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Abstract: 1. Combining species protection with land management is a central concern for nature conservation but requires a collaborative, problem-solving approach. Existing procedures do not guarantee the participation of stakeholders in the decision-making process and, thus, do not necessarily support the development of acceptable management strategies. An analytical framework is required to assess the consequences of human land use for wildlife habitats, incorporating a quantitative structure for including stakeholder opinions. We provide such a framework.
2. As an example, we used the procedure to evaluate the consequences of different building scenarios for the Turin 2006 Winter Olympic Games on potential roe deer Capreolus capreolus habitats. The analysis involved four steps: (i) three Bayesian models were developed to assess the suitability of six study areas for roe deer; (ii) the outcome of the models was converted into a habitat suitability index (HSI) for each study area; (iii) for each area, the building scenario chosen by the Olympic Games organizers was compared with alternative scenarios by means of HSI values; (iv) an HSI value was chosen as a benchmark to evaluate the ecological consequences of landscape changes.
3. The building projects chosen by the Olympic Games organizers caused changes in HSI values in each study area, especially at one site. In three of the six study areas, the chosen projects minimized the loss of suitable roe deer habitat, while in the remaining areas the alternative building locations could have reduced the negative consequences of human activities.
4. *Synthesis and applications* A habitat suitability index calculated with our procedure can be used to (i) compare different hypothetical land-use scenarios and make decisions about the location of human infrastructures to minimize habitat loss; and (ii) assess the consequences of human activities in relation to an ecological benchmark. The Bayesian approach provides a way to involve local stakeholders in the decision-making process, and thus is a useful tool for discussion of land-use policies. Our procedure could be applied to rare and common species and to assessing the consequences of all human activities involving reductions in natural habitat.
Bayesian modelling procedures for the evaluation of changes in wildlife habitat suitability: a case study of roe deer in the Italian Alps

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Summary

1. Combining species protection with land management is a central concern for nature conservation but requires a collaborative, problem-solving approach. Existing procedures do not guarantee the participation of stakeholders in the decision-making process and, thus, do not necessarily support the development of acceptable management strategies. An analytical framework is required to assess the consequences of human land use for wildlife habitats, incorporating a quantitative structure for including stakeholder opinions. We provide such a framework.

2. As an example, we used the procedure to evaluate the consequences of different building scenarios for the Turin 2006 Winter Olympic Games on potential roe deer *Capreolus capreolus* habitats. The analysis involved four steps: (i) three Bayesian models were developed to assess the suitability of six study areas for roe deer; (ii) the outcome of the models was converted into a habitat suitability index (HSI) for each study area; (iii) for each area, the building scenario chosen by the Olympic Games organizers was compared with alternative scenarios by means of HSI values; (iv) an HSI value was chosen as a benchmark to evaluate the ecological consequences of landscape changes.

3. The building projects chosen by the Olympic Games organizers caused changes in HSI values in each study area, especially at one site. In three of the six study areas, the chosen projects minimized the loss of suitable roe deer habitat, while in the remaining areas the alternative building locations could have reduced the negative consequences of human activities.

4. Synthesis and applications. A habitat suitability index calculated with our procedure can be used to (i) compare different hypothetical land-use scenarios and make decisions about the location of human infrastructures to minimize habitat loss; and (ii) assess the consequences of human activities in relation to an ecological benchmark. The Bayesian approach provides a way to involve local stakeholders in the decision-making process, and thus is a useful tool for discussion of land-use policies. Our procedure could be applied to rare and common species and to assessing the consequences of all human activities involving reductions in natural habitat.

Key-words: autologistic regression, Bayes’ theorem, ecological benchmark, generalized additive modelling, habitat loss, habitat suitability index, land use, landscape planning

Introduction

Combining species protection with land management is a central concern for nature conservation. Habitat evaluations have been proposed as key methods to tackle this problem. In particular, evaluation of habitats for wildlife has become a central concept in both land-use planning (Puttock, Shakotko & Rasaputra 1996) and wildlife management (Garcia & Armbruster 1997; Store & Kangas 2001). Current methods for evaluating the effects of human activities on wildlife habitats use biodiversity or focal-species analysis (Rossi & Kuitunen 1996; Brooker 2002) and they base wildlife–environment modelling on either qualitative or quantitative models (Rickers, Queen & Arthaud 1995; Hurme et al. 2007). Unfortunately, existing approaches do not integrate field data on species-specific landscape requirements with expert knowledge. There is growing recognition of the need to incorporate the views of diverse stakeholders within a formal management framework (Mauro & Hardison 2000).

The participation of experts and stakeholders could prove fundamental to improving the modelling procedures (Reckhow 2003) and reducing social contrasts in relation to landscape management (Young et al. 2005). The evaluation procedures should reconcile the interests of different social
groups and represent a meeting opportunity for the most significant institutions involved in land management and wildlife conservation. This would increase the stakeholders' awareness of, and support for, land-use policies. Evaluation procedures should also avoid, as much as possible, subjectivity in the final impact assessment. None the less, habitat changes associated with alternative management actions are often evaluated via the establishment of arbitrary habitat suitability classes (Rickers, Queen & Arthaud 1995); in contrast, a limit under which habitat quality and availability for wildlife are considered critical (i.e. an ecological threshold) should be defined to judge habitat changes unambiguously.

The aim of our research was to develop an analytical procedure for evaluating the consequences of human land use for wildlife habitats and suggest a framework to inform landscape management quantitatively. Such a framework should guarantee the participation of experts in the modelling procedure, via the implementation of a Bayesian approach, and the objectivity of the final assessments, via the adoption of an ecologically meaningful threshold. Both these facets are crucial to ensure the reliability of habitat evaluations, improve the modelling procedures and increase the confidence in the conclusions drawn from ecological studies.

Here, we discuss the application of Bayesian models incorporating expert knowledge to assess the consequences of different building scenarios on habitat suitability for roe deer Capreolus capreolus L. using the Turin 2006 Winter Olympic Games organized in the Susa and Chisone valleys (western Italian Alps) as a case study. In these valleys, the upgrading and expansion of road and ski infrastructures, as well as the building of new facilities, have increased the effects of human activities on the landscape and ecosystems. As the main changes in land use were to involve the area below the tree line, we applied the procedure to the roe deer. Among species sensitive to deforestation and fragmentation of woodlands, we chose the roe deer because it is a forest-dwelling ungulate whose home range size is significantly affected by woodland fragmentation (Lovari & San José 1997) and whose genetic structure may be influenced by habitat isolation (Coulon et al. 2004). The roe deer may be forced to change its diet and perhaps its pattern of habitat selection as a result of changes in forest habitat structure (Gill et al. 1996). In our study area, it plays an ecological role as a principal prey species of the grey wolf Canis lupus L. Finally, deer species show good potential as ecological indicators for forest management (Hanley 1996). They should be considered focal species for the development of large-scale ecosystem management strategies, not only because of their important ecological role but also because of their high social, aesthetic and economic value (Lehmkuhl et al. 2001).

We developed habitat suitability models for roe deer and then synthesized their outcomes into a habitat suitability index (HSI) that takes into account both the habitat quality and its availability for the species. The objectives were to determine whether: (i) HSI values can be used to compare different land-use scenarios with baseline habitat conditions; and (ii) an HSI threshold can be used to evaluate the ecological consequences of landscape changes as a result of human activities and hence identify priority areas for restoration programmes.

**Study areas**

The study areas were located in the Susa and Chisone valleys, western Italian Alps. The vegetation consists mainly of woodlands (especially larch Larix decidua Mill. and pine Pinus cembra L. woods), which cover more than 40% of the area of both valleys (Coordination of Information on the Environmental (CORINE) land cover data). The climate is continental, with a mean annual precipitation of 900 mm.

The following ungulates are present in the valleys: roe deer, red deer Cervus elaphus L., chamois Rupicapra rupicapra L., ibex Capra ibex L., mouflon Ovis orientalis Gmelin and wild boar Sus scrofa L. With the exception of ibex, the ungulates are hunted for sport in winter outside the protected areas, while the main natural predator is the grey wolf, which has recently recolonized the Susa and Chisone valleys (Avanzinelli et al. 2003).

Winter recreational activities have been developed in the uplands, leading to significant deforestation and fragmentation of woodlands (Montacchini et al. 1982) and negative effects on bird diversity (Rolando et al. 2007). Intense traffic on important roads connecting Italy with France affects both animal movement and survival in the Olympic valleys (Bona, Badino & Isaia 2006). Buildings and equipment for the Winter Olympic Games were located in six main Olympic sites (median area 13 km², range 22 km²) in both the Upper Susa Valley (Clavière, Cesana, Oulx, Bardonecchia and Sestrière sites) and the Chisone Valley (Pragelato site) (see Appendix S1 in the Supplemental material). The altitude of the study areas ranged from 1200 to 2600 m.

**Methods**

Four steps were required to develop the analytical procedure for assessing the consequences of human land use on wildlife habitats: (i) Bayesian habitat models were developed to assess the suitability of the study areas for roe deer; (ii) the outcome of the models was converted into an HSI; (iii) different land-use scenarios were compared by means of HSI values to identify the management alternative that would minimize habitat loss; (iv) an HSI value was chosen as a benchmark to evaluate the ecological consequences of landscape changes.

**DATA COLLECTION**

At each Olympic site, data on roe deer occurrence were collected in spring and autumn 2003 and 2004 through faecal pellet counts. In woodland areas, this technique has been used to estimate population density and assess the spatial distribution and habitat use of ungulates (Cairns & Telfer 1980; Freddy & Bowden 1983). Some authors (Collins & Urness 1981) have criticized the use of defecation rates as indicators of relative habitat use by deer. Leopold, Krausman & Hervert (1984), however, found that rankings of habitat use by deer determined from pellet group deposition and direct observation methods were similar and that pellet group information was of value in determining overall ranks of habitat use. Loft & Kie (1988) and Edge & Marcum (1989) compared pellet group and radiotracking methods to assess deer habitat use. According to their analyses, pellet group

counted accurately indicated which habitat received the greatest and least amount of use; thus, pellet group counts were considered appropriate to estimate deer distribution relative to topographic and disturbance factors. Since then, several authors have adopted faecal counts to infer habitat use of ungulates (Cairns & Telfer 1980; Palmer & Truscott 2003).

In our study, we used a belt-transect (1 m wide) sampling method because, according to surveys carried out in spring by the wildlife management units of the Chisone and Susa valleys, population densities were expected to be lower than 10 deer km$^{-2}$ (Mayle 1996). Moreover, to survey the study areas in a systematic and stratified way, we defined transects at 50-m intervals along the contour lines (Grossi et al. 1995). All the main types of vegetation cover in the study areas were considered and the survey effort was proportional to the extent of the study areas. The collection of the data was repeated along the same transects (69·6 km) in spring and autumn in both years. Fresh pellet groups were discriminated from old ones via analysis of their external aspect and moisture, and only fresh pellet groups were considered in the modelling procedures. The accumulation period was estimated to be equivalent to 4–5 days in both seasons, according to the modifications observed in a sample of fresh faecal material.

**BAYESIAN HABITAT SUITABILITY MODELLING**

In recent decades, the assessment of habitat suitability for wildlife has been facilitated by the development of geographic information systems (GIS) and a wide variety of procedures is now available for modelling wildlife–environment relationships (Scott, Heglund & Morrison 2002). To provide evidence that our inferences were not conditioned on a single model formulation, we adopted three modelling procedures, all of which used Bayesian inference to combine a prior model on roe deer distribution with a conditional one based on collected data regarding roe deer occurrence.

First, we identified vegetation types, aspect, slope and altitude as critical landscape features for roe deer. This choice was supported by literature data and consideration of the relevance of other variables in determining roe deer distribution in our study areas. Vegetation and topography were included in the analysis because they represent cover for many ungulate species and consequently affect important aspects of ungulate biology (Coughenour 1991; Mysterud & Ostbye 1999). Jedrzejewska et al. (1994) suggested that vegetation characteristics, through their relationship with food supply, affect ungulate numbers and distribution more than other factors, including hunting and predation. Snow cover, hunting pressure, predation and other interspecific relationships were not included in the modelling procedures because: (i) snow cover is usually dependent on other variables, including topography and vegetation (Tappeiner et al. 2001); (ii) the protected areas of our valleys did not overlap with the Olympic sites (see Appendix S1 in the Supplementary material) and no relevant differences in the management regimes were observed in our study areas; (iii) grey wolf density is low in the Susa and Chisone valleys (Avanzinelli et al. 2003) and changes in deer abundance and distribution have not been observed since the recolonization of the valleys by the predator; and (iv) chamois and red deer, which may compete with roe deer, occur at low densities in the Olympic sites. According to data provided by the wildlife management units and by other authors (La Morgia et al. 2005), the density of red deer is less than 2 deer km$^{-2}$ and the presence of chamois and red deer in the Susa and Chisone valleys does not seem to act as a major factor in determining roe deer distribution.

Vegetation types (see Appendix S2 in the Supplementary material), aspect, slope and altitude were adopted as environmental predictors of roe deer distribution and used to develop the qualitative species–habitat model. A map of vegetation types (1 : 10000: Regione Piemonte & IPLA 2005) was used to analyse habitat resources, while physical features of the landscape were derived from a digital elevation model with a 40 × 40 m resolution. Each attribute of different predictor data sets (vegetation, altitude, slope and aspect) was given a suitability value (SV; ranging from 0 to 3 for physical predictors and from 0 to 9 for vegetation types) according to previous studies on roe deer’s ecological requirements and on the basis of expert opinion (Store & Kangas 2001; see Appendix S2 in the Supplementary material). A separate raster ArcInfo GRID image was created for each predictor data set and ArcView GIS 3.1 (ESRI 1998) was used to compute the habitat SV. Habitat suitability was calculated for each grid square (i) according to the following subjective formula (partially modified from Ranci Ortigosa, De Leo & Gatto 2000):

\[
SV_{\text{prior}} = \left[SV_{\text{altitude}} + SV_{\text{slope}} + SV_{\text{aspect}} \right] \times \left( SV_{\text{vegetation type}} \right) - \text{disturbance},
\]

This formula, and the different ranges of the SVs: (i) ensured that a grid square without suitable vegetation would not be regarded as suitable; (ii) limited the contribution of physical predictors to the overall SV of each grid square, thus attributing greater importance to vegetation types.

Human disturbance was incorporated in the prior model by excluding or reducing habitat SVs near villages (data extracted from the vegetation map) and main roads (data provided by the Province of Turin). For main roads, two buffer rings (150 and 300 m) were created and habitat suitability was reduced by subtracting 2 and 1 from the SV of the grid squares, respectively, in the internal and the external buffer. Three buffer rings were created around main villages (300, 600, 900 m) and we subtracted, respectively, 3, 2 and 1 from the SV of the grid squares. The reduction of the SVs was based on expert opinion and on literature data obtained by the Infra Eco Network Europe (IENE 1996).

Experts involved in the development of the process-oriented model were identified from among the scientific staff of protected areas, as representatives of conservationists, and among local wildlife managers, representing the interests of hunters. The experts explicitly contributed to the prior modelling of roe deer–environment relationships by providing information about roe deer habitat selection in our study areas. After the development of the prior model, they were asked to evaluate its outcome and to judge whether important areas for roe deer were correctly classified in the habitat suitability map. If the most important areas were not identified, the model was subjected to parameter revision, in an iterative model-building process. When the output of the model was considered satisfactory, the habitat suitability map was submitted to an environmental consultative assembly, describing how it would be implemented and used to assess the consequences of land-use change. The stakeholders involved in this second phase included non-governmental organizations, local authorities, members of the local community, local tourism agencies, sponsors and suppliers of the Olympic Games and the representatives of the Turin 2006 organizing committee. The observations of the assembly were taken into account to tune steps 2–4 of our procedure (see Appendix S3 in the Supplementary material).

Secondly, conditional estimates of habitat suitability were obtained according to field data collected in the study areas in spring and autumn 2003 (data from 2004 was saved for assessing model performance, see below). Collecting data as described above, we recorded 1649 locations of fresh pellet groups along a total transect length of 139·2 km. A random sample of 1649 points within the surveyed transects where pellet groups were not found was used as
a pseudo-absence sample (random points were not allowed to fall within a radius of 10 m, corresponding to the average bias of GPS locations, from the presence locations). For conditional analyses, the vegetation types were grouped into three categories (woodlands, grasslands and shrublands, other vegetation types; see Appendix S4 in the Supplementary material), as not all the original vegetation types were present in all the study areas. Wilcoxon and chi-square tests were conducted to compare the median for each environmental predictor calculated for spring and autumn and the significance of each habitat attribute for discrimination between presence and pseudo-absence (Manly et al. 2002; but see Stephens et al. 2005). Any predictor significantly different between presence and pseudo-absence locations was retained to estimate conditional habitat SV via (i) a chi-square analysis (Aspinall 1992); (ii) an autologistic modelling procedure (AGLM; Augustine, Mugglestone & Buckland 1996); and (iii) a generalized additive modelling (GAM) procedure performed through the package grasper (Fivaz et al. 2004) in an R 2.1.1 environment (R Development Core Team 2005). Chi-square and autologistic analyses were performed separately for each study area before combining independent results, while in the GAM procedure presence and pseudo-absence data were appropriately weighted to allocate the same importance to the different study areas.

Finally, we predicted the Bayesian habitat suitability for roe deer by combining the prior SV provided by the qualitative model with the SV derived from the conditional models. The following formula (Aspinall 1992) was used to combine the results of chi-square analysis with the prior SV:

\[
SV_i = P_{ip} = \frac{(P_{pp} \times P_{pa})}{(P_{pp} \times P_{pa}) + (P_{pa} \times P_{ca})} \quad \text{eqn 2}
\]

where \(SV_i\) (in Aspinall 1992) = posterior suitability value of the \(i^{th}\) grid square, \(P_{ip}\) = a priori probability for presence provided by the qualitative model, \(P_{pp}\) = a priori uniform probability for pseudo-absence, \(P_{pa}\) = product of conditional probabilities for presence for the different predictor data sets, and \(P_{ca}\) = product of conditional probabilities for absence for the different predictor data sets.

The suitability surfaces derived from the prior and conditional models based on AGLM and GAM were combined using the formula from Pereira & Itami (1991):

\[
SV_i = \frac{1}{1 - \exp \left[ \log \left( \frac{1 - SV_{prior}}{SV_{prior}} \right) - \log \left( \frac{SV_{conditional}}{1 - SV_{conditional}} \right) \right]} \quad \text{eqn 3}
\]

where \(SV_{prior}\) = suitability value of the \(i^{th}\) grid square according to the prior model, and \(SV_{conditional}\) = suitability value according to the conditional model. The spatial pattern of the posterior suitability was shown on three habitat suitability maps (Fig. 1) with an output cell of 40 x 40 m.

**PERFORMANCE OF THE MODELS**

The outcomes of all models were compared against field data by producing confusion matrices for different SV. These matrices classify model results according to binary rules and enable calculation of the proportion of locations falling in four different categories: (i) the response of interest is neither observed nor predicted (true negative rate = predicted negatives/pseudo-absence locations); (ii) the model fails to predict a positive response (false negative rate = predicted negatives/presence locations); (iii) the model prediction is positive but the observation negative (false positive rate = predicted positives/pseudo-absence locations); (iv) model predictions agree that a positive response occurs (true positive rate = predicted positives/presence locations) (Gardner & Urban 2003). Data for model validation (1356 presence locations and 1320 pseudo-absence points) were collected in the study areas in spring and autumn 2004. For each model and data set, plotting multiple outcomes of confusion matrices produced a receiver operating characteristic
HSI AND LAND-USE PLANNING

For each model, the SV that maximized the TSS was used as a threshold to distinguish suitable and unsuitable areas: grid squares with an occupancy probability lower than the cut-off value were classified as unsuitable and excluded from subsequent computations. To take into account habitat area as well as habitat suitability, we calculated an HSI:

\[
\text{HSI} = \frac{\sum (SV_i \times a_i)}{A} \quad \text{eqn 4}
\]

where \(SV_i\) = posterior suitability value of the \(i^{th}\) grid square, \(a_i\) = area of the grid square with the given suitability value, and \(A = \text{total extension of the study area} (A = \sum a_i)\). HSI ranges from 0 to 1: the maximum index value is reached when all the habitat in a study area is of high quality, while lower index values indicate smaller suitable surface areas or habitat of medium and/or low quality.

This index was used to assess the consequences of different land-use plans on the wildlife habitat. For each study area and model, four scenarios were considered for the analysis (Fig. 2); they included the building project later chosen by the Olympic Games organizers plus three alternative locations of ski facilities. To evaluate the baseline habitat quality and habitat changes, we calculated the HSI threshold corresponding to the availability of a minimum amount of habitat (60% of each study area; With & Crist 1995; Kennedy, Wilkinson & Balch 2003) characterized by a minimum presence probability. This value (corresponding to an HSI of 0·18, 0·14 and 0·24 for the Bayesian chi-square model, AGLM and GAM, respectively) was used as an ecological benchmark for land-use planning, i.e. as a limit under which habitat quality and availability for wildlife were considered critical.

Results

MODEL BUILDING AND PERFORMANCE

The SV that maximized the classification accuracy (Fig. 3) of the qualitative model was 0·35, with TSS = 0·35. The true positive and true negative classification rates (TPR and TNR) were, respectively, 0·75 and 0·60.

The Wilcoxon test did not detect significant differences in the value of the environmental predictors (see Appendix S5 in the Supplementary material) when spring and autumn presence data were compared in the six study areas. Therefore, data from the two seasons were pooled and single-variable data analyses were conducted on the grouped data to assess significant differences between presence and pseudo-absence points. The Wilcoxon test on continuous variables detected an almost significant difference only between the slope values in presence and pseudo-absence points (\(W = 20, n = 6, P = 0·063\)), and the chi-square analysis revealed a significant difference (chi-square = 163·7, d.f. = 12, \(P < 0·01\)) between the frequencies of presence and pseudo-absence locations in the different vegetation types (woodlands, grasslands, other vegetation types; see Appendix S6 in the Supplementary material). Thus slope and vegetation were used in subsequent analyses to assess habitat suitability for roe deer via the three different conditional modelling procedures.

For the chi-square model, frequencies of association between attributes of predictor data sets and presence/pseudo-absence locations were calculated for classes with significant chi-square scores and used as conditional SVs in the Bayesian modelling procedure (Table 1). The SV that maximized the classification accuracy of the chi-square conditional model was 0·48 (TSS = 0·24, TPR = 0·82, TNR = 0·42). The Bayesian procedure provided a better fit of the model than the conditional one. The SV that maximized the classification accuracy of the chi-square Bayesian model was 0·30 (TSS = 0·36, TPR = 0·79, TNR = 0·57).

The resource selection function (RSF; Manly et al. 2002) obtained by fitting the AGLM with slope and vegetation types as predictor variables was:

\[
\text{RSF} = \exp[0·050(\text{slope}) - 0·245(\text{grasslands}) - 0·707(\text{woodlands}) + 1·488(\text{autocov})] \quad \text{eqn 5}
\]
The null model deviance was 4572·0 with 3292 d.f., which was reduced to 4347·4 with 3268 d.f. for the four-variable model. The reduction in the deviance was significantly large at the 0·05 level and provided evidence for selection. This AGLM (Akaike’s Information Criterion (AIC) = 4407·4) provided a better description of the data than the logistic model without the autocorrelation term (AIC = 4439·2, deviance = 4391·2, d.f. = 3274). The SV that maximized the classification accuracy of the autologistic conditional model was 0·04 (TSS = 0·19, TPR = 0·87, TNR = 0·36). The SV that maximized the classification accuracy of the autologistic Bayesian model was 0·23 (TSS = 0·35, TPR = 0·72, TNR = 0·57).

The GAM procedure allowed exploration of the shapes of species–response curves and the environmental gradients of slope and frequency of forests (see Appendix S7 in the Supplementary material). The SV that maximized the classification accuracy of the GAM was 0·71 (TSS = 0·28, TPR = 0·78, TNR = 0·50). According to the Boyce index, our presence data were positively correlated with the SVs provided by the model (Spearman’s \( \rho = 0·83 \), \( S = 15789 \), \( P < 0·01 \)). Furthermore, a significant correlation was found between the density of roe deer sightings and HSI in the 54 census units of Pellice Valley (Spearman’s \( \rho = 0·47 \), \( S = 13892 \), \( P < 0·01 \)). The SV that maximized the classification accuracy of the generalized additive Bayesian model was 0·40 (TSS = 0·40, TPR = 0·79, TNR = 0·62).

In subsequent HSI computations we referred to the Bayesian models, excluding grid squares with habitat suitability lower than the threshold SV (0·30, 0·23, 0·40, respectively, for the chi-square model, AGLM and GAM).

**Changes in HSI Values**

Based on the Bayesian model outputs, HSIs were estimated for the alternative scenarios in each study area. When the building projects chosen by the Olympic Games organizers were considered, we found changes in HSI in each study area.
have shown that the Bayesian framework allows the involvement of local stakeholders in the decision-making process and that explicitly incorporating expert opinion improves the performance of wildlife–environment models. Moreover, we found that our procedures were useful for identifying both appropriate locations of human infrastructures in order to minimize habitat loss, and priority areas for habitat restoration.

Habitat evaluations have been proposed as key methods for tackling the problem of linking wildlife conservation with land-use planning. Such habitat evaluations and wildlife–environment modelling are usually based on qualitative and quantitative models (Rickers, Queen & Arthaud 1995; Hurme et al. 2007). Aspinall (1992) suggested a modelling procedure based on Bayes’ theorem, but he adopted a uniform prior distribution of occurrence probabilities. In contrast, we suggest that explicitly incorporating expert knowledge, expressed as informative prior probability of occurrence, should play an important role in the specification of habitat suitability models. Formally incorporating expert judgements can add robustness to models, as a result of the broad knowledge of the expert (Reckhow 2003), and help to increase confidence in the conclusions drawn from ecological studies (McCarthy & Masters 2005). Bayesian statistics represent a useful tool when land-use policies are discussed, as local stakeholders can participate in the decision-making process and, being actively involved, they can become aware of and support land-use policies, reducing social contrasts in relation to landscape management. On the other hand, actual data allows assessment of the local reliability of qualitative models, improves our understanding of habitat selection in the study area and updates scientific knowledge based on new information. Hence field data on wildlife–environment relationships and conditional modelling are also essential in the Bayesian framework. Despite the clear advantages of the Bayesian approach, its use in modelling wildlife–environment relationships has been limited thus far.

The first step in our procedure was the development of a Bayesian habitat suitability model, which involved the elicitation of a prior suitability model and the estimation of SVs conditional on data collected in the study areas. To develop the conditional habitat models for roe deer, we collected field data on species-specific landscape requirements via an indirect survey technique (a common approach; Rhodes et al. 2006). In general, when impact or risk assessments are required, the best location of human infrastructures must be identified via reasonably short field studies. In such studies, budget and time constraints are often critical and data collection based on radiotelemetry may not be feasible. Moreover, if rare species are concerned, it may be difficult to capture the minimum number of animals required to carry out habitat selection analysis via radiotracking. Under these specific circumstances, indirect survey techniques could be an effective compromise for acquiring data on species occurrence. We recognize, however, that an indirect technique such as pellet group counts does not meet all statistical assumptions of resource selection studies, mainly because of the possible lack of independence between locations of faecal pellet

(Fig. 4). Despite the differences in the SV, the three modelling procedures indicated the same pattern and magnitude of HSI change. The greatest reduction was observed in the Cesana study area. In the Bardonecchia, Oulx and Cesana study areas, the chosen project minimized the loss of suitable habitat for roe deer, while in the other study areas different locations of ski facilities could have slightly reduced the negative consequences of human activities (Fig. 4).

Discussion

In this study we have used Bayesian modelling to provide a quantitative framework for the evaluation of the probable impact of land management strategies on wildlife habitat. We
groups and uncertainty in the relationship between pellet group locations and habitat use. To minimize this problem and avoid sacrificing pseudoreplication (Hurlbert 1984), we performed statistical analyses separately for each study area and then combined independent results.

In our study, the GAM provided the best fit to the field data (Fig. 3); the lack of linearity in the predictor–response relationships probably caused the poorer performance of the AGLM. When conditional suitability models were combined with the prior one, an increase in the area under the curve (AUC) and TSS of all models was observed, suggesting that the Bayesian procedure improved the performance of both the prior and conditional models. The increase ranged from 6·6% to 19·5% for the AUC, and from 50·0% to 84·2% for the TSS. In particular, the AUC of both the chi-square and the generalized additive Bayesian models was bigger than 0·7, indicating a reasonable discrimination ability appropriate for many uses of the models (Pearce & Ferrier 2000).

After validation, the Bayesian habitat suitability models for roe deer were converted to HSIs. Although this may limit the usefulness of the Bayesian approach, this conversion could bring several advantages from a practical perspective. HSIs have been developed for habitat evaluation procedures (HEP) in the USA (US Fish & Wildlife Service 1980); as in our study, they are usually expressed as an estimate of habitat conditions in a study area compared with the optimum habitat conditions for the focal species (Anderson & Gutzwiller 1994). As indices, HSIs are particularly useful for assessing the consequences of habitat modifications. In our study, they provided useful information on the probable impact of the building of ski facilities on roe deer potential habitat and they were recognized by the Environmental Consultative Agency as a suitable tool for presenting the modelling results to the public. In the Pragelato study area, the HSI of the chosen project was clearly different from the HSI of the alternative scenario number 1 (Fig. 4) and our procedure proved useful in choosing an ecologically appropriate location for the ski facility. In the other areas, the difference was less relevant than at Pragelato but our procedure could still be used to identify priority areas for restoration programmes. The Cesana study area was the one most affected by human intervention: according to both the GAM and the chi-square model, the baseline HSI value of this area was nearly reduced to the threshold value of critical habitat condition, but no alternative site was available for building the Olympic infrastructures. In the Sestrière study area, a critical landscape condition was detected as baseline, suggesting that habitat quality and availability were already critical as a result of ecological limitations and the cumulative effects of human activities (rather than of building projects for the Winter Olympics alone). None the less, since Sestrière is historically a site for winter recreational activities, the Games organizers felt it should play a role in the Turin Olympics. As a consequence, for both Sestrière and Cesana the analysis of the HSIs suggested that, in the absence of alternative locations, compensation measures should be planned to restore a minimum amount of good-quality habitat for roe deer.

We suggest that the HSI thresholds identified (0·18, 0·14, 0·24, respectively, for the chi-square model, AGLM and GAM) can be used to identify priority areas for habitat improvement measures. To draw such conclusions, the definition of the HSI thresholds was critical. For this purpose, we referred to the percolation theory of landscape ecology and considered the amount of habitat below which the negative effects of habitat fragmentation may compromise species persistence in the landscape (With & Crist 1995). Literature data (Andrén 1994; Fahrig 1998; Kennedy, Wilkinson & Balch 2003) supported our choice of the conservation of a minimum of 60% of habitat (corresponding to our HSI thresholds) as an adequate ecological benchmark for land management and for the persistence of most species, even though a higher percentage of habitat (>80%) would be appropriate for populations with a low demographic potential (Lande 1987).

Our research is focused on the description of a methodological modelling procedure: we applied it to a single species, but it could also be applied to a set of focal species (Lambeck 1997) to achieve a more complete assessment of the consequences of human activities on wildlife habitat. In general, we do not propose a taxon-based surrogate scheme for conservation or impact assessment; instead, we provide a quantitative framework to inform landscape planning, generating information vital for decisions on how development should be located to maximize wildlife presence probabilities in the landscape. Examples of habitat assessment for a single focal species are well reported in the literature, including Rickers, Queen & Arthaud (1995) and Hurme et al. (2007). Like Rickers, Queen & Arthaud (1995), we assessed habitat changes associated with alternative management actions, but we have improved on their analytical procedure. Unlike Rickers, Queen & Arthaud (1995) and the procedures commonly adopted in HEP, our method integrates expert knowledge with field data on species-specific landscape requirements. Moreover, in Rickers, Queen & Arthaud (1995) wildlife habitat changes are evaluated by a contingency table and the establishment of discrete HSI classes with arbitrary cut-offs; in contrast, we propose the application of an ecologically meaningful threshold value for the HSI, thus avoiding subjectivity in the final impact assessment.

In conclusion, our procedure will be useful in land-use planning. We provide the first example of the application of a Bayesian procedure explicitly incorporating expert opinion to estimate the probable impact of land management strategies on wildlife habitat. It can be applied to an abundant species of management concern, as in our study, but may be even more useful when dealing with rare species. Indeed, when detectability of the species is very low, information about its ecological requirements could be obtained more easily via indirect survey techniques than via direct observation of the animals. Moreover, when field signs of the species are less abundant than in our study, the Bayesian procedure will help in the development of habitat suitability models, allowing conditional suitability to be supplemented with prior knowledge.
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References


Supplementary material

The following supplementary material is available for this article.

Appendix S1. Location of the study areas.

Appendix S2. Calculation of prior suitability values.

Appendix S3. Flow chart of the a priori modelling procedure.


Appendix S5. Results of the Wilcoxon test.

Appendix S6. Effect sizes of environmental predictors for presence and pseudo-absence locations.

Appendix S7. Partial response curves of the conditional GAM.

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