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Optimization of tourism impacts within protected areas by means of genetic algorithms

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A B S T R A C T

The search for a balance between nature conservation and tourism development within protected areas is becoming an increasingly multifaceted problem worldwide, as outlined by an increasing number of authors and highlighted at several international events. Since it is unlikely that all management objectives will reach their optimum values simultaneously, an optimization approach is required to meet multiple, conflicting goals and to obtain an overall trade-off in terms of the conceived objectives.

In this paper we propose a new model for optimizing the allocation of tourist infrastructures (refuges and camping sites), and apply it to a protected area in the European Alps, where tourism has grown considerably in recent years. To reach this goal, a complex model based on genetic algorithms was required (instead of a common multicriteria analysis) to obtain a complex interplay in the form of a dynamical simulation where candidate solutions are interactively evaluated. In accordance with local actors, we selected 18 quantifiable criteria encompassing all relevant tourist activities within the study area. These were translated into geographic information system (GIS) layers, submitted to a genetic optimization procedure and compared the performances of the optimized tourist allocations with those of existing infrastructures and with worst case scenarios. Resulting tourist allocations perform very well, while existing tourist sites behaved halfway between the fittest and the least fit genetic solutions, since they prioritized logistic and safety criteria rather than ecological ones.

The proposed model is a very flexible and effective tool, easily exportable to any protected area, with implications for researchers and policymakers who aim to provide an effective balance between nature and human impact.

1. Introduction

The search for a balance between nature conservation and tourism development within protected areas is becoming an increasingly multifaceted problem worldwide, as outlined by several authors (e.g. Foley et al., 2005; Turner et al., 2007) and pointed out by several international events (Québec Declaration on Ecotourism, 2002) and documents (Europarc Federation, 2008). Tourism in protected areas is generally viewed as a primary source of promoting economic and social growth to local communities (Honey, 1999) and commonly perceived to safeguard biodiversity (e.g. Walpole et al., 2001; Lindsey et al., 2005). However, in the last few decades an increasing number of visitors along with more diverse activities are having greater impacts on nature (Song and Li, 2008). For instance, annual visits to the US National Park System and to the European Alpine Region are currently approaching 300 and 120 million respectively (Lawson et al., 2003; Alpine Space, 2007). As a consequence, negative impacts have been quickly observed for wildlife species and habitats due to air and water pollution, vegetation removal for tourist facilities and infrastructures (refuges, camping sites, roads, etc.), reductions in plant and animal fitness, habitat loss and degradation (Steidl and Anthony, 2000; Kelly et al., 2002; Manor and Saltz, 2003; Amo et al., 2006; Rossi et al., 2006; Griffin et al., 2007).

Consequently, nature conservation within protected areas needs to be planned using effective methodology to assist managers and policymakers to administer resources, assess planning decisions, avoid user conflicts and minimize negative impacts on the environment. The challenge is to identify management opportunities that maintain wildlife resources while minimizing restrictions to human recreation (DeFries et al., 2007; Ferrarini et al., 2008). Environmental decision-making recently introduced the pivotal concept of "optimization", a concept that is old in theoretical terms, but whose application to real world problems is recent (Haupt, 2004), in particular with regard to environmental topics. The process of solving a problem can be considered as a search through a mathematical space of potential candidate solutions. Since we are after

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the optimal solution, the task is one of optimization, i.e. the best compromise to reach contradictory goals. Optimization involves identifying the solution that maximizes the benefits or, alternatively, minimizes the costs while generating goal-driven scenarios. If costs are viewed in terms of impacts on biodiversity, it becomes clear that optimization might be a pivotal decision process for environmental planning. Stochastic genetic algorithms (GAs; Holland, 1975; Goldberg, 1989), inspired by biology, do just that since they are able to perform a systematic search in the space of control variables to find an input vector which controls the systems in the desired way, specified by the goal function. Instead of a common multicriteria analysis, genetic algorithms allow to get a complex interplay in the form of a dynamic simulation where candidate solutions are interactively evaluated and cannot be considered in isolation. So far, a limited number of studies make use of GAs in the environmental field (Cropper and Comerford, 2005; D'heygere et al., 2006; Liu et al., 2006; Termansen et al., 2006; Chikumbo and Steward, 2007; Dreyfus-Leon and Chen, 2007; Peacor et al., 2007; Sweeney et al., 2007); the combined use of GAs and geographic information systems (GIS) is even more uncommon (Seppelt and Voinov, 2002, 2003; Holzkamper et al., 2006), notwithstanding its great potential in environmental problem solving and decision-making.

Despite the potential for tourism to negatively affect biodiversity even in protected areas, there have been no studies purporting scientifically based solutions to the optimization of protected areas following biological, safety and logistic criteria. Accordingly, the focus of this article is on the development of a novel GAs–GIS methodology that we tested in a protected area of the Alps, where tourism recently grew considerably. We aimed to: (1) conceptualize a model for the minimization of tourism impacts within protected areas through the use of a spatially explicit GA; (2) use the model for planning new tourist infrastructures (e.g. refuges, camping sites) to be added to existent ones; (3) measure the degree of success (performance) of each of the genetically fittest solutions on the basis of the initial criteria; (4) compare the performances of the resulting tourist infrastructures with the performances of existing ones; and (5) of the least fit genetic solutions (i.e. the worst possible solutions) within the study area, in order to quantitatively and objectively evaluate the advantages provided by the proposed methodology.

The proposed model is introduced in the context of the search for a satisfactory coexistence between nature and human activities.

2. Study area

The study area is the Site of Community Importance (SCI) IT2040012, i.e. one of the more than 25 000 areas belonging to the Natura 2000 network, covering in Europe about 17% of the territory (European Commission, 2008) and instituted under the "Habitats" Directive 92/43/EEC (CEC, 1992). It is placed in the Eastern Alps, N-Italy, (coordinates: 10°14′34″E, 46°25′42″N), extending over 59.66 km^2, ranging from 1710 to 3441 m a.s.l.

The study SCI is predominantly covered by siliceous alpine and boreal grasslands (25.92% of the SCI) and siliceous screes of the montane to nival belts (19.6%), alpine and boreal heaths (10.2%) also occur. Despite its high degree of wilderness, human visits are frequent within the study area, as a consequence of the closeness to two important tourist villages (Bormio and Livigno), annually hosting several thousand visitors during summer and winter. Tourist access to the SCI is facilitated by seven refuges and two camp sites (Fig. 1), hosting more than 4000 people per year, in particular during the summer period (Province of Sondrio, 2008). Human access to the SCI is granted by 10.201 km of roads and 29.445 km of tourist walkways.

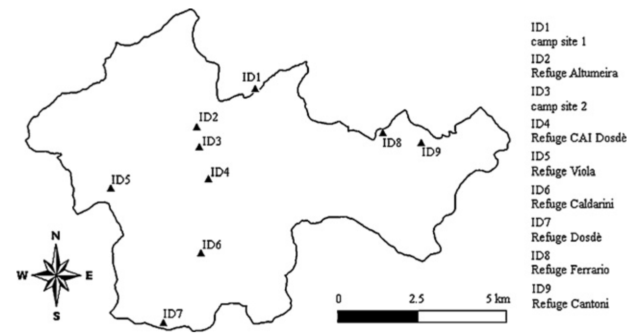

Fig. 1. The study area "Val Viola Bormina-Ghiacciaio di Cima dei Piazzi" with the current tourist sites.

3. Methods

3.1. Goal setting

Based on our ground-truth experience and on interactions with local actors (a panel of local politicians, provincial and regional administrators), we conceived a list of 18 quantitative criteria (12 factors and 6 constraints; Fig. 2) relevant to the problem under evaluation. From an ecological point of view, new tourist infrastructures should be as distant as possible from important biodiversity elements: (a) areas with an elevated patch richness (factor F1: number of European Union (EU) habitats in a 500 m × 500 m surround); (b) species-rich EU priority habitat *Nardus* grasslands (F2: distance in meters from species-rich *Nardus* grasslands); (c) ecologically vulnerable EU habitat of interest transition mires (F3: distance in meters from transition mires); (d) surveyed location of threatened or rare plant species (F4: distance in meters from location of plant species); (e) areas densely frequented by threatened or rare animal species (F5: number of animal species). These ecological criteria aim to prevent tourists threatening habitats and species that are pivotal for conservation purposes due to frequent anthropogenic access eased by the contiguity to tourist infrastructures. Following McGarigal and Marks (1995), patch richness is defined here as the number of different patch types. Species-rich *Nardus* grasslands are rare in Europe (European Commission, 2003), where they are limited to the colder mountain areas and support a wide range of species, including Atlantic, sub-Atlantic and Arctic-alpine plants, several mammal species (e.g. marmots), birds and invertebrates. They are damaged by tourists due to the collection of rare and threatened plant species, noise and accidental fires.

From a safety point of view, new tourist infrastructures should be as far as possible from grazed areas (F6: distance in meters from grazed areas) and placed where surface roughness is as flat as possible (F11: surface roughness). F6 was conceived since tourists may disturb cattle during foraging activities and vice versa, while F11 aims at privileging flat areas where the tourist access is easier and safer. Surface roughness is defined here as ratio between the surface area (i.e. true 3D area) and the flat area (2D projection) in a fixed-radius area surrounding a pixel, estimated of at least 200 m, following the advice of experts from the study area, to guarantee safer tourist access.

From a logistic standpoint, we valued five factors as significant for the new tourist infrastructures: (a) distance in meters from current tourist sites (F7), (b) from each other (F8), (c) closeness to existent tourist paths (F9: distance in meters from existing roads and/or tourist paths), and (d) to areas of aesthetic relevance (F10), (e) separation in elevation (F12). F7 and F8 aims at guaranteeing tourist sites are as spaced as possible within the study area, hence properly covering the horizontal width of the SCI. The same is true

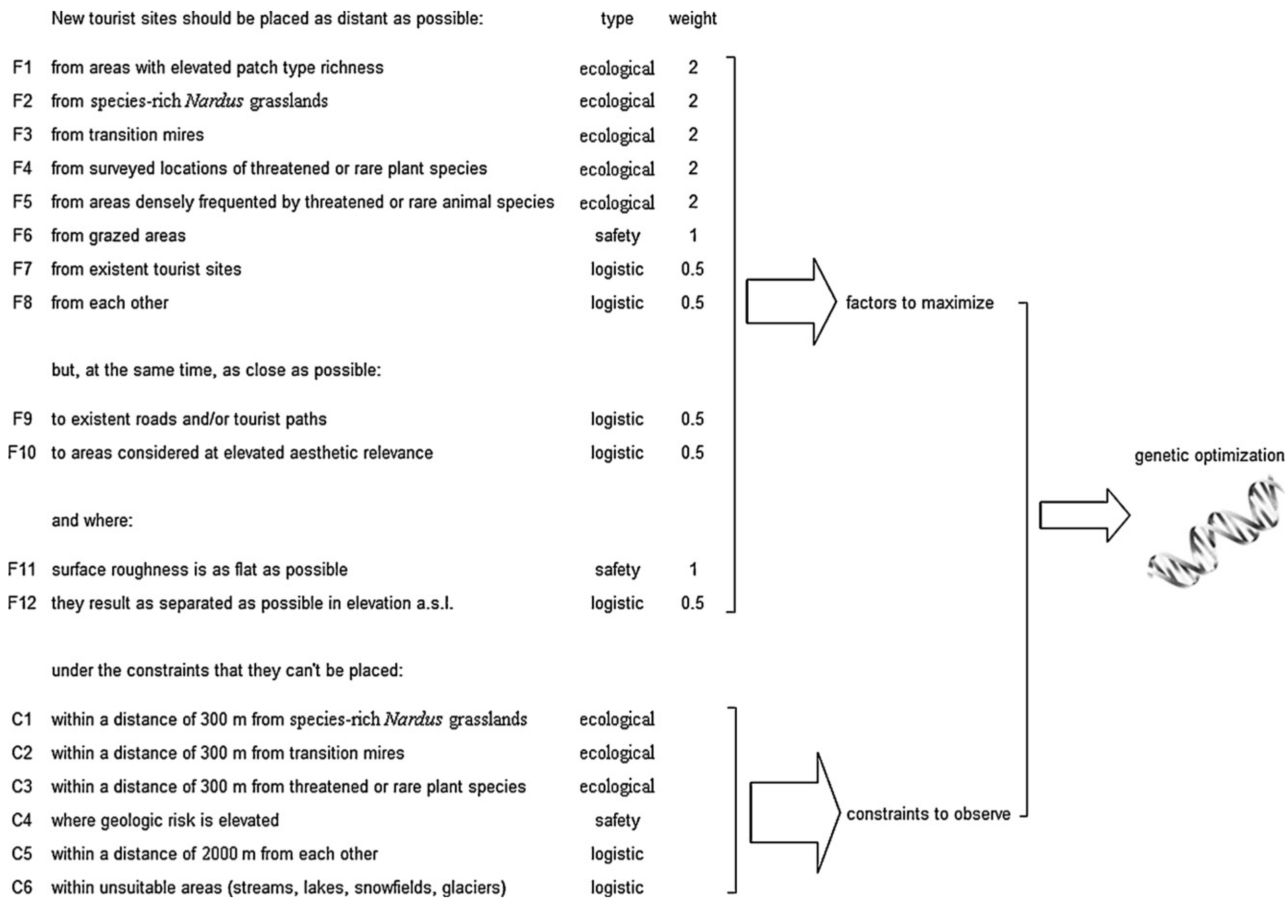

Fig. 2. Conceptual framework (12 factors and 6 constraints) employed by the proposed optimization procedure to locate new optimized tourist sites.

for F12, a factor trying to ensure tourist sites are as spaced as possible in elevation a.s.l. to cover the vertical width of the study area. F9 favours the allocation of new tourist sites near to existent tourist paths, since a more distant allocation would require additional and expensive work to plan and build new paths. F10 follows the criterion of the landscape attractiveness (Parsons and Daniel, 2002), thus favouring the allocation of new tourist sites where landscape attractiveness is higher.

Besides the previous factors, we also imposed six constraints (Fig. 2). In GIS terms, constraints refer to dichotomous criteria that exclude unsuitable areas, i.e. portions of the study area where proposed tourist infrastructures are a priori left out. Three constraints (C1, C2, C3) deal with relevant elements of biodiversity. Following our experience of the study area, we reputed 300 m as a proper safety distance to avoid tourist disturbance. C5 was conceived as a strengthening of F8 (distance from each tourist site). Finally, we excluded areas at elevated geological risk (C4) and ineligible areas (streams, lakes, snowfields, glaciers; C6).

In accordance with local actors, we decided to assign a different weight of importance to the three categories of criteria (Fig. 2). Since ecological criteria should be predominant within protected areas, ecological factors were given the highest importance (i.e. 2), while safety and logistic criteria were assigned weights equal to 1 and 0.5 respectively.

3.2. Data collection

In order to translate the above-depicted goals into GIS terms, we realized an accurate GIS model at 1:10 000 scale whose layers have been selected on the basis of the criteria employed in the GA-based site selection procedure. Land-cover was accounted by the authors, by mapping the EU-habitats (European Commission, 2003) of the SCI through 3-year long field surveys and digital orthophotos (referred to year 2000), thereby a 13-class categorical map was generated. In particular, the EU-habitats map provided the spatial information about the presence of species-rich *Nardus* grasslands and transition mires, i.e. two habitats of high conservation relevancy. Furthermore, the habitat map of the study area was analyzed using a 500 m × 500 m moving window that produced a resulting map where each pixel was given the number of patch types present within a radius of 500 m. We used this raster map as a measure of local patch richness. The occurrence of rare or threatened plant species was mapped in a 4-year period (2003–2006), using a global positioning system (GPS), with an error lower than 1 m (Appendix A). We accounted for plant species belonging indistinctly to European (Annexes of 'Habitats' Directive 92/43/EEC), Italian (Italian Red list; Conti et al., 1992; Scoppola and Spampinato, 2005) and local lists of conservation concern (Conti et al., 1997; Parolo et al., 2005). The presence of animal species belonging to annexes of Dir. 92/43/EEC ('Habitats' Directive) and Dir. 79/409/EEC ('Birds' Directive) was provided by the provincial administration of Sondrio (Appendix B). By means of digital orthophotos and field surveys we detected: (1) roads, (2) tourist paths, (3) tourist sites (refuges and camp sites) and (4) grazed areas. The digital elevation model (DEM) of the study area was digitized by the authors from available topographic maps of Lombardy Region. Surface roughness was then derived from DEM using a 200 m × 200 m moving window. Finally, a geomorphologic risk map depicting four levels of risk (null, low, average and elevated) and a map of the areas at elevated aesthetic relevance were supplied by Lombardy Region.

3.3. GAs–GIS combination

GAs consist of optimization procedures based on principles inspired by natural selection. GAs involves 'chromosomal' representations of proposed problem solutions which undergo genetic operations such as selection, crossover and mutation (Holland, 1975; Goldberg, 1989).

For the purposes of this study, a GAs procedure was developed using GAlib (Wall, 1996), a free library of genetic algorithm objects and tools for doing optimization using any representation and genetic operators. A GIS was used to prepare input data for the GAs and to analyze and visualize the resulting optimized solutions. To this aim, the study area has been partitioned into homogeneous cells (pixels) measuring 100 m × 100 m, and each cell was assigned an identification number representing a candidate solution for the optimization process. Each identification number was a gene used by the GAs procedure. Hence, a chromosome was a vector having a number of genes equal to the amount of optimized allocations we searched for. In a n-sites-to-add scenario, each chromosome is hence composed by a string of n identification numbers (pixels) that represent a feasible solution to the optimization problem. Each criterion (F1, F2, F3, etc.) was then translated into a GIS layer, hence each pixel of the SCI assumed a vector of values corresponding to the initial performance criteria. This database was then linked to the GAs as input data for finding optimal solutions. It should be noted that two factors (i.e. F8 and F12) and one constraint (C5) are spatially implicit since they are not represented by a GIS layer, instead they are dynamically calculated during the GAs process. Hence, the optimization process was based both on GIS-based (10 factors and five constraints) and numerical criteria (two factors and one constraint).

Before the optimization process, all factors have been normalized in the 0–1 interval thus making them unitless and comparable. Since they were not normally distributed, we applied a min-max normalization instead of a standardization in the form of standard deviations from mean. Following our decision framework, to solve the general case of n-sites-to-add scenario ($n > 1$), the GAs objective function (OF) was calculated as follows:

$$\mathrm{OF}_n = \sum_{1}^{n} \frac{2\mathrm{F1} + 2\mathrm{F5} + 0.5\mathrm{F9} + 0.5\mathrm{F10} + \mathrm{F11}}{2\mathrm{F2} + 2\mathrm{F3} + 2\mathrm{F4} + \mathrm{F6} + 0.5\mathrm{F7} + 0.5\mathrm{F8} + 0.5\mathrm{F12}} \quad (1)$$

where the numerator estimates the costs, while the denominator takes benefits into account. Hence the optimization goal was achieved by minimizing the cost–benefit function OF_n subject to:

$$\mathrm{C1} > 300\,\mathrm{m} \quad (2)$$

$$\mathrm{C2} > 300\,\mathrm{m} \quad (3)$$

$$\mathrm{C3} > 300\,\mathrm{m} \quad (4)$$

$$\mathrm{C4} \neq \text{“elevated geologic risk”} \quad (5)$$

$$\mathrm{C5} > 2000\,\mathrm{m} \quad (6)$$

$$\mathrm{C6} \neq \text{“unsuitable areas”} \quad (7)$$

To solve the optimized selection of just one site ($n = 1$; OF_1), factors F8 and F12 and the constraint C5 have been left out since they only deal with the case that more than one tourist site is to be searched for. Hence, OF_1 was in the form:

$$\mathrm{OF}_1 = \frac{2\mathrm{F1} + 2\mathrm{F5} + 0.5\mathrm{F9} + 0.5\mathrm{F10} + \mathrm{F11}}{2\mathrm{F2} + 2\mathrm{F3} + 2\mathrm{F4} + \mathrm{F6} + 0.5\mathrm{F7}} \quad (8)$$

Since the genetic algorithm is based on random searching for solutions, its final results cannot be identical as the starting points are randomly selected, although the other input parameters are unique. Therefore, we performed iterative processes for determining appropriate parameters. Previous research revealed that the optimal solution may be to search at a high rate of crossover, a low rate of mutation and proper population size (Kuo et al., 2000). In this study, crossover was set at a probability of 60% while mutations occur with a probability of 5%. This low setting helps to avoid getting trapped local optima during the search (D'heygere et al., 2006). The initial population consisted of 500 chromosomes that were evolved over minimal 10 000 generations. These parameters were set after preliminary experiments. In our study we apply a steady-state genetic algorithm with a one-point crossover operator (Wall, 1996) to accomplish crossover. In this case the parent genome strings are cut at some random position to produce two "head" and two "tail" segments. The "tail" segments are swapped to produce two new genomes. For parent selection the roulette wheel selection method was used (Goldberg, 1989), where the likelihood of selection is proportionate to the fitness score given by the performance criterion. After crossover and mutation, the individuals with the lowest fitness scores were removed.

3.4. Model evaluation

Since GAs do not guarantee to find the global optimum, besides the search for the fittest tourist allocations we also searched for the least fit (i.e. worst) ones. This was achieved by minimizing, instead of maximizing, the optimization goal. Then, for each genetic solution we analyzed the values of the performance criteria thus having a comparative framework revealing how much the fittest solutions are better than their nadir counterparts. We realized the same procedure to compare the detected tourist allocations with the existing tourist sites. The degree of success (DS) of a solution with regard to the performance criteria was estimated as

$$DS = \frac{x_i}{x_{highest}} \quad (9)$$

for benefit criteria (i.e. the more the best; F2, F3, F4, F6, F7), and in the form

$$DS = 1 - \frac{x_i}{x_{highest}} \quad (10)$$

for cost criteria (i.e. the less the best; F1, F5, F9, F10, F11). The degree of success of each genetic solution was then represented in the form of a web-diagram.

4. Results

The optimized solution for the one-site-to-add scenario (Fig. 3a) detected a location in the Eastern side of the SCI having a genetic (cost–benefit) score equal to 0.24. This solution performs very well (Table 1a) since it is placed where diversity in cover types is minimal (F1 = 1), the presence of threatened animal species is null (F5 = 0) and the distance from relevant biodiversity elements is satisfactory. In effect, this solution wholly satisfies five performance criteria (F1, F2, F3, F5, F6) out of 10 (Fig. 4a), in the sense that it assumes the fittest values that are allowed within the SCI with regard to these criteria. Although it represents the best global solution, it is fairly weak from three points of view, i.e. F4, F9 and F10. In effect, the selected site is not so far from locations of plant species (F4 = 1190.26 m) and not so close to existing roads and/or tourist sites (F9 = 2429.52 m) and to areas at elevated aesthetic value (F10 = 2042.03 m). When compared to the nadir (least fit) solution (cost–benefit score = 5.21) achieved by minimizing OF_1 (Fig. 3e, Table 1b), the optimized solution exhibits a substantial superiority apart for criteria F9, F10 and F11. Although the nadir solution is very unfavourable from an ecological point of view, it is not so critical from a logistic and safety viewpoint.

The optimized solution for the two-sites-to-add scenario (Fig. 3b) selected the same location as the previous scenario both

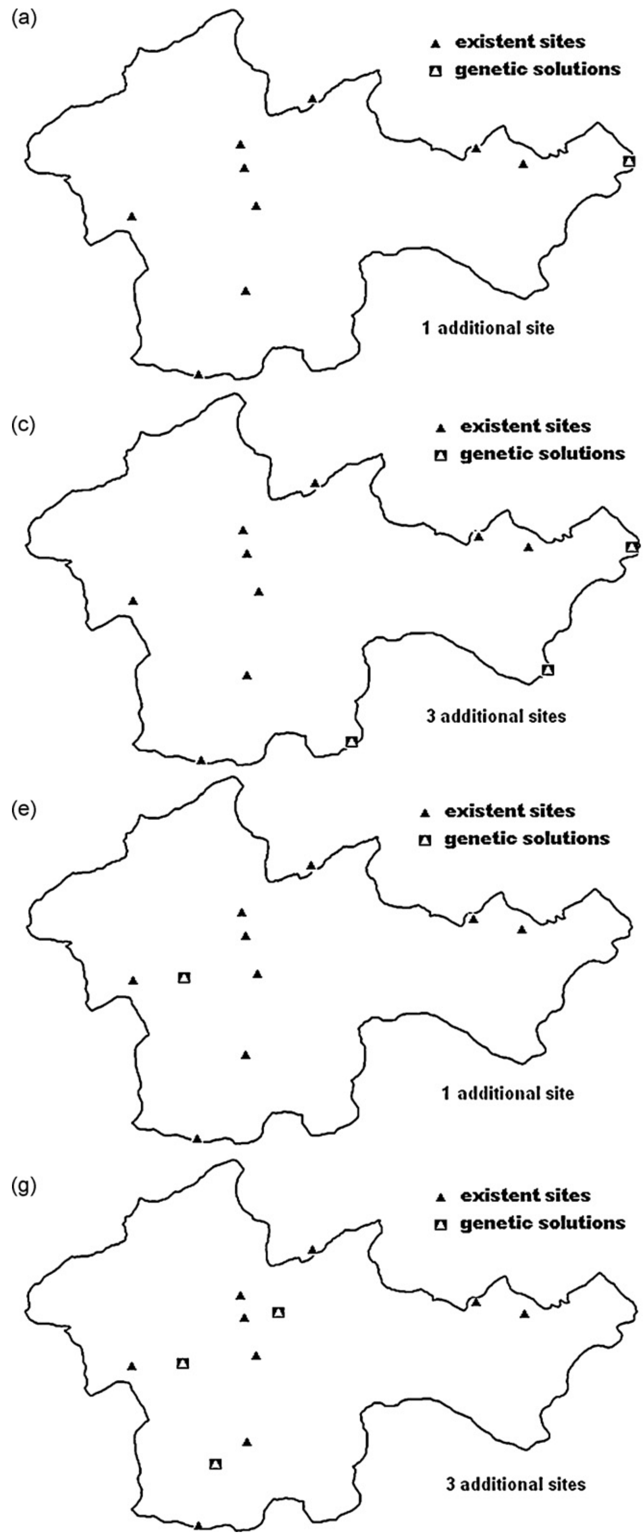

Fig. 3. The optimal solutions to the problem of adding 1 (a), 2 (b), 3 (c) and 4 (d) tourist sites to current ones, both with the worst case scenarios for 1 (e), 2 (f), 3 (g) and 4 (h) additional tourist sites.

with a location in the southern side of the SCI. These couple of sites have a genetic (cost–benefit) score equal to 0.84. This solution performs very well too (Table 1a), also because the second selected site has a degree of success equal to 100% with regard to five factors (F1, F4, F5, F10, F11) out of 10 (Fig. 4b). Instead it is weak with regard to criteria F2, F3 and, in particular, F9. This couple of sites fully satisfies the criteria of both the horizontal (F8 = 7964.33 m) and vertical (F12 = 313.02 m) distance. When compared to its nadir counterpart (cost–benefit score = 9.98; Fig. 3f, Table 1b), the fittest solution evidences undisputable advantages, in particular with regard to the ecological factors. Instead, it is fairly worse concerning F9 and F11.

The optimized solution for the three-sites-to-add scenario (Fig. 3c) detected the same solutions as the previous scenarios while adding a new site in the south-eastern portion of the SCI. This set

Table 1
Scores of the fittest (a) and least fit (b) solutions with regard to the employed criteria (F1, . . ., F12).

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
(a) Fittest scenarios												
1 additional site	1	8229.21	4715.81	1190.26	0	3857.98	2416.11		2429.52	2042.03	1.470	
2 additional sites	1	8229.21	4715.81	1190.26	0	3857.98	2416.11	7964.33	2429.52	2042.03	1.470	313.02
	1	2969.40	3198.82	2981.44	0	2632.75	2854.79		2921.62	14.76	1.076	
3 additional sites	1	8229.21	4715.81	1190.26	0	3857.98	2416.11	5439.07	2429.52	2042.03	1.470	241.07
	1	2969.40	3198.82	2981.44	0	2632.75	2854.79		2921.62	14.76	1.076	
	1	6183.57	2683.34	1061.71	0	1850.96	3022.50		2791.55	2743.85	1.207	
4 additional sites	1	8229.21	4715.81	1190.26	0	3857.98	2416.11	4901.35	2429.52	2042.03	1.470	202.13
	1	2969.40	3198.82	2981.44	0	2632.75	2854.79		2921.62	14.76	1.076	
	1	6183.57	2683.34	1061.71	0	1850.96	3022.50		2791.55	2743.85	1.207	
	1	1969.14	2049.07	2051.40	0	1853.96	2315.91		1942.06	301.21	1.078	
(b) Least fit scenarios												
1 additional site	4	782.51	337.69	338.58	8	196.32	1057.38		0.00	616.47	1.014	
2 additional sites	4	782.51	337.69	338.58	8	196.32	1057.38	2581.52	0.00	616.47	1.014	291.27
	3	333.69	768.82	393.83	8	108.08	829.54		390.59	1541.27	1.160	
3 additional sites	4	782.51	337.69	338.58	8	196.32	1057.38	3004.97	0.00	616.47	1.014	194.05
	3	333.69	768.82	393.83	8	108.08	829.54		390.59	1541.27	1.160	
	3	627.32	738.08	352.34	8	155.32	702.38		385.05	602.41	1.296	
4 additional sites	4	782.51	337.69	338.58	8	196.32	1057.38	3308.69	0.00	616.47	1.014	195.15
	3	333.69	768.82	393.83	8	108.08	829.54		390.59	1541.27	1.160	
	3	627.32	738.08	352.34	8	155.32	702.38		385.05	602.41	1.296	
	3	322.32	421.27	429.82	8	85.57	1411.11		501.17	176.29	1.066	

of sites scored a genetic (cost–benefit) score of 1.09. Although it represents the best global solution, the third site is weak from three points of view (criteria F4, F9, F10; Fig. 4c) while it is optimal concerning four criteria (F1, F5, F7 and F11). When compared to the least fit solution (cost–benefit score = 14.19; Fig. 3g; Table 1b), the fittest solution evidences considerable advantages in particular with regard to the ecological factors, while it is fairly worse concerning F9 and F11.

The optimized solution for the four-sites-to-add scenario (fitness score = 1.36; Fig. 3d) adds a further site in the central portion of the SCI. This new site is performant with regard to four criteria (F1, F5, F10 and F11; Table 1a; Fig. 4d) while it is weak referring to criteria F2 and F9. In a comparison with its nadir (cost–benefit score = 18.79; Fig. 3h; Table 1b), the fittest solution is considerably better although it is again fairly worse concerning criteria F9 and F11.

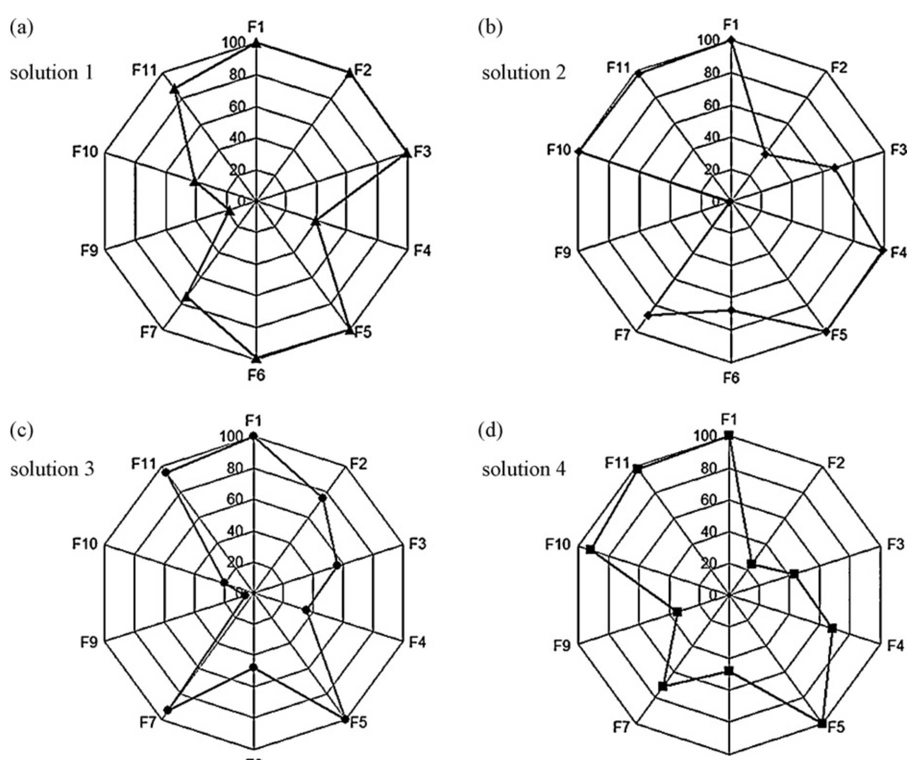

Fig. 4. Web-diagrams showing the degree of success of each of the four genetic solutions with regard to the performance factors (F1, . . ., F11) chosen to evaluate the optimized placement of new tourist sites within the study area.

Table 2
Scores of the current tourist sites (ID1, ID2, . . ., ID9) with regard to the employed criteria (F1, F2, . . ., F11).

Tourist site	F1	F2	F3	F4	F5	F6	F9	F10	F11
ID1	2	2168.13	1546.22	0	8	691.12	0	512.87	1.032
ID2	3	1025.32	293.55	0	8	397.66	0	575.78	1.114
ID3	1	540.91	54.55	122.98	8	98.42	93.95	87.21	1.037
ID4	3	5.25	387.04	252.14	8	0	18.78	0	1.002
ID5	3	4.75	405.56	124.89	8	0	6.56	1266.15	1.003
ID6	1	389.03	415.05	280.5	6	157.41	264.45	917.43	1.019
ID7	1	1654.71	2317.91	795.39	0	1236.73	0	1368.15	1.119
ID8	3	4769.22	1509.38	1043.59	5	1078.61	918.38	1351.65	1.412
ID9	2	5722.56	2380.41	235.19	1	1845.36	0	1388.85	1.088

The comparison of the genetic optimized allocations with existing tourist sites (Fig. 1) reveals, as awaited, that the latter show performances that are halfway between the fittest and the least fit genetic solutions (Table 2). ID1 and ID2 are weak with regard to criteria F1, F4 and F5, while they perform well concerning logistic and safety criteria F9, F10 and F11. ID3 has its weakness due to criteria F3, F5 and F6, but again it performs well with regard to safety and logistic criteria. ID4 and ID5 perform in an unfit manner, in particular due to criteria F1, F5 and F6. On the other hand, they privilege criteria F9, F10 and F11. On the contrary, ID7 and ID9 behave in a very satisfactory manner except for the criterion F10, finally ID6 and ID8 have intermediate performances. As a result, five existing tourist sites behave similar to the least fit solutions, two to the fittest ones and two are intermediate.

5. Discussion

Making human activities sustainable is not an easy task, in particular within protected areas where biodiversity is densely present everywhere. Instead, a satisfactory balance between nature and human activities might bear great effects for biodiversity preservation (Cocks and Ive, 1996; Westphal and Possingham, 2003). Rarely there is a single, dominant management objective, more often there are multiple, highly contrasting objectives requiring a foremost trade-off, in the form of a “win–win” solution that satisfy human needs while maintaining ecological functions. Hence, a matter of optimization arises and proper methodological tools are required.

Our paper first provides a model for an interactive, multivariate optimization of protected areas through the minimization of a weighted cost–benefit function involving many different viewpoints. Through a four-step method (i.e. choice of relevant criteria, translation into GIS terms, genetic optimization, model evaluation), we have formalized the problem of the allocation of tourist infrastructures as a mathematical optimization procedure. In accordance with local actors, due to the assigned weights of importance we searched for ecologically oriented scenarios through which the priority was on the conservation of habitats, plant and animal species. It should be noted that, from an optimization point of view, the importance is on the ratio between weights of importance and not on their absolute values. The explicit mathematical formulation of conservation planning goals led to greater objectivity and transparency in the solutions. Furthermore, the outlined method is easily exportable to any other areas where, if needed, it may be modulated in case further criteria are considered relevant. In particular, we are aware that our framework may be refined by incorporating the economic viewpoint (Drechsler et al., 2006), since conservation does not exist in an ideal world, detached of socio-economic aspects (e.g. different costs for tourist site building on the basis of the properties of the selected site). In accordance with local administrators, we will consider such aspect as funds for site realization will be available, by following the same procedure, i.e. definition of clear and quantifiable criteria to be translated into GIS terms and integrated into the optimization procedure.

It should be noted that the proposed methodology may be applied also to protected areas having no previous tourist sites. This can be simply achieved by leaving out the criterion F7 (distance from existent tourist sites). In addition, since the proposed model allows for the quantification of fitness scores of existing tourist sites, we detected five tourist locations with elevated impacts on the existing biodiversity. These sites are not consistent with nature protection objectives and might be replaced in the future by optimized sites planned through the model we devised here.

Following our approach, we detected four optimized scenarios where fittest tourist allocations resulted to be close to the limits of the SCI. This is due to the fact the central portion of the SCI favours logistic and safety criteria and, at the same time, it disadvantages the ecological criteria due to its higher density of biodiversity. In fact, the least fit solutions were placed by GAs in the middle of the study area. Fittest and least fit solutions were located very far apart, being this an additional proof that the SCI is spatially clustered with regard to the performance criteria employed in the optimization process. Existing tourist sites are similar to least fit solution, since they favour logistic and safety criteria rather than ecological ones. Two tourist sites (ID7 and ID9) are exceptions, due to their location far from the centre of the SCI.

An important question in this work is the reason for using GAs instead of easier suitability mapping methods through which site location problems are reasonably tackled using multicriteria decision methods (Voogd, 1983). These methods have been recently used to solve a wide variety of multifaceted problems, such as site prioritization for protected areas or waste management, planning of forest and agricultural resources management, and also for the assessment of environmental impacts (Wood and Dragicevic, 2007). Unfortunately, this approach is not feasible when generating a network of candidate sites where the spatial relationships between sites (criteria F8, F12 and C5) are critical and each site cannot be considered in isolation. This goal requires a complex interplay in the form of a dynamical simulation where candidate sites are interactively evaluated. An alternative approach might lie on brute-force search or exhaustive search (Menon, 2004), i.e. a trivial but very general problem-solving technique that consists of systematically enumerating all possible candidates for the solution and checking whether each candidate satisfies the problem statement. Brute-force search is simple to implement, and will always find a solution if it exists. However, its cost is proportional to the number of candidate solutions, which, in many practical problems, tends to grow very quickly as the size of the problem increases. For example, in this study we dealt with 6000 candidate solutions (pixels), hence 6000^n different combinations should be assessed to identify the best solution for n new sites to add. The problem would be computationally hard, and as such there are no known efficient polynomial-time algorithms that can solve this problem exactly (Cormen et al., 1990).

Although it was outside the scope of this paper, the proposed methodology may be employed to model optimized tourist paths as well. This may be achieved by minimizing the cost–benefit function for a number of genetically simulated paths passing through the pixels in which the study area was divided in. This goal may also be reached by making use of least-cost modelling (Ferrarini et al., 2008), a methodologically easier and computationally less demanding approach if compared to GAs. However least-cost modelling is not able to take into account planning of both suitable paths and infrastructures in a new reserve, neither a network of candidate routes where spatial relations exist among paths. This goal requires GAs for a complex simulation in a holistic perspective.

The optimized selection of tourist locations resembles the problem of reserve network design (Noss, 2003; Williams et al., 2004). By the way, the model proposed in this work is very different from the previous worldwide reserve network algorithms like, for instance, Marxan (Possingham et al., 2000) and ResNet (Sarkar et al., 2002). First, our model does not rely on the critical assumption commonly made by reserve selection algorithms, that selection units are independent of each other. As depicted above, in our model spatial relations between sites are critical and each site is not considered in isolation. Secondly, the proposed model is extremely flexible, thus allowing the introduction of whatever criterion is needed. Instead, commonly used reserve selection algorithms (e.g. Marxan and ResNet) are rigid, in that they provide a pre-determined set of criteria. Thirdly, our model incorporates not only biotic criteria but also abiotic ones, for instance referring to safety and logistics. In addition, since GAs are blind (i.e. they are not cognizant of when it reaches an optimal solution) there is no guarantee that a global maximum is reached. Therefore, to evaluate the validity of this approach, it is imperative to demonstrate that such models do actually converge to the appropriate solution. This is why our model used a simple but effective answer to the problem, based on the comparison of the discovered fittest solutions with nadir solutions and with existing tourist sites. This gave us a quantitative assessment of how satisfactory the detected optimized solutions are. In the one-site-to-add scenario, the fittest solution had a cost–benefit ratio about 20 times better than the least fit one (0.24 versus 5.21), about 12 times in the two-sites-to-add scenario (0.84 versus 9.98), 13 times in the three-sites-to-add scenario (1.09 versus 14.19) and 14 times in the four-sites-to-add scenario (1.36 versus 18.79). For interpretative purposes, the representation of the degree of success of each genetic solution in the form of a web-diagram was useful as well.

Our model has important implications for managers and researchers seeking to minimize human impacts in wilderness recreation areas with nature conservation goals. It is a step forward towards systematically settling a satisfactory coexistence between nature and human activities by dynamically solving multiple, nonlinear, highly contrasting objectives. Moreover, this work may contribute to unify criteria and data coming from different biological and ecological sciences such as botany (criteria F4 and C3), zoology (F5 and C3), ecosystem (F2, F3, C1 and C2) and landscape (F1 and F10) ecology, following safety and logistic criteria as well, to achieve an overall optimization of the humans-nature balance.

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Appendix A

List of threatened or rare plant species surveyed within the study area over a period of 3 years. The last column relates to the number of growing sites.

	Dir. 92/43/EEC	IT Red List	IT 1020	Local list	Locations
Aconitum variegatum subsp. *paniculatum* (Arcang.) *Negodi*			R	3	
Androsace obtusifolia All.					3
Aquilegia vulgaris L.				RR	1
Arnica montana L.	V				85
Artemisia genipi Weber	V				2
Astragalus depressus L.				R	1
Betula pubescens Ehrhart				R	3
Carex canescens L.					13
Carex davalliana J.E. Smith					4
Carex lepidocarpa Tausch					1
Carex panicea L.					5
Carex paupercula Michx.					13
Carex rostrata Stokes					1
Chamorchis alpina (L.) L.C.M. Richard				R	4
Cicerbita alpina (L.) Wallr.				R	6
Eriophorum vaginatum L.					7
Gentiana anysodonta Borbas				R	2
Goodyera repens (L.) R. Br.				R	1
Koeleria hirsuta Gaudin				R	2
Linnaea borealis L.		LR	Yes	R	1
Lloydia serotina (L.) Reichenbach					2
Luzula luzulina (Vill.) Dalla Torre and Sarnth.				R	1
Lycopodium annotinum L.	V				6
Lycopodium clavatum L.	V			R	1
Moneses uniflora (L.) A. Gray					1
Papaver aurantiacum Loisel.					2
Poa chaixi Vill.				R	5
Polystichum aculeatum (L.) Roth				R	1
Potentilla frigida Villars				R	2
Ranunculus trichophyllus Chaix subsp. *trichophyllus*					5
Ribes petraeum Wulfen				R	2
Salix caesia Villars				R	2
Salix glaucosericea Floderus				R	2
Saussurea alpina (L.) DC. subsp. *alpina*				R	10
Saxifraga hostii subsp. rhaetica (Engl.) Braun-Blanq.				R	1
Sempervivum wulfenii Mert. and W.D.J. Koch				R	7

Appendix A (*Continued*)

	Dir. 92/43/EEC	IT Red List	IT 1020	Local list	Locations
Sparganium angustifolium Michaux			Yes	R	4
Trichophorum alpinum (L.) Pers.				R	4
Trientalis europaea L.		LR	Yes	RR	3
Woodsia alpina (Bolton) Gray				R	2

Dir. 92/43/EEC stands for ‘Habitats’ Directive 92/43/EEC (V = Annex V).
IT Red List stands for Italian Red List (LR = low risk).
IT 1020 refers to Scoppola and Spampinato (2005).
Local list refers to Parolo et al. (2005) (R = rare; RR = very rare).

Appendix B

Interaction between animal species and hosting habitats within the study area.

Species	Dir. 92/43/EEC	Dir. 79/409/EEC	EU habitat												
			3130	3220	4060	4080	6150	6230	6430	6520	7140	8110	8220	8340	9420
Alectoris graeca Meisner		I	A	A	B	B	C + D	C	A	C	A	B	A	A	A
Aquila chrysaetos L.		I	A	A	B	B	C	C	B	C	B	C	D	A	B
Eptesicus nilsonii Keyserling et Blasius	IV		C	C	B	A	A	C	B	C	C	A	A	A	B
Glaucidium passerinum L.		I	A	A	A	A	A	A	A	A	A	A	A	A	C + D
Gypaetus barbatus L.		I	A	A	C	B	C	C	B	C	B	C	D	A	B
Lagopus mutus L.		I	A	A	A	B	C	C	A	A	A	D	B	B	A
Lepus timidus L.	V		A	B	C + D	C	C	C	B	B	B	B	A	A	C
Pipistrellus pipistrellus Schreber	IV		C	C	B	A	A	C	B	C	C	A	A	A	B
Tetrao tetrix L.		I	A	B	C + D	A	B	B	B	A	A	A	A	A	C + D
Tetrao urogallus L.		I	A	A	C + D	A	A	A	B	A	A	A	A	A	C + D

A: occasional habitat; B: regular habitat; C: preferred habitat for feeding; D: preferred habitat for reproduction/nidification.
Sign “+” means that two kinds of interaction between species and habitat have been observed.

References

Alpine Space, 2007. Alpine Space Programme. Interreg III B, Project Booklet 2000–2006, European Union Community Initiative Programme.

Amo, L., Lopez, P., Martin, J., 2006. Nature-based tourism as a form of predation risk affects body condition and health state of Podarcis muralis lizards. Biol. Conserv. 131, 402–409.

CEC (Commission of the European Communities), 1992. Council directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora, Brussels.

Chikumbo, O., Steward, G.A., 2007. A stand basal area model for plantation grown New Zealand kauri. Ecol. Model. 209, 367–376.

Cocks, D., Ive, J., 1996. Mediation support for forest land allocation: the SIRO-MED system. Environ. Manage. 20 (1), 41–52.

Conti, F., Manzi, A., Pedrotti, F., 1992. Libro rosso delle piante d'Italia. TIPAR, Roma.

Conti, F., Manzi, A., Pedrotti, F., 1997. Liste Rosse Regionali delle Piante d'Italia. WWF Italia, Società Botanica Italiana, University of Camerino, Camerino, Italy.

Cormen, T.H., Leiserson, C.E., Rivest, R.L., 1990. Introduction to Algorithms. MIT Press, New York, USA.

Cropper Jr., W.P., Comerford, N.B., 2005. Optimizing simulated fertilizer additions using a genetic algorithm with a nutrient uptake model. Ecol. Model. 185, 271–281.

D'heygere, T., Goethals, P.L.M., Niels De Pauw, N., 2006. Genetic algorithms for optimisation of predictive ecosystems models based on decision trees and neural networks. Ecol. Model. 195, 20–29.

DeFries, R., Hansen, A., Turner, B.L., Reid, R., Liu, J., 2007. Land use change around protected areas: management to balance human needs and ecological function. Ecol. Appl. 17, 1031–1038.

Drechsler, M., Johst, K., Wätzold, F., Westphal, M.I., 2006. Integrating economic costs into the analysis of flexible conservation management strategies. Ecol. Appl. 16, 1959–1966.

Dreyfus-Leon, M., Chen, D.G., 2007. Recruitment prediction with genetic algorithms with application to the Pacific Herring fishery. Ecol. Model. 203, 141–146.

European Commission, 2003. Interpretation manual of European Union habitats, Luxembourg.

European Commission, 2008. EU Biodiversity action plan report: http://ec.europa.eu/environment/nature/biodiversity/comm2006/bap_2008.htm (last update: 23.12.08).

Europarc Federation, 2008. The European Charter for sustainable tourism in protected areas. Europarc Federation, Grafenau, Germany.

Ferrarini, A., Rossi, G., Parolo, G., Ferloni, M., 2008. Planning low-impact tourist paths within a Site of Community Importance through the optimisation of biological and logistic criteria. Biol. Conserv. 141, 1067–1077.

Foley, J.A., DeFries, R., Asner, G.P., Barford, G., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309, 570–574.

Goldberg, D.E., 1989. Genetic Algorithms in Search Optimization and Machine Learning. Addison-Wesley, Reading, USA.

Griffin, S.C., Valois, T., Taper, M.L., Mills, L.S., 2007. Effects of Tourists on Behavior and Demography of Olympic Marmots. Conserv. Biol. 21, 1070–1081.

Haupt, R.L., 2004. Practical Genetical Algorithms. Wiley, London, UK.

Holland, J.H., 1975. Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control and artificial intelligence. University of Michigan Press, Ann Arbor, USA.

Holzkamper, A., Lausch, A., Seppelt, R., 2006. Optimizing landscape configuration to enhance habitat suitability for species with contrasting habitat requirements. Ecol. Model. 198, 277–292.

Honey, M., 1999. Ecotourism and Sustainable Development: Who Owns Paradise? Island Press, Washington, DC.

Kelly, C., Pickering, C.P., Buckley, R.C., 2002. Impacts of tourism on threatened plant taxa and communities in Australia. Environ. Manage. 4, 37–44.

Kuo, S.F., Merkley, G.P., Liu, C.W., 2000. Decision support for irrigation project planning using a genetic algorithm. Agric. Water Manage. 45, 243–266.

Lawson, S.R., Manning, R.E., Valliere, W.A., Wang, B., 2003. Proactive monitoring and adaptive management of social carrying capacity in Arches National Park: an application of computer simulation modelling. J. Environ. Manage. 68, 305–313.

Lindsey, P.A., Alexander, R.R., du Toit, J.T., Mills, M.G.L., 2005. The potential contribution of ecotourism to African wild dog *Lycaon pictus* conservation in South Africa. Biol. Conserv. 123, 339–348.

Liu, G., Han, S., Zhao, X., Nelson, J.D., Wang, H., Wang, W., 2006. Optimisation algorithms for spatially constrained forest planning. Ecol. Model. 194, 421–428.

Manor, R., Saltz, D., 2003. Impact of human nuisance disturbance on vigilance and group size of a social ungulate. Ecol. Appl. 13, 1830–1834.

McGarigal, K., Marks, B.J., 1995. Fragstats: spatial pattern analysis program for quantifying landscape structure. Gen. Tech. Rep. PNW-GTR-351. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Menon, A. (Ed.), 2004. Frontiers of Evolutionary Computation. Kluwer Academic Publishers, Dordrecht, The Nederland.

Noss, R.F., 2003. A checklist for wildland networks design. Conserv. Biol. 5, 1270–1275.

Parolo, G., Rossi, G., Ferranti, R., 2005. La flora di particolare interesse fitogeografico della provincia di Sondrio: un primo inventario per la sua conservazione. Biogeographia 26, 79–97.

Parsons, R., Daniel, T.C., 2002. Good looking: in defense of scenic landscape aesthetics. Landscape Urban Plan. 60, 43–56.

Peacor, S.D., Allesina, S., Riolo, R.L., Hunter, T.S., 2007. A new computational system, DOVE (Digital Organisms in a Virtual Ecosystem), to study phenotypic plasticity and its effects in food webs. Ecol. Model. 205, 13–28.

Possingham, H.P., Ball, I.R., Andelman, S., 2000. Mathematical methods for identifying representative reserve networks. In: Ferson, S., Burgman, M. (Eds.), Quantitative Methods for Conservation Biology. Springer-Verlag, New York, pp. 291–305.

Province of Sondrio, 2008. Piano di gestione pilota del SIC IT 2040012 Val Viola Bormina Ghiacciaio di Cima dei Piazzi. Sondrio, Italy.

Québec Declaration on Ecotourism (1992). Québec City, Canada, 22 May 2002. http://www.world-tourism.org/sustainable/IYE/quebec/anglais/declaration.html.
Rossi, G., Parolo, G., Zonta, L.A., Crawford, J.A., Leonardi, A., 2006. *Salix herbacea* L. fragmented small population in the N-Apennines (Italy): response to human trampling disturbance. Biodivers. Conserv 15, 3881–3893.
Sarkar, S., Aggarwal, A., Garson, J., Margules, C., Zeidler, J., 2002. Place prioritization for biodiversity content. J. Biosci. 27, 339–346.
Scoppola, A., Spampinato, G., 2005. Atlante delle specie a rischio di estinzione (CD rom). In: Scoppola, A., Blasi, C. (Eds.), Stato delle conoscenze sulla flora vascolare d'Italia. Palombi Editori, Roma.
Seppelt, R., Voinov, A., 2002. Optimization methodology for land use patterns using spatially explicit landscape models. Ecol. Model. 151, 125–142.
Seppelt, R., Voinov, A., 2003. Optimization methodology for land use patterns-evaluation based on multiscale habitat pattern comparison. Ecol. Model. 168, 217–231.
Song, H., Li, G., 2008. Tourism demand modelling and forecasting. A review of recent research. Tourism Manage. 29, 203–220.
Steidl, R.J., Anthony, R.G., 2000. Experimental effects of human activity on breeding Bald Eagles. Ecol. Appl. 10, 258–268.
Sweeney, A.W., Beebe, N.W., Cooper, R.D., 2007. Analysis of environmental factors influencing the range of anopheline mosquitoes in northern Australia using a genetic algorithm and data mining methods. Ecol. Model. 203, 375–386.
Termansen, M., McClean, C.J., Preston, C.D., 2006. The use of genetic algorithms and Bayesian classification to model species distributions. Ecol. Model. 192, 410–424.
Turner II, B.L., Lambin, F.E., Reenberg, A., 2007. The emergence of land change science for global environmental change and sustainability. PNAS 104, 20666–20671.
Voogd, H., 1983. Multi-Criteria Evaluation for Urban and Regional Planning. Pion, London.
Wall, M., 1996. GAlib: A C++ Library of Genetic Algorithm Components, version 2.4. Massachusetts Institute of Technology, USA, Available from: http://lancet.mit.edu/ga/.
Walpole, M.J., Goodwin, H.J., Ward, K.J.R., 2001. Pricing policy for tourism in protected areas: lessons from Komodo National Park, Indonesia. Conserv. Biol. 15, 218–227.
Westphal, M.I., Possingham, H.P., 2003. Applying a decision-theory framework to landscape planning for biodiversity: follow-up to Watson et al. Conserv. Biol. 17, 327–329.
Williams, J., ReVelle, C.S., Levin, S.A., 2004. Using mathematical optimization models to design nature reserves. Front. Ecol. Environ. 2, 98–105.
Wood, L.J., Dragicevic, S., 2007. GIS-based multicriteria evaluation and fuzzy sets to identify priority sites for marine protection. Biodivers. Conserv. 16, 2539–2558.