individual subobjectives. To facilitate this choice and enhance its transparency, the subobjective functions are all normalized to the range [0,1]. We also define these functions so as to make the overall problem the minimization of *E*.

Overall *w*-weighted land suitability is evaluated in the first instance as the sum

$$LS = \Sigma_i\, w_n A_{in}$$

The value of the subobjective function *S* is given by the normalizing expression

$$S = (LS_{max} - LS)/(LS_{max} - LS_{min})$$

where LS_{max} is the value of *LS* when each land unit *i* is assigned its maximum weighted suitability, $\max_n(w_n A_{in})$, and LS_{min} is the value of *LS* when each land unit *i* is assigned its minimum weighted suitability, $\min_n(w_n A_{in})$.

Following Fischer and Church (2003), the compactness of the total areas assigned to the various land uses is evaluated in the first instance through calculation of the total length *UB* of the boundaries of connected areas allotted to a single use (hereinafter "use patches"):

$$UB = \Sigma_n^{N}\, \Sigma_{rn}^{Rn}\, P_{rn}$$

where P_{rn} is the length of the boundary of the r_n-th of the R_n use patches with use *n*. Calculation of the boundary lengths is facilitated by the fact that the land units are unit squares, which likewise facilitates identification, for normalization purposes, of the maximum and minimum possible values of *UB*: the maximum value UB_{max}, which would be realized if the area I_n allotted to each use *n* consisted of I_n isolated land units, is $4I$; and the minimum, UB_{min}, which corresponds to the doubtless unrealizable situation in which each use occupies a single square area, is $4\,\Sigma_n^{N}\, I_n^{½}$. The normalized subobjective function *UC* is given by the expression

$$UC = (UB - UB_{min})/(UB_{max} - UB_{min})$$

Finally, the subobjective function *GC* is defined similarly to *UC* in terms of the length of the boundaries of "use group patches", *GB.*

2.3. The annealing schedule

The annealing schedule of an SA procedure determines the thoroughness of the search for the optimum. In general, it is recommended that the initial value of *T* ensure that about 80% of trials are successful at this stage; this value will depend on both the way in which the objective function varies with configuration, and the configuration generating scheme, and must be identified by trial and error for each problem. In this work, the number of iterations employed at each value of *T* was approximately 25*I* and, following Boyland *et al.* (2004), each reduction of *T* was effected by multiplication by a constant factor, which was 0.98. Annealing was halted when fewer than five trials with worse values of *E* had been accepted during the 25*I* iterations with the current value of *T* and at least 300 values of *T* had been employed.

3. Application to Terra Chá

The 1,832 km^2 of Terra Chá are distributed between a broad southern plain in which the main towns and most farming activity are located, and a hilly northern area devoted predominantly to forestry and environmental protection. Some 53% of the total area is agricultural land, and some 7,700 of its approximately 47,000 inhabitants are farm workers.

The land uses listed for Terra Chá in the Galician Agricultural Statistics yearbook for 2001 were regrouped for this study on the basis of land area occupied and similarity, similar minority uses being grouped together. As a result, the following thirteen crops or covers were distinguished: maize fodder, pluriannual green fodder, other fodder crops (kale, beet), meadow, pasture, wheat, other cereals (rye, oats), potatoes, other vegetables, fruit, eucalyptus, softwood, and deciduous hardwood. These thirteen uses were then grouped in the following five use groups: fodder (maize, pluriannual green fodder, other fodder crops, meadow and pasture), cereals (wheat and other cereals), intensive agricultural crops (potatoes, other vegetables and fruit), productive forest (eucalyptus and softwood), and protective woodland (deciduous hardwood).

The suitability of each 100 m × 100 m land unit for each of the above uses was taken from Santé and Crecente (2005a). The total areas to be occupied by the various uses were determined using a decision support system employing multiobjective linear programming (Santé and Crecente 2005b). More specifically, the interactive STEP method implemented in that system was used for joint optimization of economic, social and environmental objectives, prioritized in this order. The resulting total areas are listed in Table 1.

<Table 1 about here>

Also listed in Table 1 are the weights w_n given to the various uses. These weights were obtained as if they were to be used in an analytic hierarchy decision process (Saaty 1980), on the basis of subjective comparison of all pairs of uses with regard to their economic importance.

With the areas, use weights and suitabilities described above, SA solutions were generated for eleven different sets of subobjective weights α_j (Table 2): one in which the only objective was maximization of overall w-weighted land suitability (option A in Table 2), three in which relative weights of 3:1 (the weight of the first subobjective is three times higher than the weight of the second subobjective), 1:1 and 1:3 were given to maximization of suitability and use area compactness (options B-D); three in which these same relative weights were given to maximization of suitability and use group area compactness (options E-G); and four in which all three subobjectives were considered, with relative weights of 1:1:1, 2:1:1, 1:2:1 and 1:1:2 (options H-K). In addition, solutions maximizing suitability were sought, for the same set of total areas, by hierarchical optimization (ranking uses in accordance with the w_n values of Table 1), by ideal point analysis (with the weights w_n of Table 1 as objective weights, and using the Euclidean distance), and by MOLA (with the weights of Table 1 and an area tolerance of 100 ha).

All calculations were performed on a PC with 512 Mb of RAM, a 40 Gb hard disc, and an Intel Pentium processor running at 1.4 GHz.

<Table 2 about here>

4. Results and discussion

Hierarchical optimization, ideal point analysis, and MOLA only optimize land suitability, without considering the spatial distribution of land uses. This is why the characteristics of the solutions obtained for Terra Chá by these three methods were compared to the solution provided by SA when the only objective was maximization of the suitability of the land units for the uses assigned to them (see Table 3). SA offered the solution with the greatest total suitability value, about 1% better than that achieved by MOLA, but took almost 60 times longer than MOLA and, more importantly, in the SA solution the total area allotted to each use was very much more fragmented than in the MOLA solution (see also Fig. 2). Overall, when used only to maximize total suitability, SA thus appears to be inferior to MOLA, which itself tends to generate excessively fragmented solutions (Bosque and García 2000). Hierarchical optimization achieved the least fragmentation, with about 6% fewer use patches than in the MOLA solution, but its suitability was also lower, by about 4%. The solution afforded by ideal point analysis was inferior to the MOLA solution as regards both suitability and fragmentation. Note that, although SA achieved the best total suitability, it did not achieve the best suitability for each individual use (see Table 4).

<Table 3 about here>

<Figure 2 about here>

In Fig. 2 it can be observed that the main difference between the outcomes of the four methods is the location of intensive agricultural crops, mainly vegetable and fruit crops. In the maps obtained with SA and MOLA, the entire vegetable crop area is located in the vicinity of the main village of Terra Chá, located in approximately the centre of the region. In the SA map, this crop area is concentrated to the south of the village, whereas in the MOLA map it is distributed along the main roads leading from the village. In the map provided by ideal point analysis, the vegetable crops are distributed in the vicinity of several villages. In the map obtained with hierarchical optimization these crops are even more dispersed, with small areas in the surroundings of several villages and roads. The spatial allocation of fruit crops is similar in the maps obtained with SA and ideal point analysis, being located along the region's main highway which intersects its south-west corner, and in the results of MOLA and hierarchical optimization, where the fruit crops are located in two small regions of low suitability in the vicinity of Terra Chá. In the case of fodder crops, the SA solution is also more similar to the MOLA map, especially in the case of maize. The pluriannual fodder crops are dispersed across the maps obtained with the four methods, mainly on the hierarchical optimization map, whereas with ideal point analysis these crops are quite concentrated in the eastern part of the region, which has significant livestock activity. The SA and MOLA maps provide intermediate distributions between the former two examples. In the case of meadows, the SA and MOLA maps are again quite similar, comprising the river Miño region. Hierarchical optimization provides a similar distribution, albeit more compacted, whereas the ideal point analysis map is quite different. Pasture is distributed in small areas on the four maps, mainly in the mountainous zones. In the case of forest land uses, hardwood forest is allocated in a similar way with the four methods, located mainly in areas with high slope and protected by the Nature Network. The location of the other two forest land uses is also very similar with the four methods, especially between SA and MOLA. In short, the land use solutions provided by SA and MOLA are quite similar and differ from the solutions of hierarchical optimization and ideal point analysis.

Interestingly, the inferiority of SA with regards to computation time was considerably less marked when the size of the problem was increased by using land units sized $20\,\text{m} \times 20\,\text{m}$ instead of $100\,\text{m} \times 100\,\text{m}$, so that the total number of land units was 4,339,725. In this situation, SA (with an appropriate number of iterations at each temperature) took 12 h, MOLA 3.5 h, ideal point analysis 7.5 h, and hierarchical optimization 45 min.

<Table 4 about here>

Table 5 shows that whenever one of the compactness subobjectives was included in the SA objective function along with the suitability subobjective, the solution obtained exhibited the expected considerable decrease in *UB* - by as much as a factor of 2.8 - with respect to the option A solution obtained optimizing for suitability alone. Solutions B-K were also more compact than any of the solutions obtained using other methods to optimize for suitability. Reducing α_1 always reduced the suitability of the solution, but in no case did suitability fall as low as the value achieved when hierarchical optimization was used to optimize suitability. When only use patch compactness was included (options B-D), both *UB* and *GB* were always reduced by more than a factor of 2, and both *UB* and *GB* decreased as α_2 increased. This can be seen graphically in Fig. 3, where a small region of Terra Chá is presented to show how isolated pixels disappear and how larger land use patches are created as α_2 increases. By contrast, when only use group patch compactness was included (options E-G), *UB* was reduced by at most a factor of 1.4, and although *GB* decreased with increasing α_3 (see also Fig. 4), *UB* was greater with $\alpha_3 = 0.75$ than with $\alpha_3 = 0.50$. Varying α_2 with $\alpha_3 = 0$ also caused greater variation in *UB*, *GB* and suitability than varying α_3 with $\alpha_2 = 0$.

Comparison of solution I with solutions B and E shows that splitting the weight assigned to compactness between use compactness and use group compactness achieves, with only a small reduction in suitability, *UB* and *GB* values that are only slightly greater than when all the compactness weight is assigned to α_2 or α_3. With respect to solution A, solution I reduces *UB* by 61% and *GB* by 68% in exchange for a reduction in suitability of only 2.3%. Further increasing α_2 and α_3 at the expense of α_1 (option H) had the expected effects on compactness. This option shows that the use of SA, assigning the same weight to each objective function, provides a much better spatial distribution of land uses than hierarchical optimization, ideal point analysis and MOLA, as well as a higher suitability value than hierarchical optimization and ideal point analysis. Comparison of the solutions obtained with $\alpha_1 = 0.25$ (D, G, J and K) confirms that sharing weight between use compactness and use group compactness achieves better values of both *UB* and *GB* than when all the compactness weight is assigned to either α_2 or α_3, albeit at the expense of suitability.

The number of subobjectives with non-zero weight in the objective function had practically no effect on run time.

<Table 5 about here>

<Figures 3, 4 about here>

5. Conclusions

When the area of land to be alloted to each of a number of uses is given *a priori*, SA is a feasible approach to the distribution of these areas among land units on the basis of the suitability of the units for each use and the compactness of the resulting use patches and use group patches. Application of this approach to a rural area in which thirteen uses belonging to five use groups were to be allotted to some 182,168 land units suggests that when only suitability is optimized, SA is superior to hierarchical optimization, ideal point analysis, and MOLA, offering solutions that have better suitability but are more fragmented than those achieved by the other methods. For problems of the size indicated above, run time of SA on a medium-range desktop computer is a matter of hours rather than minutes, but is not prohibitive. The greatest weakness of the SA approach is precisely that, to avoid a prohibitive computational burden, it relies on being fed good *a priori* land use areas.

The inclusion of compactness in the SA objective function allows the achievement of significantly more compact solutions at the price of a relatively small reduction in suitability. Inclusion of only use compactness in the objective function leads to greater overall improvement than inclusion of only use group compactness, but inclusion of both achieves results that are better than with either alone. This means that a better value of use patch and use group compactness will be achieved if the compactness weight is shared between both subobjectives than if all the weight is assigned to one of them.

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LEGENDS FOR TABLES AND FIGURES

Table 1. Total areas and weights w_n for each use *n* in Terra Chá problem.

Table 2. Subobjective weighting schemes used in SA optimization to solve Terra Chá problem.

Table 3. Characteristics of solutions obtained for Terra Chá problem by hierarchical optimization, ideal point analysis, MOLA and SA when used exclusively to maximize total suitability.

Table 4. Suitabilities of individual uses obtained for Terra Chá problem by hierarchical optimization, ideal point analysis, MOLA and SA when used exclusively to maximize normalized total suitability *S*.

Table 5. Total suitability (*LS*), total use patch boundary length (*UB*) and total use group patch boundary length (*GB*) of SA solutions obtained for Terra Chá problem with subobjective weightings of Table 2, together with corresponding run times.

Figure 1. Pseudo-code summary of SA procedure.

Figure 2. Solutions obtained for Terra Chá problem by *a*) SA, *b*) MOLA, *c*) ideal point analysis (IPA) and *d*) hierarchical optimization (HO) when used exclusively to maximize total suitability.

Figure 3. Effects of α_2 in land use patches in a small area of solutions obtained by SA with various weighting scheme options: a) A, b) C, c) B, d) D.

Figure 4. Solutions obtained by SA for use groups of Terra Chá problem with various weighting scheme options: *a*) A, *b*) F, *c*) E, *d*) G.

Table 1

	Area (ha)	Weight w_n
Maize	31 799	0.2037
Wheat	2509	0.0147
Other cereals	181	0.0070
Potatoes	2408	0.0108
Pluriannual green fodder	28 835	0.1483
Other fodder crops	3025	0.0208
Vegetables	15 530	0.0557
Fruit	264	0.0083
Meadow	32 473	0.2770
Pasture	5129	0.0289
Eucalyptus	8247	0.0401
Softwood	23 161	0.0773
Deciduous hardwood	28 607	0.1074

Table 2

Option	α_1	α_2	α_3
A	1	0	0
B	0.50	0.50	0
C	0.75	0.25	0
D	0.25	0.75	0
E	0.50	0	0.50
F	0.75	0	0.25
G	0.25	0	0.75
H	0.34	0.33	0.33
I	0.50	0.25	0.25
J	0.25	0.50	0.25
K	0.25	0.25	0.50

Table 3

	Hierarchical optimization	**Ideal point analysis**	**MOLA**	**SA (option A)**
Total suitability (*LS*)	122 726	125 146	127 312	128 705
Mean use patch area (ha)	25.33	22.94	24.00	14.86
Use patch boundary (*UB*, km)	13 779.6	14 879.6	13 864.2	16 184.8
Use group patch boundary (*GB*, km)	9345.6	10 170.0	9440.4	11 220.8
No. of use patches	7352	8195	7833	12 674
Largest use patch (ha)	19 680	17 548	17 682	18 511
Smallest use patch (ha)	1	1	1	1
Run time	5 min.	19 min	5 min	4 h. 57 min.

Table 4

	Hierarchical optimization	**Ideal point analysis**	**MOLA**	**SA** (α_1=1, α_2=0, α_3=0)
Maize fodder	21 240.3	20 322.2	21 819.6	21 848.6
Wheat	736.6	781.7	666.5	859.1
Other cereals	11.2	12.0	10.0	19.0
Potato	545.6	642.9	464.0	641.2
Pluriannual green fodder	16 078.3	20 747.6	17 051.7	19 132.7
Other fodder crops	1273.3	2227.2	948.9	1343.9
Vegetables	9524.3	11 231.3	11 768.9	11 006.2
Fruti	22.0	88.0	59.0	85.0
Meadow	25 893.9	21 219.1	25 063.5	24 958.9
Pasture	3134.0	3085.0	3158.0	3173.0
Eucalyptus	4109.1	5472.3	5412.6	4965.3
Softwood	19 764.3	19 269.5	20 092.0	20 159.4
Deciduous hardwood	20 393.0	20 047.1	20 797.2	20 512.9

Table 5

Option ($\alpha_1/\alpha_2/\alpha_3$)	**Total suitability (*LS*)**	**Use patch boundary (*UB*, km)**	**Use group patch boundary (*GB*, km)**	**Run time**
A (1/0/0)	128 705	16 184.8	11 220.8	4 h. 57 min.
B (0.5/0.5/0)	126 037	6073.8	4293.4	4 h. 56 min.
C (0.75/0.25/0)	127 201	7096.0	5078.2	4 h. 56 min.
D (0.25/0.75/0)	125 668	5776.6	4084.6	4 h. 51 min.
E (0.5/0/0.5)	126 162	11 870.2	3455.2	4 h. 54 min.
F (0.75/0/0.25)	126 828	12 097.8	4019.6	4 h. 53 min.
G (0.25/0/0.75)	126 013	11 955.6	3387.0	4 h. 53 min.
H (0.34/0.33/0.33)	125 303	5873.8	3405.8	4 h. 56 min.
I (0.5/0.25/0.25)	125 787	6249.8	3590.4	4 h. 52 min.
J (0.25/0.5/0.25)	123 160	5684.4	3516.2	4 h. 56 min.
K (0.25/0.25/0.5)	125 026	5900.0	3251.0	4 h. 56 min.

Figure 1

```
Initialize T
Number_of_Ts := 1
Generate starting solution Sc
Ec := E(Sc)
Moves_uphill := 0
Do while Number_of_Ts ≤ Number_of_Ts_Limit OR
        Moves_uphill > Moves_uphill_Limit
  Moves := 0
  Moves_uphill := 0
  Do while Moves ≤ Moves_Limit
    Generate trial solution St
    Et := E(St)
    If Et ≤ Ec
      Sc := St
      Ec := Et
      Moves := Moves + 1
    Else
      P := Random_number_in_(0,1)
      If P < exp(-(Et - Ec)/T)
        Sc := St
        Ec := Et
        Moves := Moves + 1
        Moves_uphill := Moves_uphill + 1
      Endif
    Endif
  Enddo
  T := T × Cooling_constant
  Number_of_Ts := Number_of_Ts + 1
Enddo
```

Figure 2

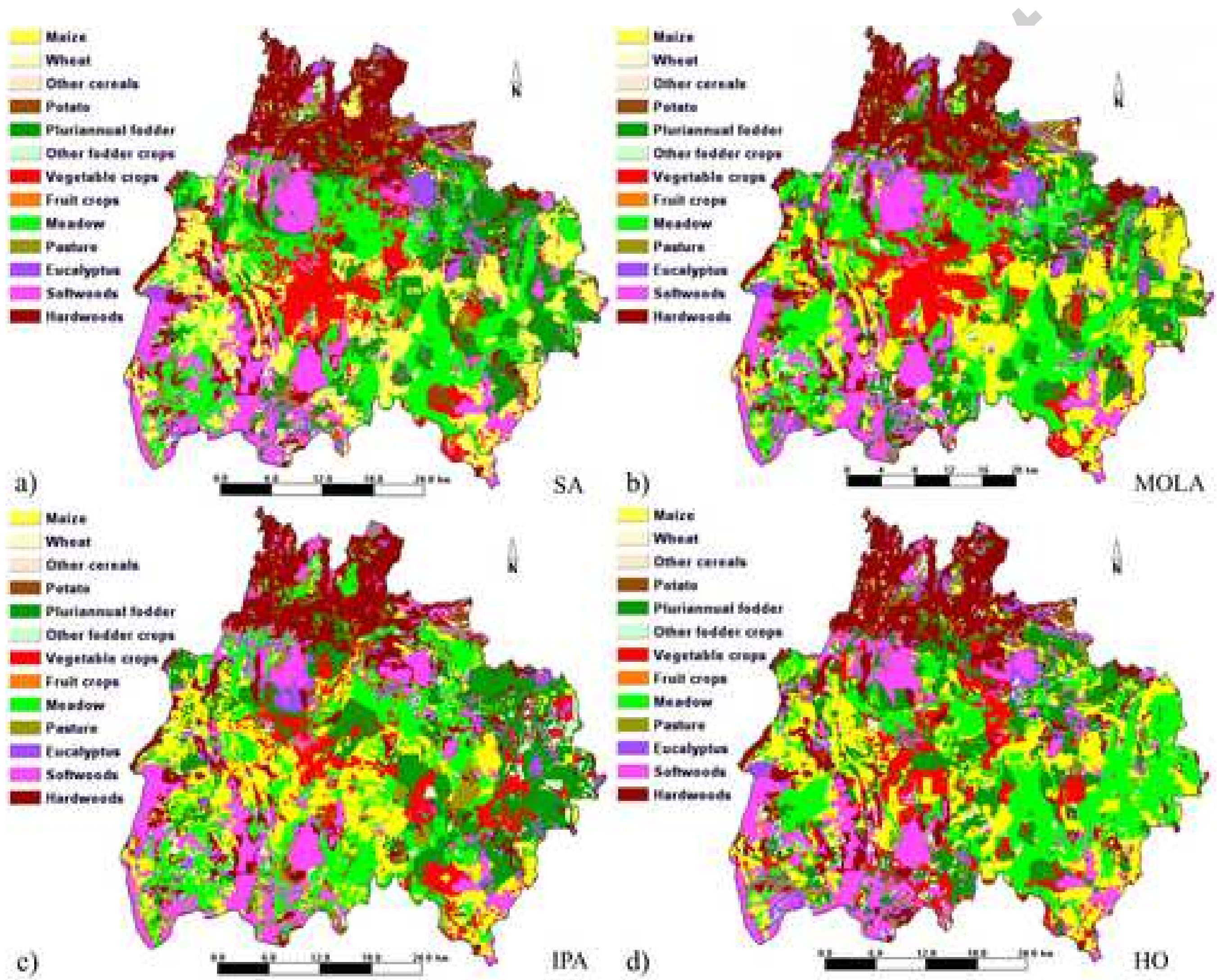
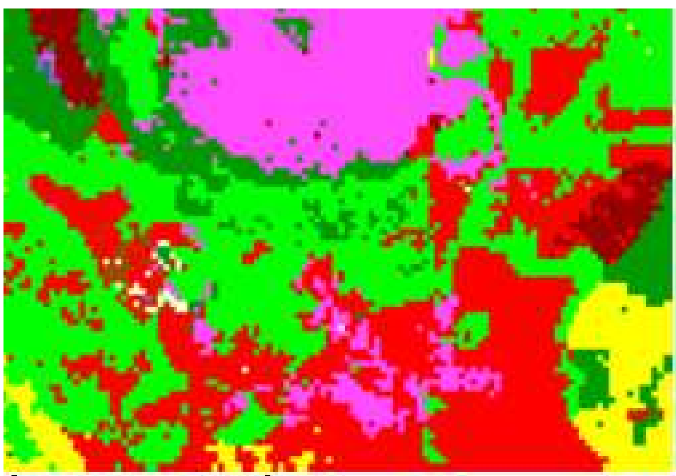
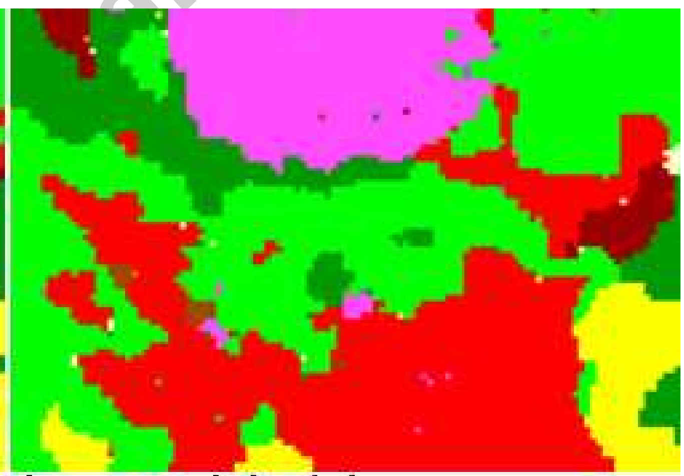

Maize
Wheat
Other cereals
Potato
Pluriannual fodder
Other fodder crops
Vegetable crops
Fruit crops
Meadow
Pasture
Eucalyptus
Softwoods
Hardwoods
N
a)
SA
Maize
Wheat
Other cereals
Potato
Pluriannual fodder
Other fodder crops
Vegetable crops
Fruit crops
Meadow
Pasture
Eucalyptus
Softwoods
Hardwoods
N
b)
MOLA
Maize
Wheat
Other cereals
Potato
Pluriannual fodder
Other fodder crops
Vegetable crops
Fruit crops
Meadow
Pasture
Eucalyptus
Softwoods
Hardwoods
N
c)
IPA
Maize
Wheat
Other cereals
Potato
Pluriannual fodder
Other fodder crops
Vegetable crops
Fruit crops
Meadow
Pasture
Eucalyptus
Softwoods
Hardwoods
N
d)
HO

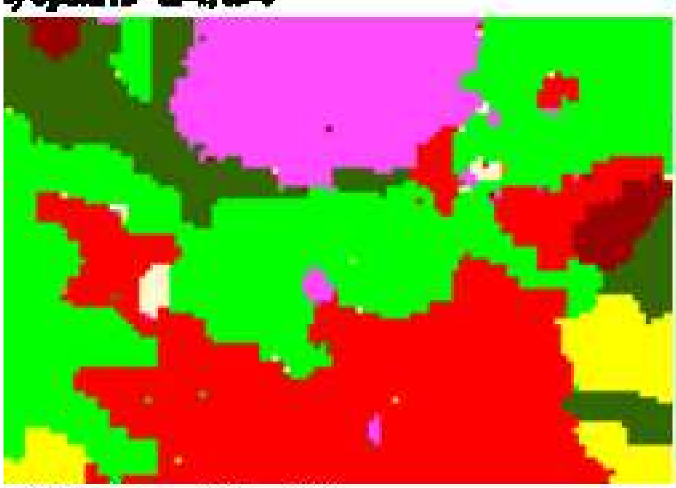
Figure 3



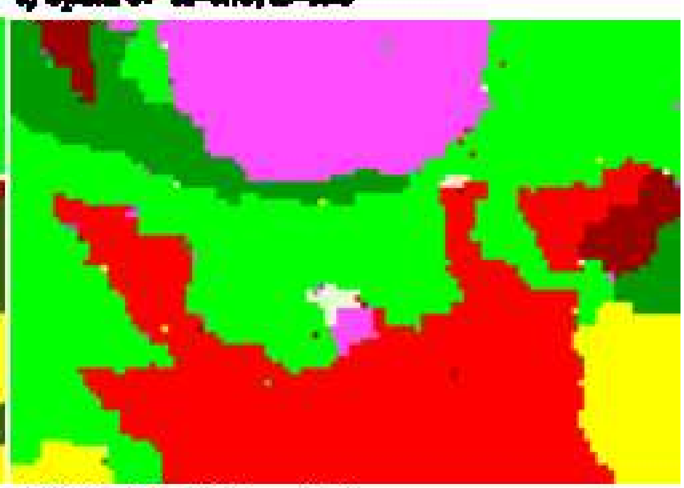
a) Option A: α_1=1, α_2=0



b) Option C: α_1=0.75, α_2=0.25

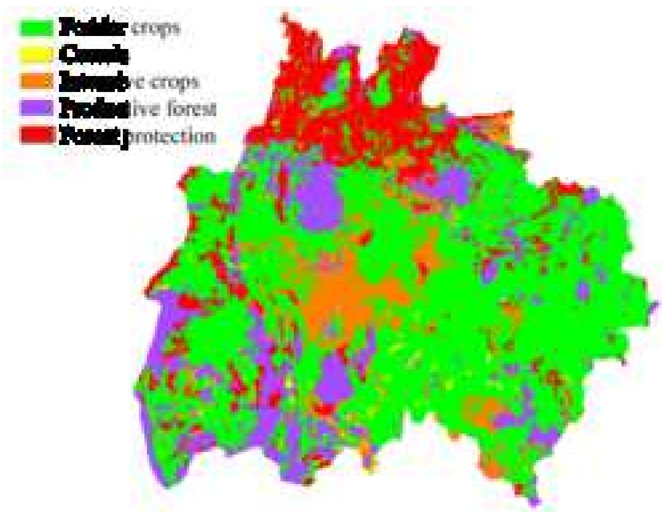


c) Option B: α_1=0.50, α_2=0.50

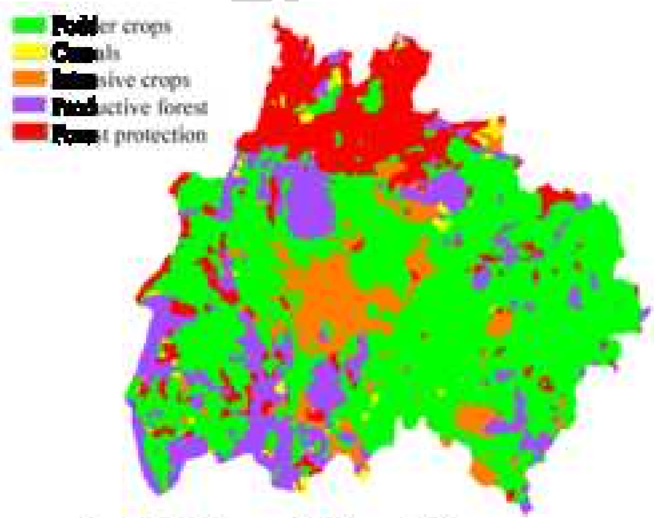


d) Option D: α_1=0.25, α_2=0.75

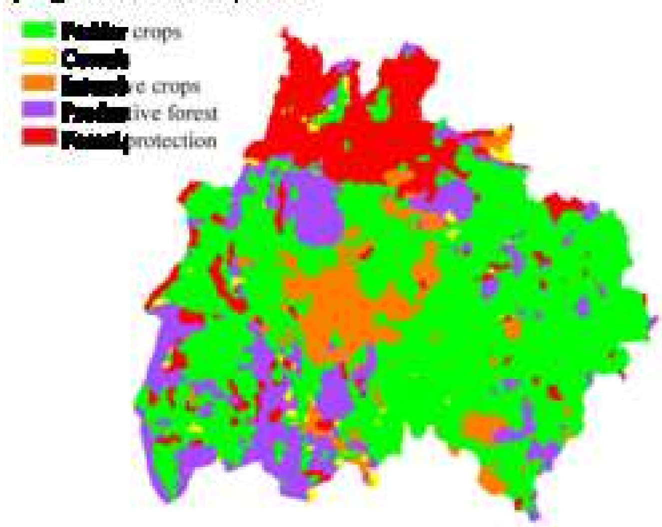
Figure 4



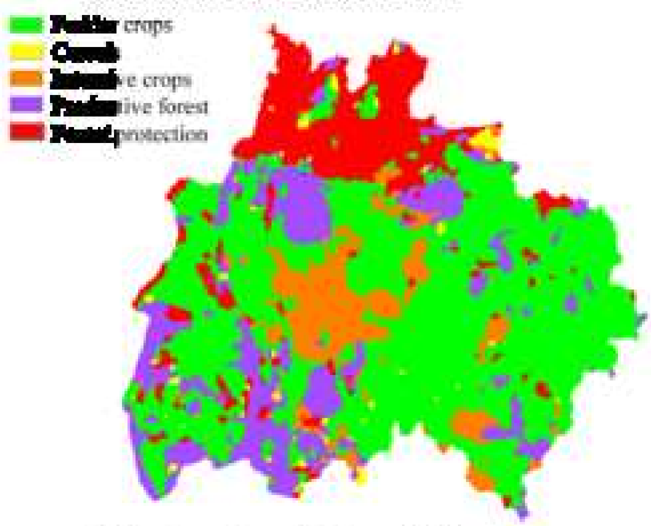
a) Option A: ω=1, ω=0



b) Option F: ω=0.75, ω=0.25



c) Option E: ω=0.50, ω=0.50



d) Option G: ω=0.25, ω=0.75