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# Incorporating climate change into conservation planning: Identifying priority areas across a species' range

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**Abstract.** Theoretical and practical approaches associated with conservation biogeography, including ecological niche modeling, have been applied to the difficult task of determining how to incorporate climate change into conservation prioritization methodologies. Most studies have focused on identifying species that are most at risk from climate change, but here we asked which areas within a species' range climate change threatens the most. Here we explore methods for incorporating climate change within the Wildlife Conservation Society's (WCS) Range-Wide Priority Setting (RWPS) framework. We used ecological niche models to estimate exposure to climate change and incorporated these estimates into habitat quality scores for re-prioritization of high-priority areas for conservation. Methods such as these are needed to guide prioritization of geographically specific actions for conservation across a species' range.

**Keywords.** bioclimate envelope, climate change, conservation planning, ecological niche modeling, *Panthera onca*, species distribution modeling

## Introduction

The growing field of conservation biogeography uses theories, principles, and analyses to address problems related to the conservation of biodiversity (Ladle and Whittaker 2011). A key focus of the field has been the problem of climate change, which presents a potentially important threat to biodiversity (Parmesan and Yohe 2003, Thomas et al. 2004). In particular, climate change is expected to cause some areas to become less suitable for species' survival, while other areas become more suitable, resulting in shifts in species' distributions (e.g., Raxworthy et al. 2008) and increasing the likelihood of local and global extinctions (Parmesan et al. 1999, Pounds et al. 1999). Most studies to date have focused on documenting observed impacts on species' distributions, abundance, phenology, and body size (e.g., Rosenzweig et al. 2008) or predicting future impacts including extinction risk (e.g., Thomas et al. 2004). However, there is now a pressing need to develop practical methods for incorporating climate change within conservation planning (Mawdsley et al. 2009, Ackerly et al. 2010, Boutin 2010, Carvalho et al. 2011, Crossman et al. 2012) and conservation organizations are beginning to develop prioritization approaches that take climate change into account (e.g., Foden et al. 2008, CCWAPWG 2009).

Here we explore how frameworks focused on spatial priority setting across a species' range, such as the International Union for the Conservation of Nature's Species Conservation Strategy planning framework (IUCN/SSC 2008) or the Wildlife Conservation Society's (WCS) Range-Wide Priority Setting (RWPS; Medellin et al. 2001, Sanderson et al. 2002), could incorporate climate change. Under these frameworks, conservation organizations or national governments have already prioritized species for conservation, using a range of criteria (SEMARNAT 2001, WCS 2011[1], IUCN 2012[2]). The task at hand is therefore not to identify which species are most vulnerable, but rather to identify which areas within a priority species'

1. http://www.wcs.org/saving-wildlife.aspx accessed 24 October 2012
2. http://www.iucnredlist.org/ accessed 24 October 2012

  

range are the most important for long-term survival.

We present a case study in which we used ecological niche models (ENMs, or 'species distribution models'; Franklin 2009, Peterson et al. 2011) to incorporate climate change into the range-wide conservation planning process under the RWPS framework. Although we explored methods within the framework of RWPS, comparable analyses could utilize planning tools such as Marxan (Ball et al. 2009) and Zonation (Carroll et al. 2010). We took as an example species the jaguar (*Panthera onca*), which is the best documented case study for RWPS and for which data concerning the species' known range, conservation units, and scoring from a previous assessment are available (Medellin et al. 2001, Sanderson et al. 2002, Zeller 2007). However, our focus is on developing a methodological approach that could be applied to a wide variety of species, rather than on jaguar conservation, and to emphasize this we refer to a generic case-study 'species' rather than the jaguar. We used ENMs to estimate exposure to climate change across the species' range and incorporated these estimates into scores to define the highest-priority areas for conservation. Range-wide conservation planning frameworks such as RWPS often incorporate a wide variety of threats, including habitat destruction and disappearance of prey species, but data are seldom available to include information on future threats such as climate change. Finding a practical way to incorporate future threats into these frameworks will be critical to increasing the likelihood of long-term survival for many threatened species. The exercise we undertook here was exploratory in nature and we present it not so much as a proposed final methodology but rather as illustrative of a straightforward way that climate change may be incorporated rapidly into on-the-ground conservation planning using existing frameworks and tools.

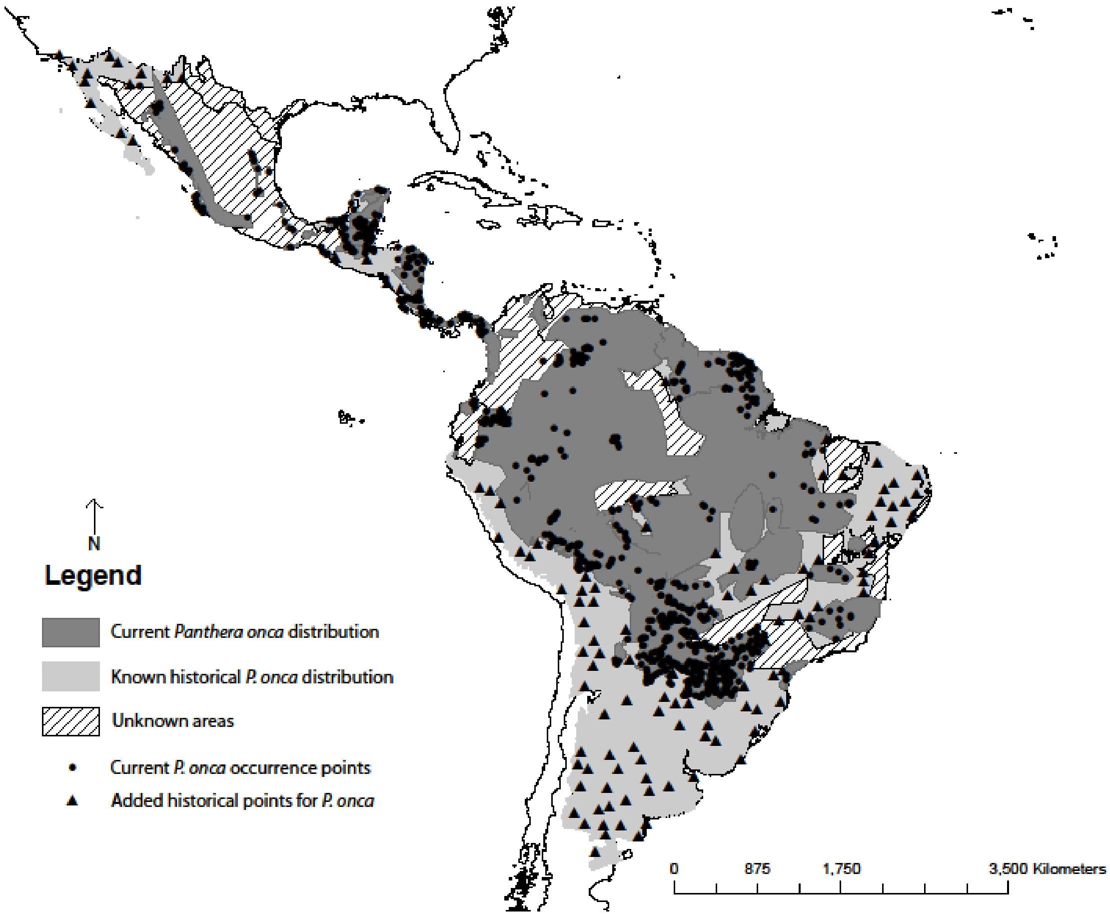


**Figure 1.** Occurrence points used to construct *Panthera onca* distribution models. Current points represent observations from 1989–1999 (a total of 731 points; Sanderson et al. 2002) and historical points (120) were randomly sampled from the known historical range of *P. onca.*

  

## Methods

### *Ecological niche models*

Many recent studies have used correlative ENMs to prioritize areas for conservation (e.g., Kremen et al. 2008). ENMs use associations between species' occurrence records and environmental variables to characterize the environments within which a species can exist. Locations that are climatically suitable for the species can then be identified under both current and future climates (for an introduction to ENMs, see Pearson 2007[3]). The advantages and disadvantages of these models have been widely discussed in the literature (e.g., Pearson and Dawson 2003, Dawson et al. 2011). The framework we present could use either correlative or mechanistic models (Kearney and Porter 2009), although we use correlative ENMs here. ENMs can be used to identify the parts of a species' range that are expected to experience large changes in temperature and precipitation, and can therefore be informative about a species' exposure to climate change (Dawson et al. 2011).

Prior RWPS assessments of jaguar conservation (Medellin et al. 2001, Sanderson et al. 2002, Zeller 2007) resulted in the prioritization of 51 high-priority areas for conservation. For our case study here, we term these simply Species Conservation Units (SCUs). These SCUs fall within 36 Geographic Regions (GRs) defined by distinct habitat types and bioregions across the species' historic range (Sanderson et al. 2002). The prior range-wide planning process amassed a set of 731 species' occurrence records (Figure 1) from sightings spanning 1989–1999, which we used to calibrate and test our models. Since jaguars have been extirpated from part of their historical range (especially in the south) for reasons that are unlikely to be primarily climatic (Sanderson et al. 2002), we included in our models 120 additional points that were randomly sampled from the known historical range, as defined in Sanderson et al. (2002). This number of additional points resulted in a roughly comparable overall density of points across the current and historical ranges. We included points from the historic range since our goal was to capture the full bioclimate envelope of the species (Pearson and Dawson 2003), rather than an envelope that is curtailed by non-climatic factors.

We used temperature and precipitation predictor variables from the WorldClim dataset at two and a half arc-minute resolution (Hijmans et al*.* 2005). We used 18 out of 19 of the 'bioclim' variables, which represent annual trends (e.g., mean annual temperature and precipitation), seasonality, extremes (e.g., temperature of the coldest month), and quarterly summaries. We excluded one of the 19 bioclim variables, *temperature annual range,* from the analysis because correlations between variables meant we could not calculate Mahalanobis distances (see below) when this variable was included. We assembled the 18 bioclim variables for the current climate and for eight future climate scenarios, generated from two General Circulation Models (GCMs: HadCM3 and CCMA), two emissions scenarios (A2 and B2), and two time frames (2050s and 2080s). These scenarios are based on the IPCC's third assessment report[4]. The correlation patterns among climate variables in our study region were very similar between the current climate and the future climate scenarios, with the same pairs of variables showing relatively weak correlations ($|r| < 0.8$) and strong correlations ($|r| > 0.9$) across time frames.

We used two different ENM approaches: maximum entropy, as implemented in the software Maxent (version 3.3.3; Phillips et al. 2006), and Mahalanobis typicalities, calculated using our own code, neither of which require species' absence records. By incorporating predictions from two methods that are conceptually quite different, we aimed to take into account the variability that can occur from the use of alternative models (Thuiller et al. 2004, Pearson et al. 2006).

The maximum entropy method (Phillips et al. 2006) estimates the unknown probability distribution defining a species' distribution from incom-

**3.** http://ncep.amnh.org/ accessed 24 October 2012
**4.** http://www.worldclim.org/ accessed 24 October 2012

plete information by finding the probability distribution of maximum entropy (that which is closest to uniform), subject to constraints imposed by the known distribution of the species and environmental conditions across the study area (Phillips et al. 2004, 2006). We set the regularization parameter (a variable selection method employed in Maxent to reduce the likelihood of overfitting) at one after testing a range of settings from one to ten and determining that a regularization of one resulted in the highest area under the receiver operating characteristic curve (AUC) values. Other parameterizations (convergence threshold, maximum number of iterations, and feature selection) followed recommendations by the model developers (Phillips et al. 2006, Phillips and Dudik 2008). Maxent has been shown to perform well compared with other ENM approaches (Elith et al. 2006).

Mahalanobis distance is a measure of dissimilarity between a vector of independent variables and some representation of an ideal or optimal condition (Clark et al. 1993). In this study, the optimal condition represents the species' niche as described by the mean and variance of the 18 climatic predictor variables associated with the occurrence points. The larger the Mahalanobis distance, the further the test vector is from the ideal condition, i.e., the centroid of the species' niche as represented in multidimensional variable space. Other studies have shown that ENMs generated with Mahalanobis distances have good predictive performance for jaguars (Torres et al. 2008, Rodríguez-Soto et al. 2011). We converted Mahalanobis distances to typicalities (Clark et al. 1993), which scale distances from zero to one, with one being closest to the optimal condition or best representation of the species' niche, and zero being the farthest away.

To evaluate the predictive ability of both Maxent and Mahalanobis models under current climate conditions, we carried out four-fold partitioning and calculated the AUC and the omission rate with a binomial test of statistical significance under a threshold where 90% of calibration occurrences were predicted correctly (Peterson et al. 2011).

### *Predicted distributions under climate change*

We combined results from a suite of two ENMs, two GCMs, two emissions scenarios, and two time frames (total of 16 predictions) to provide a summary of predictions, focusing on the 51 SCUs identified by our case study RWPS (Sanderson et al. 2002).

We first calculated the mean suitability prediction within each SCU for the current climate data, and then for all 16 future projections. Second, from the mean prediction values within each SCU, we calculated the percent change ([(predicted value – current value) / current value] x 100) for each GCM, emissions scenario, and time frame (Figure 2). We consider that the change in mean suitability across a SCU is a more appropriate measure than change on a per-cell basis because jaguar home ranges are much larger than our cell resolution (Rabinowitz and Nottingham 1986, Cranshaw and Quigley 1991). To test whether taking the mean value across SCUs resulted in the masking of contradictory results within a SCU, we chose three SCUs comprising a combination of highly suitably and unsuitable habitat and calculated proportional change for each grid cell within the SCU, instead of the mean value. For one of these SCUs, individual model predictions did vary considerably between the mean value and per-grid-cell approach, with the final consensus across models for this SCU changing from *likely to stay the same* to *no clear signal* (see category definitions below). However, using a per-grid-cell approach did not affect results in the other SCUs we tested. Also, given the large home ranges of jaguars and the fact that climate models do not realistically predict at very fine resolutions, doing the analysis on a per-grid-cell basis could introduce a degree of false precision.

We then placed the percent change in a category to summarize each model prediction: *Large Increase* = increase of +50% or more; *Increase* = +15 to +49%; *Same* = –14% to +14%; *Decrease* = –15 to –49%; *Large Decrease* = –50% or more extreme. For each time frame (2050s, 2080s), we then summarized the number of models predicted to change in each of the five categories for a given SCU: *clearly decreasing* = most

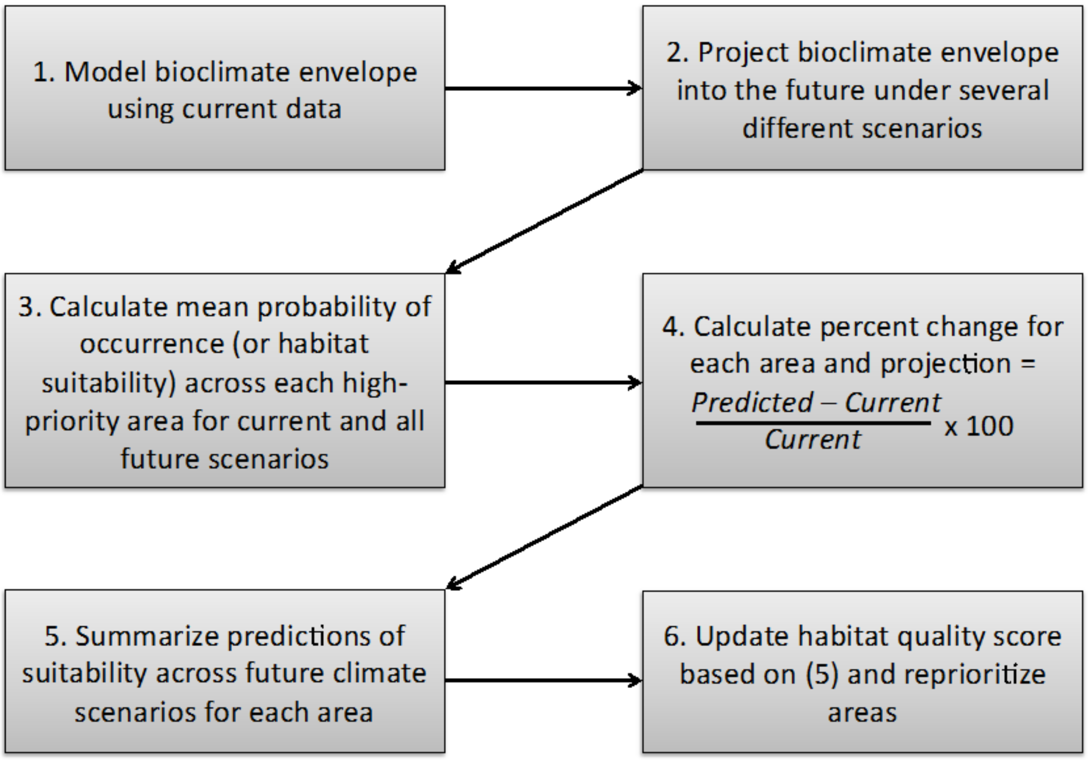


**Figure 2.** Flow diagram outlining our methodology for incorporating climate change predictions into Range Wide Priority Setting (RWPS).

models predict decreasing suitability, with only one or two models predicting suitability staying the same; *likely to decrease* = more than half of the models predict decreasing suitability; *likely to stay the same* = more than half of the models predict suitability staying the same; *likely to increase* = more than half of the models predict increasing suitability; *clearly increasing* = most models predict increasing suitability, with only one or two models predicting suitability staying the same. If none of the above categories applied to a SCU, we classified it as having *no clear signal*.

To explore the relative contribution of uncertainty factors to variation in our model predictions, we performed two generalized linear models, one for each time frame (2050s or 2080s) with the percent change values as the dependent variable and ENM, GCM, and emissions scenario as the independent variables, which were all categorical with two levels each. The models were run using the *glm* function in the R statistical environment, specifying an identity link function and with a Gaussian distribution of errors (R Development Core Team 2007).

### *Re-Prioritization of Species' Conservation Units*

The original prioritization of SCUs (Sanderson et al. 2002) was generated by scoring each SCU for six weighted factors: size, connectivity, habitat quality, hunting of jaguar, hunting of prey, and population status. Jaguar experts determined a weight for each factor to indicate the relative importance of each variable to long-term survival and placed each SCU in one of three score categories (zero – low probability of long term survival, one – medium probability, or three – high probability) for each factor and then multiplied the score by the factor weight and summed to obtain the SCU prioritization score. The score categories skip over a score of two to give higher weight to SCUs with the highest probability of supporting long-term survival.

We incorporated the climate-change predictions into the 'habitat quality' factor. In cases where the SCU was predicted to increase in climatic suitability across scenarios for a given time frame (2050s or 2080s), we shifted the habitat quality score up one category. Conversely, for SCUs with a predicted decrease in climatic suitability (clearly decreasing or likely to decrease), we shifted the habitat quality score down one category. For SCUs that were either likely to stay the same or had no clear signal in terms of changes in climatic suitability, the habitat quality score was left as originally assigned. Once we adjusted the habitat quality score to reflect expected changes in climatic suitability, we recalculated the prioritization score for the 2050s and the 2080s. We then ranked SCUs within Geographic Regions (GRs) according to their revised scores to ensure that priority areas were distributed across all significant habitat types in the species' range (following Sanderson et al. 2002). All SCUs that fell wholly or partially within a GR were ranked relative to other SCUs within the same GR.

## Results

Maxent models overall showed strong ability to predict observed distributions: AUC = 0.770–0.820; omission error = 0.090–0.152, $P < 0.01$ in all folds. Mahalanobis models also showed reasonable predictive ability: AUC = 0.681–0.723; omission error = 0.099–0.160, $P < 0.01$ in all folds (see Supplementary Appendix for figures showing all predicted distributions[5]).

Out of 51 SCUs, model projections for the 2050s show 12 SCUs clearly decreasing and 16 likely to decrease in suitability, with nine likely staying the same in suitability and one likely to increase in suitability (Figure 3a). None of the SCUs was clearly increasing in suitability. The models provided no clear signal for 13 SCUs. Model projections for the 2080s were similar to those from the 2050s, though 19 SCUs shifted to categories representing greater confidence in a decrease in suitability (Figure 3b).

Our generalized linear model showed that choice of ENM method accounted for the largest part of the variation in model projections, similar to other studies (e.g. Dormann et al. 2008, Buisson et al. 2010). For models for the 2050s, this difference accounted for 28.7% of variation in percent-change values, while type of GCM accounted for 18.9%, and emissions scenario for 10.0%. For models for the 2080s, ENM accounted for 54.1% of the variation in percent change values, GCM for 45.5% and emissions scenario for 2.57%.

When we updated the original prioritization results (Sanderson et al. 2002) to include the climate change predictions, the highest ranked SCU (s) changed in five out of 36 GRs for the 2050s and four GRs for the 2080s (see Supplementary Table S1[5], which lists new prioritization scores and rankings for all SCUs within each GR).

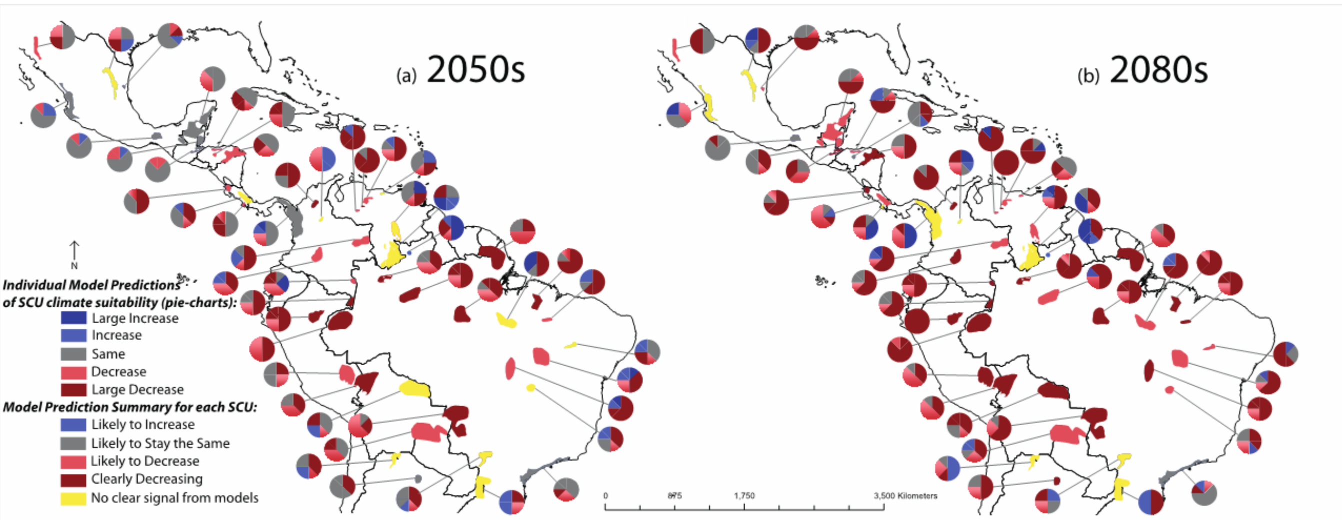


**Figure 3.** Summary of model predictions for the 2050s (a) and 2080s (b). Pie charts show the details of individual model predictions averaged across SCUs as described in the methods. The color of the actual SCU polygons corresponds to summary predictions across all models.

**5.** http://dx.doi.org/10.5531/sd.cbc.1

  

## Discussion

This work demonstrates a practical approach for incorporating future climate scenarios into existing range-wide conservation planning frameworks. In the light of the threat to biodiversity that climate change poses, there is a pressing need for this kind of relatively simple, index-based approach that can be applied rapidly to a wide variety of species in different parts of the world.

Although we might not expect climate change to be very important for jaguars compared with other non-climatic threats, such as hunting and habitat disturbance (because jaguar biology is less directly connected to temperature and precipitation than the biology of some other species), our results show that incorporating it can make a difference in spatial priority setting. For species that have more clear climatic constraints relating to their thermal physiology (Buckley et al. 2012), and that are therefore expected to show substantial shifts in response to climate change (e.g., butterflies, birds, plants; Parmesan and Yohe 2003), or for species with limited dispersal abilities that may be at a distinct disadvantage in their capacity to respond to climate change, incorporating future climate-change scenarios into the spatial priority setting process will be even more critical.

By including two different ENMs and several future climate scenarios, our approach recognizes that there are important sources of uncertainty inherent in using ENMs (e.g., Pearson et al. 2006, Beaumont et al. 2008). Future applications would benefit from incorporation of additional models (e.g., ensemble ENMs [Araújo and New 2007] and mechanistic models [Kearney and Porter 2009]) and new ways to quantify and understand uncertainties (e.g., Elith et al. 2010, Carvalho et al. 2011). However, such applications will require additional observations and perhaps experimental data. For example, for the development of mechanistic models in wide-ranging species, data on reproduction and growth under food limitation, individual energy intake, and energy expenditure towards movement may be important (e.g. Molnar et al. 2010). Such data may only be available through long-term capture–recapture or monitoring studies of the focal species. Future implementations that are to be used in conservation planning should also use the most up-to-date climate scenarios available, such as those from the IPCC's Fourth Assessment Report (see, for example CCAFS Climate Layers[6]). Despite multiple uncertainties, we contend that ENMs can provide useful information for the planning process, not in predicting actual future distributions, but in estimating parts of a species' range that will be most exposed to climate change (c.f., Dawson et al. 2011).

We conducted the work presented here after a range-wide conservation planning workshop, but our approach could be incorporated directly into an ongoing workshop for improved predictive ability. For example, several ENMs for the focal species could be presented at the workshop, with each ENM utilizing a different set of predictor variables tailored to the physiological and life history requirements of the focal species (as opposed to a generalized set; Synes and Osborne 2011). The modeled future scenarios could then be incorporated into the prioritization process, either by adjusting the habitat quality score as we did here, or by taking a variety of alternative approaches that cater to the characteristics of a given species or situation, as discussed below.

The approach taken by experts at the original jaguar RWPS workshop was to include factors that can be seen as both positive (habitat quality, large area of SCU, connectivity) and negative (hunting of jaguars, hunting of prey) in relation to jaguar conservation. Therefore, the final prioritization score would be highest in the best areas for jaguar populations. Here, we followed the same approach for incorporating future climate change scenarios, scoring habitat quality as lower when climate change predictions showed a likely decrease in habitat suitability, leading to lower prioritization scores for those SCUs. Our choice to quantify changes in climate suitability with a percent change index reflects this approach because percent change assigns a higher weight to in-

**6.** http://www.ccafs-climate.org accessed 24 October 2012 creases in suitability than to decreases; for example, an increase from 0.1 to 0.9 represents a +800% change, while a decrease from 0.9 to 0.1 represents a –88.9% change (Figure 4). As such, an area with currently high suitability must have a substantial reduction before being classified as decreasing, ultimately prioritizing areas with high long-term conservation value.

In practice, therefore, our method assigns higher conservation priority to SCUs in which climate change is expected to result in increases in habitat suitability, and lower priority to places expected to experience decreases in suitability. In cases where conservation actions can do little to reduce a future threat or mitigate its impacts, as is the case for climate change, this prioritization framework is appropriate. However, in cases where it is distinctly possible to prevent or mitigate the impacts of a future threat, such as potential deforestation, conservation practitioners may want to consider the opposite approach, prioritizing places where negative changes will occur unless conservation action is taken, and avoiding investment in places that will remain stable or improve even without conservation action. To explore this alternative approach, we reanalyzed our data prioritizing areas expected to experience the most change in climate suitability rather than the least change (see full results under "Option 2" in our Supplementary Table S1[5]). Here, we increased the habitat factor score by one when climate change was expected to make an area less suitable, as opposed to decreasing the score by one as in our initial adjustment. With our data, this re-prioritization did not result in changes in the rankings of SCUs within geographic regions compared to the original rankings of Sanderson et al. (2002), but it might for another species with different characteristics.

Setting conservation priorities for species is conceptually difficult and can mean different things to different practitioners (Chadès et al. 2008). One viewpoint is that priority should be given to the most threatened populations, while another viewpoint is that priority should be given to large or stable populations with low threats, such as the tiger source sites of Walston et al. (2010). The general approach that we explored here could easily be adjusted to reflect different criteria for prioritization, which, for example, might focus on areas that are most, rather than least, at risk.

Indeed, there is much flexibility within the approach we present for developing a scoring system that is appropriate for the particular species and regions being assessed. For instance, workshop participants may choose to be more conservative and only adjust the score in cases that are clearly increasing or decreasing, thus not weighting cases that are likely to increase or decrease, in contrast to the approach we used here. Alternatively, participants may choose to weight exposure to climate change more heavily than we have done here, for example in the case of a species that is known to be very vulnerable to climate change. To explore this approach, we reanalyzed our data giving additional weight to the climate change-related factor (habitat quality; see full results under "Option 3" in our Supplementary Table S1[5]). Here, we increased the weighting multiplier of the habitat quality factor by ten (from 23 to 33) and decreased the weighting multiplier of the other factors by two (for a discussion of weighting multipliers in RWPS, see Sanderson et al. 2002). This re-analysis resulted in new changes to the ranks in different GRs as compared to our initial adjustment, with the highest ranked SCU(s) changing in five out of 36 GRs for the 2050s and also for the 2080s (see Supplementary Table S1[5]). Another prioritization option for species that are highly vulnerable to climate change would be to include exposure to climate change as a separate weighted factor instead of incorporating it into habitat quality as we have done here.

The RWPS framework has now been used by conservation organizations for a variety of species including eastern chimpanzees (Plumptre et al. 2010), North American bison (Sanderson et al. 2008) and American crocodile (Thorbjarnarson et al. 2006). Range-wide prioritization is typically an initial step in strategic planning to save a species. Following the prioritization process, experts identify objectives and strategic actions to reach the goals for the species, within the constraint of lim-

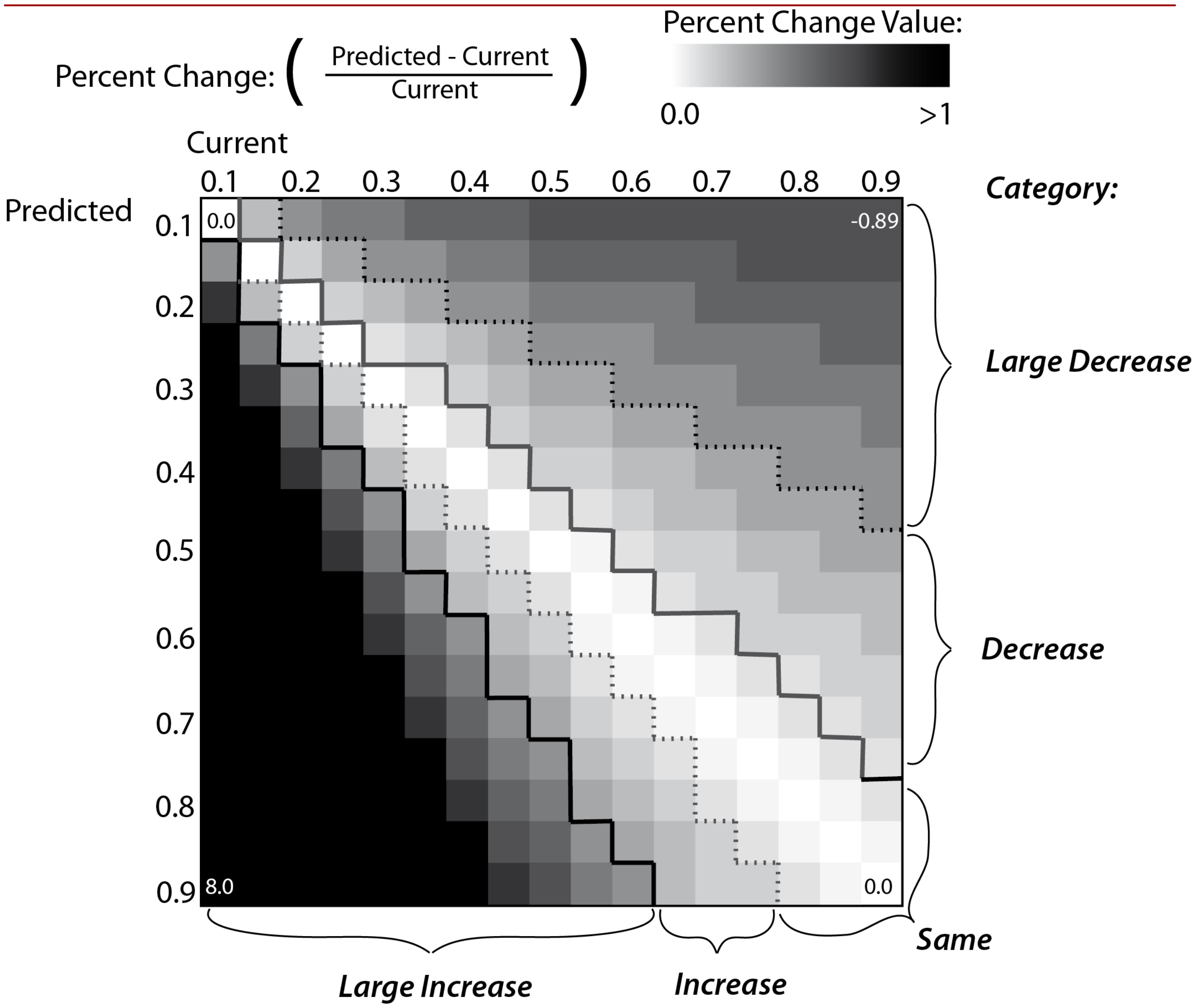


**Figure 4.** Visualization of how percent change in climate suitability (dark shading for high absolute values and light shading for values near zero) correspond to categories of changes (shown by lines, Large Decrease: < –50% change, Decrease: –15 to –49%, Same: –14.9 to +14% change, Increase: +15 to +49% change, Large Increase: > +50%). Percent change values and categories result in more changes being classified in the Large Increase category.

ited funding. The kind of methodology that we have explored here shows potential for incorporating the threat of climate change into these conservation prioritization initiatives.

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