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Assessing conservation relevance of organism–environment relations using predicted changes in response variables

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Summary

1. Organism–environment models are used widely in conservation. The degree to which they are useful for informing conservation decisions – the conservation relevance of these relations – is important because lack of relevance may lead to misapplication of scarce conservation resources or failure to resolve important conservation dilemmas. Even when models perform well based on model fit and predictive ability, conservation relevance of associations may not be clear without also knowing the magnitude and variability of predicted changes in response variables.

2. We introduce a method for evaluating the conservation relevance of organism–environment relations that employs confidence intervals for predicted changes in response variables. The confidence intervals are compared to a preselected magnitude of change that marks a threshold (trigger) for conservation action. To demonstrate the approach, we used a case study from the Chihuahuan Desert involving relations between avian richness and broad-scale patterns of shrubland. We considered relations for three winters and two spatial extents (1- and 2-km-radius areas) and compared predicted changes in richness to three thresholds (10%, 20% and 30% change). For each threshold, we examined 48 relations.

3. The method identified seven, four and zero conservation-relevant changes in mean richness for the 10%, 20% and 30% thresholds respectively. These changes were associated with major (20%) changes in shrubland cover, mean patch size, the coefficient of variation for patch size, or edge density but not with major changes in shrubland patch density. The relative rarity of conservation-relevant changes indicated that, overall, the relations had little practical value for informing conservation decisions about avian richness.

4. The approach we illustrate is appropriate for various response and predictor variables measured at any temporal or spatial scale. The method is broadly applicable across ecological environments, conservation objectives, types of statistical predictive models and levels of biological organization. By focusing on magnitudes of change that have practical significance, and by using the span of confidence intervals to incorporate uncertainty of predicted changes, the method can be used to help improve the effectiveness of conservation efforts.

Key-words: biological significance, confidence intervals, conservation decision making, conservation effectiveness, response magnitude, response uncertainty, statistical predictive models, thresholds for conservation action

Introduction

Numerous statistical approaches for predictive modelling are commonly used in conservation (reviewed in Guisan & Zimmermann 2000), and assessing the conservation relevance of organism–environment associations embodied in predictive models has become essential. To inform policy or on-the-ground management decisions, it is important to use associations with strong practical relevance; otherwise, scarce conservation resources may be misapplied and the conservation issue at hand may worsen. Conservationists can evaluate

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the relevance of associations that originate from statistical models with criteria that assess model fit (e.g. R^2, Neter, Wasserman & Kutner 1989; AIC, Burnham & Anderson 2002) and criteria that assess a model's predictive ability (e.g. area-under-the-curve statistics and classification rates, Fielding & Bell 1997; Scott *et al.* 2002; mean-squared prediction error and prediction sum of squares, Neter, Wasserman & Kutner 1989).

Yet, even when models perform well based on these criteria, conservation relevance of associations may not be clear without also knowing the magnitude and variability of predicted changes in response variables. The conservation relevance of an association would be supported if a substantial change in a predictor variable resulted (through the mathematics of the predictive relationship) in a major change in the response variable, and if this predicted change had low variability. Large predicted changes in response variables would warrant conservation attention because of the magnitude of their potential ramifications, and it would be easier to justify use of scarce conservation resources to promote or control large changes if uncertainty about predicted responses was low.

The method we introduce employs confidence intervals, which have often been recommended for interpreting the biological importance of statistical results (e.g. Gerard, Smith & Weerakkody 1998; Hoenig & Heisey 2001). A key advantage of confidence intervals is that they provide both the magnitude and variability of an estimate. Our approach evaluates the conservation relevance of organism–environment relations by comparing confidence intervals for the magnitude of predicted changes in response variables to a preselected magnitude of change that marks a threshold (trigger) for conservation action. If major changes in environmental conditions result in predicted changes that exceed the threshold for conservation action, these relations are considered to be conservation relevant.

As examination of an issue from several perspectives often yields a clearer view of reality, we envision that this approach would best be used in conjunction with, not as a substitute for, other quantitative criteria for conservation relevance such as those mentioned previously. Here, we illustrate the method with a case history that considers the conservation relevance of associations between avian richness and broad-scale patterns of dominant vegetation.

Through effects on resources for various populations, spatial patterns of the dominant vegetation are expected to dictate or constrain the spatial patterns of all of the other organisms in a system (Turner, Gardner & O'Neill 2001). Broad-scale patterns of a system's dominant vegetation type should strongly influence the number of other species that occur in that system because organisms depend on vegetation for various resources and conditions. This expectation may be particularly warranted for the number of bird species because birds depend significantly on vegetation for food, shelter and reproduction.

Knowledge about this issue is pertinent to avian conservation for two related reasons. First, bird species richness is one aspect of avian biodiversity that is frequently used to evaluate broad-scale conservation potential (e.g. Chown *et al.* 2003; Waltert, Mardiastuti & Mühlenberg 2004) and to inform broad-scale conservation planning (e.g. Jiguet *et al.* 2005; Pidgeon *et al.* 2007). Second, relatively simple assessment approaches are useful for expediting conservation decisions in crisis situations (Mittermeier & Forsyth 1997); although other avian metrics (e.g. survival, reproduction and community composition) are valuable for evaluating avian biodiversity, estimates of richness can be easier to obtain.

Considering these issues, we used our method to test the hypothesis that system-wide avian richness (richness of species irrespective of their primary vegetation affinities) was strongly associated with broad-scale patterns of shrubland, the dominant vegetation type in our Chihuahuan Desert study area. We tested this hypothesis for three winters and two spatial extents (1- and 2-km-radius areas).

Materials and methods

STUDY AREA

During 1999–2002, data were collected in Big Bend National Park (BBNP), a 3205-km^2 area on the Texas–Mexico border (29°19′42″N, 103°12′21″W) that lies within the subtropical Chihuahuan Desert. Gutzwiller & Barrow (2001) and White *et al.* (2008) provide information about the Park's topography, elevations, soils, precipitation, temperatures, land-cover types and common plant species.

SAMPLING SITE ESTABLISHMENT

Roadsides were used as starting points for paths that led to sampling sites (Gutzwiller & Barrow 2008). We determined locations of path starting points using systematic sampling with a random start (Cochran 1977), and we positioned successive starting points so that neighbouring sampling sites were separated by ≥ 4 km. The average distance between sampling sites and roads was 0·4 km, and the average distance between sampling sites and developed areas was 10·8 km (Gutzwiller & Barrow 2003). The same bird sampling sites were used during all three winters (1999–2000, 2000–2001 and 2001–2002).

BIRD SAMPLING

Each year between mid-December and late February, the winter bird season in BBNP (Wauer 1996), observers conducted a 20-min unlimited distance point count (Ralph, Sauer & Droege 1995) at each of 70 sampling sites every 9 days (eight counts total at each site each year). Observers collected data under standard conditions of precipitation, wind speed and air temperature (Gutzwiller & Barrow 2003). Techniques used to avoid time-of-day biases, detect flushed birds, avoid double counting of birds and to preclude observer effects are described in Gutzwiller & Barrow (2003). The same two observers sampled the same sites each year.

LAND-COVER MAP

We used a land-cover map developed for research aimed at understanding bird–landscape relations in BBNP and the surrounding region. To control the computational expense of intensive simulation analyses for climate-related studies in our broader research programme, the resolution of the land-cover map was set at 60 m (White *et al.* 2008). We used ERDAS Imagine software (http://www.erdas.com/

tabid/84/currentid/1050/default.aspx) and Landsat-5 Thematic Mapper (TM) data from March 1999 to construct the land-cover map. Overall map accuracy was 77% with a κ value of 0·63, which indicated substantial agreement (Landis & Koch 1977) between observed and mapped land-cover types.

DOMINANT VEGETATION

Big Bend National Park is dominated by shrublands (White *et al.* 2008), and for the landscapes involved in the present analysis, shrubland had a much higher mean percent cover than did the other five land-cover types (Table 1). We therefore considered shrubland to be the dominant vegetation type. Dominant plant species for shrubland were *Larrea tridentata*, *Florensia cernua*, *Agave lechuguilla*, *Prosopis* spp. and *Acacia* spp.

LANDSCAPE METRICS

Broad-scale patterns of vegetation can influence the occurrence of bird species and hence avian species richness in a landscape (Andrén 1994; Gutzwiller & Barrow 2001), and both landscape-composition and -configuration variables have been used to characterize broad-scale patterns. Ecologists have used percent cover for a given vegetation type as a measure of landscape composition, whereas patch size, patch density, edge density or similar variables have been used to characterize landscape configuration (Villard, Trzcinski & Merriam 1999; Turner, Gardner & O'Neill 2001). As bird species often respond to conditions of composition, and the relative influence of configuration variables on avian richness can vary with composition conditions (Andrén 1994), it is important to include both composition and configuration variables in studies of richness–landscape relations.

For composition we measured percent of the landscape covered in shrubland. For configuration we measured the following variables for shrubland: patch density, mean patch size, coefficient of variation of patch size, and edge density. All five variables were measured within 1- and 2-km-radius circles that were centred on the bird sampling sites. These spatial extents are within the range of extents for which significant bird–landscape relations have been found in our study area (e.g. Gutzwiller & Barrow 2001, 2002) and elsewhere (e.g. Robinson *et al.* 1995; Hamer, Flather & Noon 2006). All landscape metrics were obtained using FRAGSTATS software (McGarigal *et al.* 2002).

ESTIMATION OF SYSTEM-WIDE RICHNESS

We included all bird species in the analyses (not just those species that were facultative or obligate users of shrubland) because the purpose of the analysis was to examine whether the dominant vegetation dictated the spatial distribution of the rest of the system. In the case considered here, the system included all bird species that were present at the study sites. Consequently, our response variable was system-wide richness (richness of species irrespective of their primary vegetation affinities) at a site for a given winter.

To adjust system-wide richness estimates for detection probability, we applied SPECRICH2 (http://www.mbr-pwrc.usgs.gov/software/specrich2.html). This software uses model $M(h)$ from program CAPTURE (White *et al.* 1978; Rexstad & Burnham 1991) to estimate the total number of species at a site from species presence–absence data gathered during multiple counts at that site. SPECRICH2 is based on capture–recapture models that assume a closed population of species. The data for each winter suggested an increase in species richness from count one to count two and a decrease in richness from count seven to count eight, whereas we detected most species during counts two to seven each year (K. J. Gutzwiller, unpublished data). Consistent with these results, fig. 1 in Wauer (1996) indicates little if any change in the number of species present in BBNP from late December to mid-February. We therefore applied SPECRICH2 only to data collected during counts two to seven each year; the inclusive dates for these counts during the three winters were 27 December to 18 February. Logistical problems prevented us from obtaining usable data for one or two individual point counts each winter. In these cases, the system-wide richness estimate for a site was based on data from five point counts; for all other sites, system-wide richness estimates were based on six counts.

REGRESSION ANALYSES

To assess relations between system-wide richness and shrubland variables, we used negative binomial regression. This form of regression is appropriate when the dependent variable is a count, and it avoids the problems of overdispersion that often plague Poisson regression analyses of count data (Allison 1999). We used the glm.nb( ) function from the MASS package in the R statistical environment (R Development Core Team 2005) to fit regressions; we applied the log link function, which fit variation in system-wide richness as a multiplicative function of the predictor variables.

The analysis involved three stages of regression modelling. The first stage assessed whether system-wide richness was associated with two factors (visibility and observers) potentially related to bird detection. The second stage examined whether system-wide richness was associated with broad-scale spatial trends. The third stage examined relations between system-wide richness and shrubland variables while controlling for extraneous sources of variation (visibility, observers and spatial trend variables) found to be important in the first two stages of analysis.

In the first stage of modelling, we included visibility (whether the observer could see farther than 100 m in all directions from the sampling site) and observer identity as indicator variables (Gutzwiller & Barrow 2008). In stage two of the modelling, we included first-,

Table 1. Summary statistics for percent cover of six land-cover types within 1- and 2-km-radius extents for 70 landscapes in Big Bend National Park, Texas

Land-cover type	One-km-radius extent	Two-km-radius extent
Shrubland	80·1 ± 15·8 (39·0–96·2)	81·6 ± 14·1 (38·3–96·8)
Grassland	11·3 ± 15·4 (0·0–56·3)	11·5 ± 13·9 (0·0–57·4)
Roads	5·8 ± 2·0 (1·5–13·6)	3·9 ± 1·5 (1·7–8·3)
Yucca-ocotillo	2·1 ± 4·3 (0·0–29·0)	2·0 ± 2·9 (0·0–13·9)
Montane forest	0·4 ± 2·5 (0·0–19·2)	0·6 ± 4·2 (0·0–34·1)
Riparian	0·4 ± 1·9 (0·0–14·7)	0·4 ± 1·1 (0·0–7·6)

Additional details about land-cover types are available from White *et al.* (2008) and J. D. White (unpublished data). Values are given as mean ± SD (range).

second- and third-order polynomial terms of the geographic coordinates of the sites (spatial trend variables). The latter variables are commonly used to avoid statistical problems associated with broad-scale autocorrelation and were mean-centred before analyses (Buckland & Elston 1993; Gutzwiller & Barrow 2008). In stages one and two, we used AIC_c statistics (Burnham & Anderson 2002) to identify the most parsimonious and best-fit model involving extraneous variables. Stages one and two of the analyses were conducted for each winter separately.

In the third stage of the regression analyses, for each of the six combinations of spatial extent and winter, we fit four models relating system-wide richness to shrubland variables; there was one model for each of the four possible two-variable combinations of shrubland cover and a shrubland configuration variable (patch density, mean patch size, coefficient of variation of patch size, or edge density). In this stage we statistically controlled for variation in system-wide richness associated with visibility, observer identity and spatial trends by including these variables in regression models if they emerged as important variables during the first- or second-stage analyses (Gutzwiller & Barrow 2008). We did not consider interaction effects involving shrubland cover and configuration variables because we did not have adequate replication for the factor-level combinations involved. Models from the third stage of the analyses were examined for evidence of spatial autocorrelation and an inappropriate distributional model by assessing whether the ratio of a model's residual deviance to its d.f. was close to 1·0 (Schabenberger & Pierce 2002).

Including shrubland cover with each of the configuration variables in separate regression models enabled us to account for possible effects of shrubland cover on shrubland configuration variables (Gustafson & Parker 1992). Through the least squares equations, multiple regression properly accounts for such effects (Freckleton 2002) when relations between explanatory variables are linear. When scatter plots indicated that linearizing relations was clearly needed, we transformed variables to improve linearity between shrubland cover and configuration variables. We did not use residuals (from regressions of configuration variables on shrubland cover) to control for effects of shrubland cover on shrubland configuration because this use of residuals leads to biased parameter estimates in regression (Freckleton 2002 and references therein).

Fitting separate models for the different combinations of shrubland cover and the four shrubland configuration variables enabled us to assess the importance of shrubland variables without the higher level of collinearity (Neter, Wasserman & Kutner 1989) that would have been present had we included all of the configuration variables in a single model. By fitting separate models for different spatial extents, we avoided collinearity associated with the same variable for the two extents. By fitting separate models for each winter, we precluded potential problems of temporal autocorrelation among winters (Gutzwiller & Barrow 2008).

CONFIDENCE INTERVALS AND CONSERVATION RELEVANCE

Statisticians recommend that researchers use confidence intervals to help develop a better understanding of the biological importance of statistical results (Gerard, Smith & Weerakkody 1998; Hoenig & Heisey 2001). We used confidence intervals for regression coefficients to calculate confidence intervals for percent change in mean system-wide richness. The emphasis of our research was not on statistical significance but on whether a substantial change in a shrubland variable would generate a change in system-wide richness that was of practical importance. We reasoned that if a major change within the range of observed values for a shrubland variable had little effect on system-wide richness, that shrubland variable would probably not be very relevant to conservation efforts. To assess whether a shrubland variable had a conservation-relevant association with system-wide richness, we calculated the percent change in system-wide richness that would result (through predictions from the regression model) from a 20% change in the shrubland variable.

Ecological, socio-political and economic issues unique to each situation require conservationists to identify on a case-by-case basis the levels of magnitude in a predicted response variable that would trigger conservation action. During the last 40 years, the abundances of many bird species in the USA have changed by 20–30% or more; these magnitudes of change have been characterized as strong or dramatic and have prompted concern for declining species, optimism for increasing species and a call for additional avian conservation efforts at the national level (e.g. North American Bird Conservation Initiative 2009). Similar or greater conservation interest would probably be generated if changes of this magnitude occurred in avian richness. Depending on such factors as the uniqueness of the bird assemblage, whether endangered or threatened species were involved, and the number and nature of developing environmental threats, smaller changes in richness may also prompt significant conservation responses.

We therefore compared the percent change in predicted mean system-wide richness to three levels of change in richness (10%, 20% and 30%) that conceivably may generate conservation action depending on the circumstances. Using different preselected magnitudes of change enables one to consider not only several thresholds of change that conservationists might reasonably use in decision making but also to assess whether the results are threshold dependent.

For a 20% change (positive or negative) in the observed range of a shrubland variable, we computed estimates and confidence intervals for percent change in mean system-wide richness. We used negative binomial regression and a log link function to fit the regressions. Therefore, to obtain each estimate and confidence interval, we first exponentiated a multiple (0·20) of the estimate and of the endpoints of the confidence interval (profile likelihood) for the regression coefficient associated with a unit change in the shrubland variable. We then multiplied the estimate and endpoints (proportions) by 100%. Specifically, for a predictor variable X_1, the estimate of percent change in mean system-wide richness was computed as $100\% \times \{\exp[(0{\cdot}20(\max X_1 - \min X_1))\hat{\beta}_1]\}$, and the associated 90% confidence interval endpoints were computed as $100\% \times \{\exp[(0{\cdot}20(\max X_1 - \min X_1)) \times$ upper (or lower) 90% confidence interval endpoint for $\beta_1]\}$. These computations are possible because the linear predictor in the logarithmic scale is invariant to reparameterization of the design matrix; that is, $\hat{\beta}(y, XA) = A^{-1}\hat{\beta}(y, X)$ (Koenker 2005:39).

Such confidence intervals estimate the expected value (mean) of the distribution of percent change of predicted values (Ott & Longnecker 2001); consequently, the confidence intervals were for percent change in mean system-wide richness, not percent change in system-wide richness for an individual observation. Exponentiation resulted (correctly) in slightly asymmetrical confidence intervals. We used the confint( ) function from the R statistical environment to estimate 90% confidence intervals. We used an *a priori* $\alpha = 0{\cdot}10$ (instead of 0·05) for confidence intervals to improve the chance of detecting conservation-relevant associations between system-wide richness and shrubland variables.

For each threshold (10%, 20% and 30%), we recorded shrubland associations as conservation relevant when point estimates and confidence intervals for percent change in mean system-wide richness

Table 2. Summary statistics for shrubland configuration variables within 1- and 2-km-radius extents for 70 landscapes in Big Bend National Park, Texas

Shrubland variable (unit)	One-km-radius extent	Two-km-radius extent
Patch density (no. per 100 ha)	1·7 ± 1·3 (0·6–6·1)	0·9 ± 0·9 (0·2–4·8)
Mean patch size (ha)	81·6 ± 51·7 (9·0–149·8)	207·9 ± 164·6 (9·1–596·7)
CV of patch size (%)	117·5 ± 66·0 (19·4–318·0)	174·0 ± 113·8 (7·4–458·0)
Edge density (m ha^{-1})	48·1 ± 25·3 (12·3–99·2)	44·9 ± 22·2 (10·2–97·1)

CV, coefficient of variation. Values are given as mean ± SD (range).

exhibited three characteristics: the point estimate was at or beyond the particular threshold, many values in the confidence interval were beyond the particular threshold, and the confidence interval did not overlap 0% change.

We plotted point estimates and confidence intervals for percent change in mean system-wide richness by year and spatial extent. For clarity, we only marked the 20% threshold on each graph. However, one can mark each graph's ordinate with the other two thresholds we considered, or other thresholds of interest, and the results for those thresholds will be readily apparent. For the sake of brevity, we provided detailed graphical analysis of the results for only the 20% threshold, and we simply summarized results from the analyses involving the 10% and 30% thresholds.

Results

SYSTEM-WIDE RICHNESS

System-wide richness adjusted for detectability was (mean ± SD, range): 14·0 ± 6·9, 2–42 species for the 1999–2000 winter; 20·3 ± 12·4, 3–60 species for the 2000–2001 winter and 13·9 ± 9·0, 1–42 species for the 2001–2002 winter. During the six counts involved in the present analysis, we detected 49 species for the 1999–2000 winter, 69 for the 2000–2001 winter, 63 for the 2001–2002 winter and 81 for the three-winter period (Appendix S1). All of the species detected during the study were native species.

SHRUBLAND VARIABLES

For both the 1- and 2-km extents, most of the ranges for shrubland cover (Table 1) and shrubland configuration variables (Table 2) were large, and most of the magnitudes of the means were not similar to the magnitudes of the associated minimum or maximum values. These results indicate that the present analysis involved considerable variation in broad-scale shrubland conditions.

REGRESSION ANALYSES

As covariates, visibility was important in models for the winters of 1999–2000 and 2000–2001, observer was important in models for the winter of 2000–2001, and first-order (linear) spatial trends involving easting and northing coordinates were important in models for the winters of 2000–2001 and 2001–2002. Residual deviance-to-d.f. ratios (mean 1·11, range 1·06–1·13) indicated that our results were free of problems associated with spatial autocorrelation and an inappropriate distributional model.

MAGNITUDE OF SHRUBLAND ASSOCIATIONS

For models that involved both shrubland cover and shrubland patch density, only shrubland cover for the 2-km extent during the winter of 1999–2000 exhibited a conservation-relevant association (Fig. 1a). The confidence interval was above 0% change, indicating that the relation between system-wide richness and shrubland cover was positive. For patch density, relations approaching conservation relevance were suggested for the 2-km extent during the winter of 1999–2000, and for the 1-km extent during the winter of 2001–2002. Although both of these confidence intervals had point estimates near the threshold, and both contained many values above the threshold, conservation relevance was not supported in either case because the intervals overlapped 0% change (Fig. 1a).

For models that involved both shrubland cover and shrubland mean patch size, we used the $\log_{10}$ of mean patch size to linearize the relation between mean patch size and shrubland cover. Shrubland cover for the 1-km extent during the winter of 2001–2002 had a conservation-relevant association that was positive (Fig. 1b). Cover associations approaching conservation relevance were suggested for the 2-km extent for the winters of 2000–2001 and 2001–2002, but both confidence intervals overlapped 0% change; so, these relations were not considered to be conservation relevant. Shrubland mean patch size for the 1-km extent during the winter of 2001–2002 had a conservation-relevant association (Fig. 1b). The confidence interval was below 0% change, indicating that the relation between system-wide richness and mean patch size was negative. Relations that were close to being conservation relevant occurred for mean patch size at the 2-km extent during the winters of 2000–2001 and 2001–2002.

For models that involved both shrubland cover and the coefficient of variation of shrubland patch size, the associations with shrubland cover for the 2-km extent in the winters of 1999–2000 and 2001–2002 were close to being conservation relevant (Fig. 1c). The coefficient of variation of shrubland patch size for the 1-km extent in the winter of 2001–2002 exhibited a positive conservation-relevant relation, and this variable for the 2-km extent during the same winter had an association that was close to being conservation relevant.

For models that involved both shrubland cover and shrubland edge density, no conservation-relevant relations were found (Fig. 1d). Near-relevant associations for both variables occurred at the 2-km extent during the winter of 2001–2002.

Summarizing the results for the 10% and 30% threshold levels, we observed seven and zero conservation-relevant associations respectively. The seven associations that were

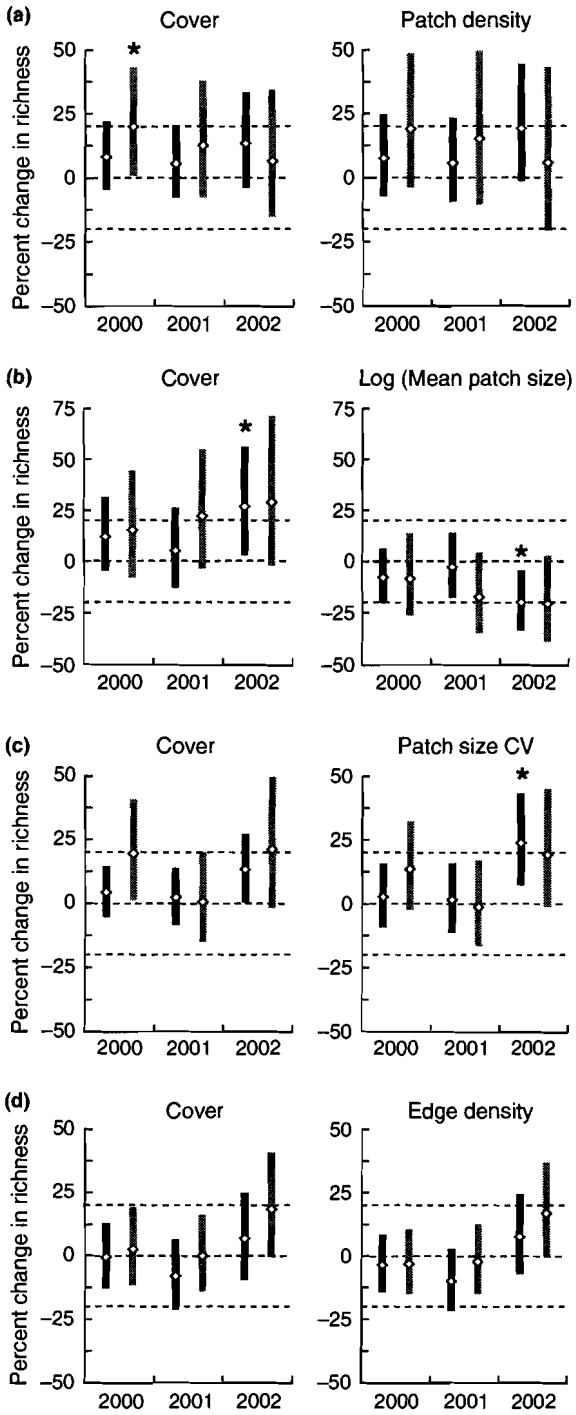

Fig. 1. Point estimates (diamonds) and 90% confidence intervals (bars) for percent change in mean system-wide bird richness, given a 20% change in shrubland cover and a 20% change in (a) shrubland patch density, (b) $\log_{10}$ of shrubland mean patch size, (c) shrubland patch size coefficient of variation (CV) and (d) shrubland edge density. Intervals are for 1- (black bars) and 2-km (grey bars) extents, and for the winters of 1999–2000 (2000), 2000–2001 (2001) and 2001–2002 (2002). Upper and lower dashed lines mark 20% changes in mean system-wide richness. An asterisk above a confidence interval indicates a conservation-relevant association for the 20% threshold.

conservation relevant at the 10% level were shrubland cover for the 2-km extent during the winter of 1999–2000 (Fig. 1a); shrubland cover and shrubland mean patch size for the 1-km extent during the winter of 2001–2002 (Fig. 1b); shrubland cover for the 2-km extent during the winter of 1999–2000 (Fig. 1c); shrubland cover and coefficient of variation of shrubland patch size for the 1-km extent during the winter of 2001–2002 (Fig. 1c) and shrubland edge density for the 2-km extent during the winter of 2001–2002 (Fig. 1d).

FREQUENCY OF STRONG SHRUBLAND ASSOCIATIONS

Based on chance alone, one would expect 10% (α for 90% confidence interval) of the relations examined to be identified as conservation relevant. For our case study, this would be 4·8 (0·10 × 48 relations) or approximately five intervals for a given threshold level. Based on the 10%, 20% and 30% thresholds, we observed seven, four and zero conservation-relevant relations respectively.

Discussion

CONSERVATION IMPLICATIONS

Within the ranges of observed values for shrubland metrics, system-wide richness was not associated with spatial patterns of shrubland in BBNP to a degree that was very relevant to conservation. Conservation relevance for seven of 48 (15%) confidence intervals (10% threshold), four of 48 (8%) confidence intervals (20% threshold) and zero of 48 (0%) confidence intervals (30% threshold) implied that important shrubland associations were far from pervasive, regardless of the threshold used. Overall, there was little evidence that the relations embodied information that was of practical importance.

We illustrated the method using avian richness, but response variables could include occurrence or abundance of a species, survivorship, physiological condition, reproduction, community composition and other metrics that are important in conservation. Landscape-related predictor variables were involved in our case study, but predictors could include many different biotic and abiotic variables measured at various temporal and spatial scales or levels of biological organization. Thus, the method has broad applicability for various types of ecological relations and conditions.

ASSESSING CONSERVATION RELEVANCE

In conjunction with other sources of information (e.g. measures of model fit and predictive accuracy), confidence intervals for percent change in predicted response variables can be used to help evaluate the conservation relevance of organism–environment relations. Importantly, the method presented here incorporates not only the magnitude of estimates (point estimates) but also their variability (confidence limits). In conservation decision making, one runs the risk of using limited conservation resources inappropriately. Thus, knowing which environmental influences are important and understanding the

uncertainty associated with these influences is essential. Our method identifies magnitudes of predicted changes that are of practical significance, and it incorporates uncertainty associated with predicted changes by considering the span of confidence intervals for the changes.

Conservationists can establish a threshold for conservation action using the criteria that reflect the most important issues in a particular situation. Different criteria (or combinations thereof) may be important. The nature of these criteria may be biological (population viability), social (trends in perceptions about sustainable activities), cultural (traditions for valuing environmental resources), economic (profit margins for alternate uses of natural resources) or have some other origin. The approach we demonstrated yields practical information, is applicable to associations embodied in various types of statistical predictive models and can be implemented readily by those with moderate statistical training.

We illustrated how to compute estimates and confidence intervals for percent change in the mean of predicted values from negative binomial regression, given a substantial (20%) change in a predictor variable. Conservationists also commonly use ordinary least squares and logistic regression in predictive modelling (Guisan & Zimmermann 2000). To compute an estimate and 90% confidence interval for percent change in the mean of the predicted value for a relation from an ordinary least squares regression, assuming a 20% change in a predictor, one would make the following calculations. For a predictor variable X_1, the estimate would be $100\% \times [(0{\cdot}20(\max X_1 - \min X_1)) \times \hat{\beta}_1]$ and the associated 90% confidence interval endpoints would be $100\% \times [(0{\cdot}20(\max X_1 - \min X_1)) \times$ the upper (or lower) 90% confidence interval endpoint for $\beta_1]$ (Koenker 2005:39). To compute an estimate and 90% confidence interval for the mean percent change in probability of occurrence for a logistic regression relation (with a logit link function), assuming a 20% change in a predictor, one would make the following calculations. The estimate would equal $100\% \times \{1 + \exp[(0{\cdot}20(\max X_1 - \min X_1)) \times (-\hat{\beta}_1)]\}^{-1}$ and the associated 90% confidence interval endpoints would equal $100\% \times \{1 + \exp[(0{\cdot}20(\max X_1 - \min X_1)) \times$ the negative of the upper (or lower) 90% confidence interval endpoint for $\beta_1]\}^{-1}$ (Neter *et al.* 1996:600).

Different values of percent change for a predictor can be used, and these values can be chosen based on the amount of change that generates concern in a given situation. For example, if effects of human development, climate change, succession, fire or exotic species were projected to change a predictor by 10%, and that level of change caused concern about potential effects on a response variable, the value of 10% (0·10 substituted for 0·20 in the formulas above) would be used to compute an estimate and confidence interval for percent change in the mean of the response variable. The conservation relevance of the association involving this predictor would then be assessed by comparing the computed estimate and confidence interval to a value of change in the response variable identified *a priori* as a threshold (trigger) for conservation action.

THE IMPORTANCE OF SCALE

Our method itself is scale invariant because the formulas for the confidence intervals, and the protocol for comparing confidence intervals to threshold points, do not vary with scale. However, if response and predictor variables are not measured at temporal and spatial scales that are pertinent to the organisms and activities under study, one cannot expect the resulting relations to have much ecological meaning (see Wiens 1989:227–244; Keane & Morrison 1999; Naugle *et al.* 1999) or to be conservation relevant. There is much to be gained by ensuring that measurements are made at scales that relate closely to the temporal and spatial scales of the phenomena to be modelled.

Consider a scenario in which a conservationist wanted to determine whether reduction in the density of understorey vegetation caused by prescribed fire would affect local densities of amphibians. The burn was conducted across a wetland complex during late winter before amphibians were active. The conservationist proposed to conduct surveys for amphibians at the wetlands in early spring, but a colleague suggested that surveys also be conducted during late spring when air temperatures would be higher. With reduced shade from understorey plants after the fire, the soil and near-ground environment may be warmer, drier and hence more stressful for amphibians, and information about amphibian density under these conditions would more completely answer questions about the effects of the fire on amphibian density. The conservationist extended the temporal scale of sampling to include late spring, thereby including temperature conditions that could realistically influence amphibian density. To improve detection of amphibians that were near the wetlands but not at or in the water *per se*, the colleague further suggested that dry lowlands surrounding the wetlands should be surveyed. The conservationist expanded the spatial scale (extent) of the original survey sites so that amphibians adjacent to the wetlands could be represented in the data. With these changes, the surveys were more capable of reflecting temporal and spatial factors that could influence estimates of amphibian density. As a consequence, the conservationist had a better chance of learning whether prescribed fire truly had conservation-relevant influences on local densities of amphibians.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Names of bird species and the percentage of 70 sites at which species were detected during three winters in Big Bend National Park, Texas.

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