



Defining spatial conservation priorities in the face of land-use and climate change

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ABSTRACT

Creating and managing protected areas is critical to ensure the persistence of species but dynamic threats like land-use change and climate change may reduce the effectiveness of protected areas planned under a static approach. Here we defined spatial priorities for the conservation of non-flying mammals inhabiting the Cerrado Biodiversity Hotspot, Brazil, that overcome the likely impacts of land-use and climate change to this imperiled fauna. We used cutting-edge methods of species distribution models combining thousands of model projections to generate a comprehensive ensemble of forecasts that shows the likely impacts of climate change in mammal distribution. We also generate a future land-use model that indicates how the region would be impacted by habitat loss in the future. We then used our models to propose priority sites for mammal conservation minimizing species climate-forced dispersal distance as well as the mean uncertainty associated to species distribution models and climate models. At the same time, our proposal maximizes complementary species representation across the existing network of protected areas. Including land-use changes and model uncertainties in the planning process changed significantly the spatial distribution of priority sites in the region. While the inclusion of land-use models altered the spatial location of priority sites at the regional scale, the effects of climate change tended to operate at the local scale. Our solutions already include possible dispersal corridors linking current and future priority sites for mammal conservation, as well as a formal risk analysis based on planning uncertainties. We hope to provide decision makers with conservation portfolios that could be negotiated at the decision level.

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1. Introduction

Human population growth has triggered many threats to biodiversity like global changes, overexploitation, pollution, and introduction of invasive species (Brook et al., 2008; Schipper et al., 2008; Hoffmann et al., 2010; Maclean and Wilson, 2011; Mantyka-Pringle et al., 2011). Among these threats, land-use change and climate change are considered the worst (Sala et al., 2000; Thomas et al., 2004; Pereira et al., 2010) and they have a clear synergistic effect (Brook et al., 2008; Asner et al., 2010; Mantyka-Pringle et al., 2011). Further, assessments of future global changes predict that biodiversity will continue to decline (Sala et al., 2000; Pereira et al., 2010).

Climate change causes selective micro-evolutionary pressures in species, favoring individuals capable of dispersing either locally or regionally to track suitable habitats (Holt, 1990; Parmesan and Yohe, 2003; Parmesan, 2006; Dawson et al., 2011). Given the prop-

er timeframe, the dispersal process can result in range shifts that have been of great importance for species dealing with past and current climatic changes; thus, it is likely that dispersal should have great importance in the future (Graham and Grimm, 1990; Lyons, 2003; Parmesan and Yohe, 2003). However, human-driven landscape modifications may block dispersal from current to the future suitable habitats increasing species extinction risk by their synergistic effect with changing climates (Brook et al., 2008; Asner et al., 2010; Hof et al., 2011; Mantyka-Pringle et al., 2011).

The main issue here is that climate change, as well as other dynamic threats, poses a new challenge to the static way conservation planning is usually done (Hannah, 2010). Conservation biology has proposed creative solutions to deal with these threats, most focusing on the establishment of protected areas (Williams et al., 2005; Lawler, 2009; Mawdsley et al., 2009; Hannah, 2010; Dawson et al., 2011; Mawdsley, 2011; Loyola et al., 2012). Creating and managing protected areas is critical to ensure the persistence of species but these dynamic threats may reduce the effectiveness of protected areas planned under a static approach (Araújo et al., 2004; Hannah, 2010; Dobrovolski et al., 2011a,b). It seems necessary to incorporate species' range shifts in spatial conservation plans to ensure their effectiveness in the future (Araújo et al.,

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2004; Hannah et al., 2007; Hannah, 2010). Some recent studies did have included the effects of the future climate change aiming to deliver more effective conservation plans, but they usually ignore land-use changes (e.g. Hannah et al., 2007; Carroll et al., 2010) and considered subjective values or unrealistic species' dispersal capacity (e.g. Carroll et al., 2010).

Species distribution models (SDMs) have been used to predict the present and future species' distributions although different methods for modeling species distribution and different climate models (e.g. coupled Atmosphere–Ocean General Circulation Models, AOGCMs) may produce very distinct results increasing uncertainties in the projections and their applicability to conservation (Araújo and New, 2007; Diniz-Filho et al., 2009; Loyola et al., 2012). The inclusion and reduction of uncertainties in conservation planning is therefore important to increase the quality of spatial solutions (Regan et al., 2009; Wilson, 2010).

Here we developed spatial conservation plans that accommodate species' range shifts induced by climate change and landscape change predicted by a land-use model. Further, we measured and reduced uncertainties associated with SMDs, and modeled the dispersal capacity of each species aiming at minimizing the distance between their current and future distributions along priority sites for conservation.

2. Methods

2.1. The case study

We used mammals and the Brazilian Cerrado (a woodland savanna) as our case study for several reasons. First, the Cerrado has an enormous vegetation complexity that includes grassland, savanna and forest, harboring a highly threatened biodiversity (Myers et al., 2000; Klink and Machado, 2005; Ribeiro and Walter, 2008). Second, high rates of land conversion have already transformed more than half of its two million km² in anthropogenic land use (Klink and Machado, 2005). Although this region has been included in previous conservation schemes (see Brooks et al., 2006 for a review), currently only 2.2% of its area is under strictly protection (IUCN I–IV categories, see Klink and Machado, 2005). Third, it has been demonstrated that the effect of climate change and land-use change could be strong in the Cerrado given that climate change results in large species' range shifts and high rates of habitat conversion impedes species from tracking suitable habitats (Klink and Machado, 2005; Diniz-Filho et al., 2009; Loyola et al., 2012). Fourth, mammals are under many threats from local to global scale, which results in a faster extinction rate than those recorded by background extinction (Schipper et al., 2008; Barnosky et al., 2011). It is also a well-known group both in terms of their natural history and evolution, making the access to biological traits easier than in other groups. Finally, planning for the conservation in the Neotropics in the face of climate and land-use changes are among the most cutting-edge and important topics in the science of spatial conservation prioritization (Moilanen et al., 2009a).

2.2. Land use model

We modeled land use changes with variables from different sources. We compared the Cerrado land use between 2002 and 2008 (<http://siscom.ibama.gov.br/monitorabiomas/index.htm>) to generate a matrix of transition probability between native areas to anthropogenic areas. We modeled the land use with the module Land Change Modeler – LCM, available in Idrisi Taiga Version (Eastman, 2009), using the following explanatory variables: digital elevation model and annual accumulated precipitation (www.worldclim.org), proximity to roads, proximity to recent

deforested areas and proximity to cities (<http://mapas.mma.gov.br/i3geo/datadownload.htm>). LCM is a machine learning procedure that uses Markov Chains to project future land-use conditions. In order to evaluate model precision, we inverted the maps from 2002 and 2008 and the expected land-use was projected back into 1990. Then we generated a total of 458 control points to cover the entire Cerrado by doing a visual inspection of MrSID images from 1990 (<https://zulu.ssc.nasa.gov/mrsid/>). Finally, we predicted the land use in 2050 with a spatial resolution close to 500 × 500 m.

2.3. Species distribution models

We updated previous lists of non-flying mammals occurring in the Cerrado (Marinho-Filho and Juarez, 2002; Marinho-Filho et al., 2007) and obtained 154 species range maps (see Table A1) from the International Union for Conservation of Nature (IUCN version 2011; <http://www.iucnredlist.org/technical-documents/spatial-data#mammals>). We mapped the extent of occurrence maps of each species to the resolution of 0.1° × 0.1° of latitude/longitude (about 11,200 m in the Equator line) that covered the full extent of the Cerrado. From these maps, we derived species presences and absences considering that all cells inside the limits of a range map are presences and those outside the range map are absences (see Diniz-Filho et al., 2009).

We obtained the following current climatic variables from the WorldClim database (www.worldclim.org/current): annual mean temperature, mean diurnal range in temperature, temperature seasonality, annual precipitation, precipitation seasonality and precipitation of coldest quarter. These variables were generated by an interpolated climate data from 1950 to 2000 periods (Hijmans et al., 2005). We used the same climate variables projected into the future (year 2050) by three Atmosphere–Ocean General Circulation Models (AOGCMs: CCCMA CGCM2, CSIRO-MK2.0 and UKMO_HADCM3) of the B2a emission scenario. These variables were generated by application of delta downscaling method on the original data from Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (available by International Centre for Tropical Agriculture in <http://ccafs-climate.org>). This method assumes changes in climates only over large distances and the relationships between variables are maintained from current towards the future (see <http://ccafs-climate.org/> for more details). We rescaled both current and future climate variables to our grid resolution.

We used presence and absence data derived from species range maps and the climatic variables to model species distributions (see Fig. 1). The use of these data is still incipient in the SDM literature (but see Lawler et al., 2009; Diniz-Filho et al., 2009; Loyola et al., *in press* for recent examples). However, in regions with poor knowledge about species distribution and under high threat such as the Cerrado such approach may be a first assessment to identify general priorities that can be revised after data improvement (Lemes et al., 2011). This hierarchical approach is one of the proposals of conservation biogeography (Whittaker et al., 2005).

To generate SDMs, we used nine modeling methods, which differ both conceptually and statistically (Franklin, 2009). We grouped them into three separate sets (distance, statistical and machine-learning methods), and applied the ensemble forecasting approach within each set (see Fig. 1 and text below). We chose to keep these three different sets of SDMs separated to highlight the differences model prediction the performance of the methods as well as the consequences of their differences in our final prioritization scenarios. Distance methods (henceforth, DIST) were BIOCLIM (Busby, 1991), Euclidian and Gower distances (Carpenter et al., 1993). Statistical methods (STAT) were Generalized Linear Models (GLM; Guisan et al., 2002), Generalized Additive Models

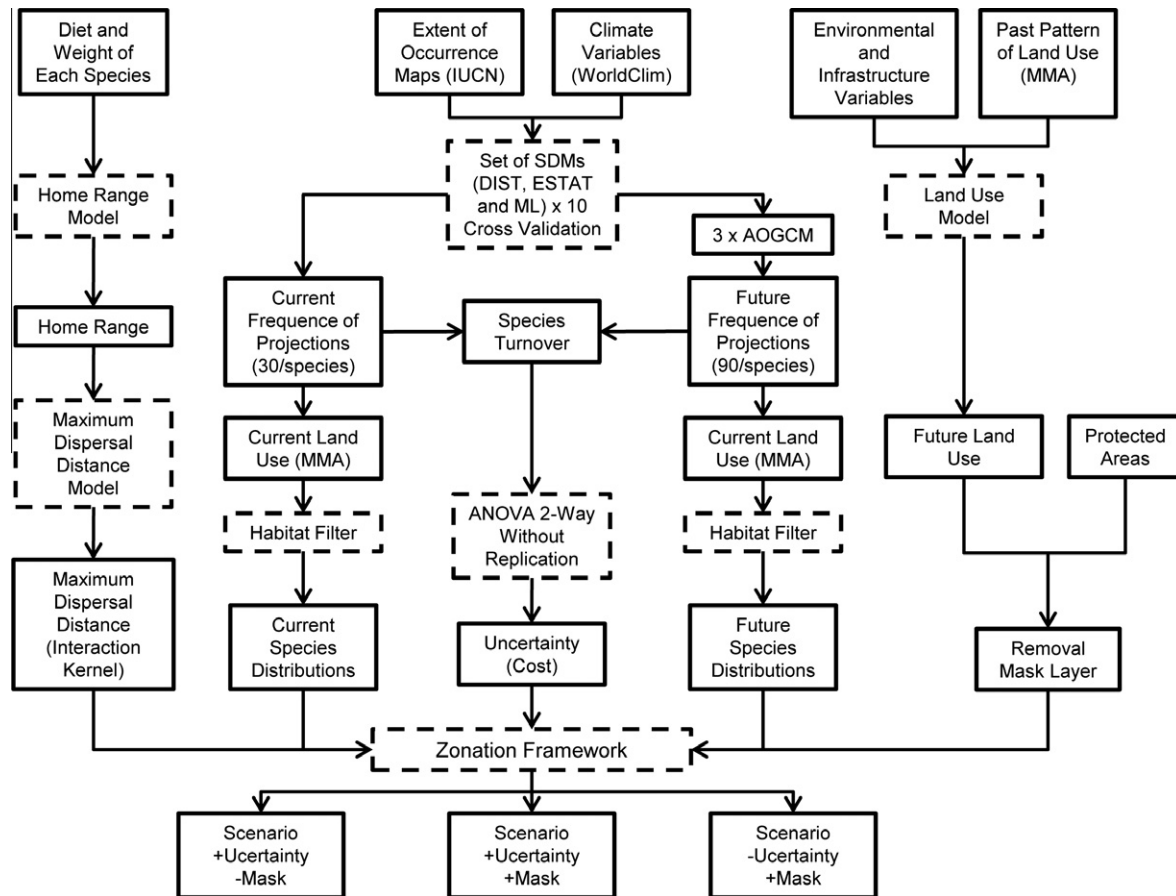


Fig. 1. A schematic representation of the methods used to generate the scenarios of spatial conservation plans for non-flying mammals in the face of land-use changes and climate changes expected for the Cerrado Biodiversity Hotspot. We fitted three SDM per set of ensemble (DIST, STAT, ML), projected models into the future (2050) based on three AOGCMs, and produced consensus maps among projections within each set. We then filtered the predicted distribution of each species by the habitat in which species occur to obtain current and future distribution maps of each species. We quantified the uncertainty associated to SDMs and AOGCMs for each site and modeled the maximum dispersal distance as proportional to the diet and body weight of species. We also modeled future land-use changes in the Cerrado. Finally, we used the distributions maps, the dispersal distance, model uncertainty, future landscape, and the current network of protected areas to generate spatial prioritization scenarios. See text for further explanations.

(GAM; Hastie and Tibshirani, 1986) and Multivariate Adaptive Regression Splines (MARS; Friedman, 1991) that were represented by the inherent statistical methods of modern regressions (Franklin, 2009). Finally, machine-learning methods (ML) were Maximum Entropy (MaxEnt; Phillips et al., 2006; Phillips and Dudík, 2008), Random Forest (Breiman, 2001), and Genetic Algorithm for Rule Set Production (GARP; Stockwell and Noble, 1992). Details on these methods can be found elsewhere, in particular in Franklin (2009).

We partitioned randomly the data of each species into 75% for calibration (or train) and 25% for validation (or test), and repeated this process 10 times (i.e. a cross-validation) maintaining the observed prevalence of species. We did this procedure using the 75% of random presences to presences-only methods and 75% of random presences and absences to presence-absences methods. We converted continuous predictions in presence and absences finding the threshold with maximum sensitivity and specificity values (actually minimum 1-specificity value) in the ROC curve to calculate the True Skill Statistics (TSS) (Allouche et al., 2006). The TSS range from -1 to $+1$, where values equal $+1$ is a perfect prediction and values equal or less of zero is a prediction no better than random (Allouche et al., 2006). We used TSS as our measure of model performance.

We did the ensembles of forecasts to produce more robust predictions and reduce the uncertainties owing to the modeling process (Araújo and New, 2007; Marmion et al., 2009). We projected

distributions into future climate and obtained 90 projections per species within each set of methods (3 modeling methods \times 3 AOGCMs \times 10 randomly partitioned data) and 30 projections per species for current climate (3 modeling methods \times 10 randomly partitioned data). Then we generated the frequency of projections weighted by TSS for each species and timeframe within each set of methods (Fig. 1, see also Diniz-Filho et al., 2009; Loyola et al., in press). We considered the presence of a species only in cells with 50% or more of frequency of projections, but we hold a continuous value when this occurred.

We reclassified land-use classes in 2008 (our “current landscape”) changing the specific classes (i.e. each type of vegetation cover) to more inclusive classes (e.g. savanna). We used forest, savanna, grassland and anthropogenic (e.g. agriculture, pasture, urban influence) as classes. Then, we quantified the proportion of each class in each grid cell. We compiled information about the habitat in which species were sampled (forest, savanna and grassland), body weight and food habits (carnivore, herbivore and omnivore) for each species from the literature including papers, books and theses. We considered that a given species could use a particular habitat if it was found in that habitat at least once. Hence, every species can occur in more than one habitat.

Finally, we “filtered/corrected” each species’ frequency of projection map by the presence of the species’ habitat (i.e. type of vegetation cover) in the cell (a habitat filtering process, Fig. 1). This

means that we only let the value in frequency of projection for cells in which the species' habitat occur, according to our current landscape. We used this procedure to reduce commission errors (false positive) inherent to extent of occurrence maps (following the suggestions of Lemes et al., 2011; and Rondinini et al., 2011). Note that we could have used habitat as a predictor in the SDM if we had local species' occurrences and land use map at the same resolution (i.e. small grain size). However in the absence of these data we decided to use the habitat filtering process a posteriori. From the conceptual point of view, our approach is preferable because we did not remove sites that, as a set, represent better the climatic niche of the species. Those sites would have been lost if we included habitat directly in our models.

2.4. Measuring and mapping uncertainties

We calculated species turnover between current and future modeled distributions in each cell as $(G + L)/(SR + G)$, where “G” was the number of species gained, “L” the number of species lost and “SR” is the current species richness found in each cell (Fig. 1). Then we used the total sum of squares from a two-way Analysis of Variance (ANOVA) without replication (Sokal and Rohlf, 1995) to calculate the uncertainties of each cell following the protocol recently proposed by Diniz-Filho et al. (2009) and Loyola et al. (2012) (Fig. 1). We did the ANOVA using species turnover as our response variable, and modeling methods and AOGCMs as independent factors. Finally we calculated the percent of variation found in each cell relative to the total variation found in all cells. This relative variation was projected into the Cerrado, revealing where there was more uncertainty in our model projections.

2.5. Spatial conservation planning

We used the Zonation framework and software (Moilanen et al., 2005) to rank and select the best sites for conservation investment in the Cerrado aiming at safeguarding all species of non-flying mammals. We also minimized SDM uncertainties and the geographic distance between the centroids of the current and future species distribution induced by climate change and land-use change. We set spatial priorities using the Zonation reverse heuristic algorithm and calculated the marginal loss of a cell (i.e. the relative contribution of the cell to achieve the conservation goal) using the original core-area cell removal rule (Moilanen et al., 2009b for details). The Zonation algorithm generates a nested hierarchical ranking of the region maximizing the highest occurrence level (in our case, the frequency of current and future projections of each species) divided by the cost of the cell (here, the combined uncertainty associated to our ensembles of forecasts) and accounting for species' range complementarity (see Moilanen et al., 2009b).

The algorithm can minimize the distance between current and future species distributions according to its dispersal ability (Rayfield et al., 2009; Carroll et al., 2010). Here we estimated the home range of each species as being proportional to its diet and body weight according to the model proposed by Kelt and Van Vuren (2001). Then, we assumed that the maximum dispersal distance of a species was proportional to its home range according to Bowman et al. (2002) (Fig. 1). We modulated the importance of some sites using a mask layer that forced the inclusion of current established protected areas in the analyses, thus indicating areas that complement the current network of protected areas in the Cerrado. We also forced the exclusion of sites with little vegetation cover in 2050 (i.e. first quartile of the frequency of vegetation cover distribution) to measure the influence of land-use change in the definition of spatial priorities. This also avoids regions with little

conservation value to be selected, threatening the persistence of species (Fahrig, 2001).

We sought for priority sites to reduce the impact of land-use and climate change in the species distribution considering the species dispersal distance and uncertainties arising from SDMs. For this, we created three different conservation-planning scenarios by varying some components of a comprehensive scenario to test the influence of SDM uncertainty and land-use change in our spatial plans. The scenarios were: (1) a conservation plan considering only the costs of SDM uncertainty; (2) a scenario considering only land-use change (using the vegetation mask layer); and (3) a third scenario that took into consideration both SDM uncertainty and land-use changes (a comprehensive scenario). For practical purposes, here we show only the top 17% sites of landscape in all scenarios according to the target defined for terrestrial environment from Aichi Biodiversity Targets to 2020 (Convention on Biological Diversity, 2010).

3. Results

The land-use model classified correctly 83.1% of native or anthropogenic areas predicted in 1990 and projected habitat loss mainly in central and southern regions of the Cerrado in 2050 (Fig. 2). Species distribution models had good predictive accuracies with TSS being always higher than 0.50 – most species (65% on average) with values higher than 0.7 (Fig. A1). Our models predicted that some species would disappear from the Cerrado in 2050 (6.4% in STAT and 8.4% in DIST and ML). Overall, current patterns of average frequency of projection and species richness increased from north to south, with peaks in the southeast (Fig. 3A–C). Species' range shifts induced by climate change intensified these patterns (Fig. 3D–F). Yet, there were differences among sets of SDM, being DIST the most divergent one (Fig. 3A–F). Our habitat filtering approach reduced on average 7.7% and 7.3% current and future occurrences of species, respectively, with variation between SDM set and species' IUCN status (Table A2). Places with low uncertainty (Fig. 3G–I) were concentrated in regions with high frequency of projections in the future (Fig. 3D–F) although with little or no vegetation cover in current time; which will probably lose more vegetation in the future (Fig. 2).

Diversity patterns reflected in our spatial plans. The scenario that considered the costs of SDM uncertainties indicates priorities mainly in the central and southern regions of the Cerrado (Fig. 4A–C), where there are high average proportion of species range projections (Fig. 5A–C) and low uncertainty (Fig. 5D–F). On the other hand, scenarios considering land-use change indicated priorities mainly in the central and northern regions (Fig. 4D–I). Based on current human pressures, these regions would still hold native vegetation in the future, as well as a low average proportion of range projections (Fig. 5A–C), and high uncertainty (Fig. 5D–F). Differences in uncertainty and species projections between scenarios with or without vegetation cover increased from DIST to ML (Fig. 5).

Performance curves measuring the effectiveness of spatial plans that did not take land-use changes into consideration decreased, whereas those solutions accounting for land-use changes had some deviations (Fig. 5). These deviations were caused by the forced exclusion of sites with high frequency of projection (but little vegetation cover in the future), and by the inclusion of sites with low frequency of distribution (some current established reserves) in the top 17% of cells. Therefore at the same proportion of the Cerrado and with the same amount of uncertainty, the scenarios that did not consider land-use changes captured higher average proportion of species distribution (Fig. 5).

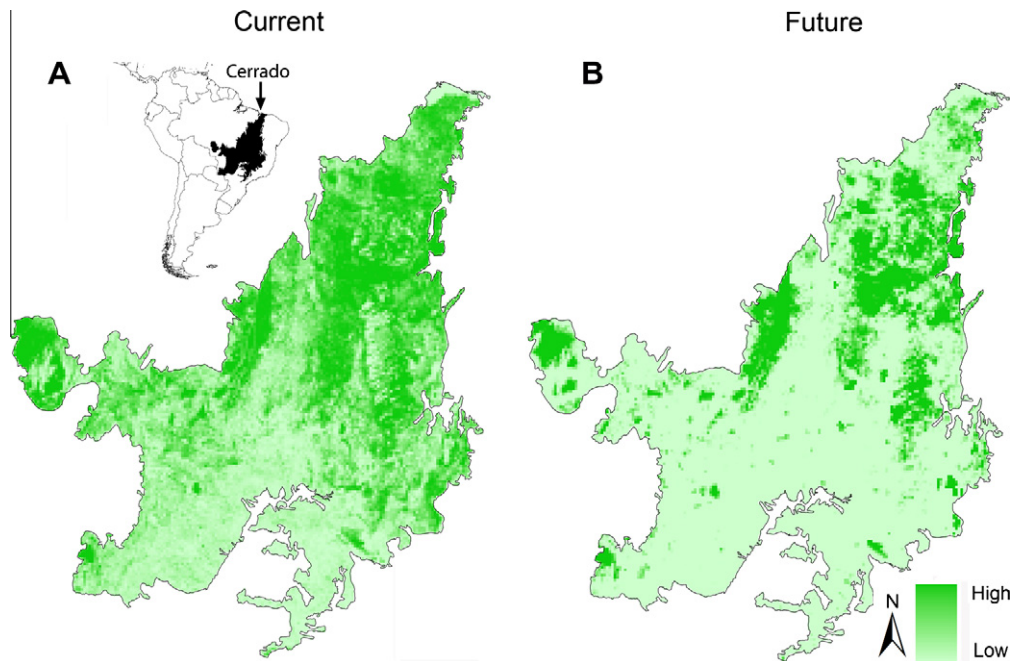


Fig. 2. The Cerrado extent in black, and the proportion of native vegetation for current time (A) and for the future (B), according to our land-use model. Color intensity is proportional to the proportion of native vegetation in the cell. Color legend is not absolute, and do not necessarily represent the same values in both maps. Grid cells have a $0.1^\circ \times 0.1^\circ$ spatial resolution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Scenarios ignoring future land-use projections prioritized sites that are important both now and in the future. However, they did not force the inclusion of protected areas in top priority sites, or the exclusion of sites with low native vegetation in the future (Fig. 4A–C). Therefore, we tested the importance of current protected areas and which are the best sites for conservation investment if current landscape remains unchanged or the implementation of new protected areas occurs before land-use changes in the landscape. Moreover the last view neglects the minimization of future socio-economic conflicts. In contrast, the other scenarios were complementary to current protected areas and would avoid future conflicts between anthropogenic and conservation land-uses (*sensu* Balmford et al., 2001) (Fig. 4D–I). Despite differences among sets of SDM there were 71.22% of average spatial overlap among scenarios (Fig. 4G–I).

4. Discussion

Our analyses suggest methodological and possible spatial solutions to cope with the interaction between land-use change and climate change accounting, at the same time, for the dispersal distance of species and uncertainty of SDMs that can be applied to others regions and taxonomic groups. So far, few studies offered solutions to deal with the synergistic effects of these global changes in conservation planning (but see Araújo, 2009; Possingham et al., 2009).

From an applied perspective, we highlight the importance of conservation scenarios that minimize future conflicts with other competing land uses and the uncertainties of the species distribution modeling process (see Fig. 4G–I). Further, we suggest the ML set of SDMs as the best option because of its best model accuracy (i.e. highest TSS values) in prediction species distributions. Therefore, we suggest that Fig. 4I should be used in negotiations with relevant stakeholders and decision makers. The inclusion of the land use changes in the site-selection exercises is critical to avoid future conflicts between human activities and land protection. However, our scenario that did not considered land-use changes

suggests that the benefits of conservation actions focused on the reduction of habitat conversion can afford better levels of species protection. Spatial priorities in the Cerrado changed at the regional scale (toward north) when land-use changes were included in conservation scenarios, whereas SDM uncertainty had marked differences only at the local scale. Further, considering land-use change end up protecting a smaller average proportion of each species distribution when compared to scenarios that did not consider this effect. This finding indicates a difficult choice between minimizing future conflicts between anthropogenic and conservation land uses or maximizing the proportion of species' range protected.

The Cerrado have been pinpointed as priority by world conservation schemes that meet different criteria (Brooks et al., 2006; Loyola et al., 2009), and conservation planning at the biome scale has been formulated with different scenarios and for different taxonomic groups (see Diniz-Filho et al., 2008 for an example). Our approach has the advantage of incorporating future threats in the choice of priorities. However, the impossibility of validating future predictions of species distribution (Araújo and Guisan, 2006) highlights the importance of accounting for SDM uncertainty in spatial conservation plans. Uncertainty can be minimized if derived from application of the ensemble of forecasting approach and explicitly included in spatial planning analyses. Moreover, the ensemble of forecasts is an important method to avoid problems with false positive and negative in the species distributions, range shifts and range expansion or contraction that can affect the conservation priorities (Araújo and New, 2007). Here, including uncertainties had little impact in the level of species protection, but a considerable change in the spatial location of priority sites.

SDMs usually do not consider the dispersal ability of species, making simple assumptions about dispersal (unlimited or no dispersal) (see García et al., 2012 for a recent example). However the dispersal distance is a species-specific trait with great variation among species being related to home range, diet, and body weight in mammals (Kelt and Van Vuren, 2001; Bowman et al., 2002). This is an important trait determining if a given species can overcome land-use and climate changes by dispersing to future available

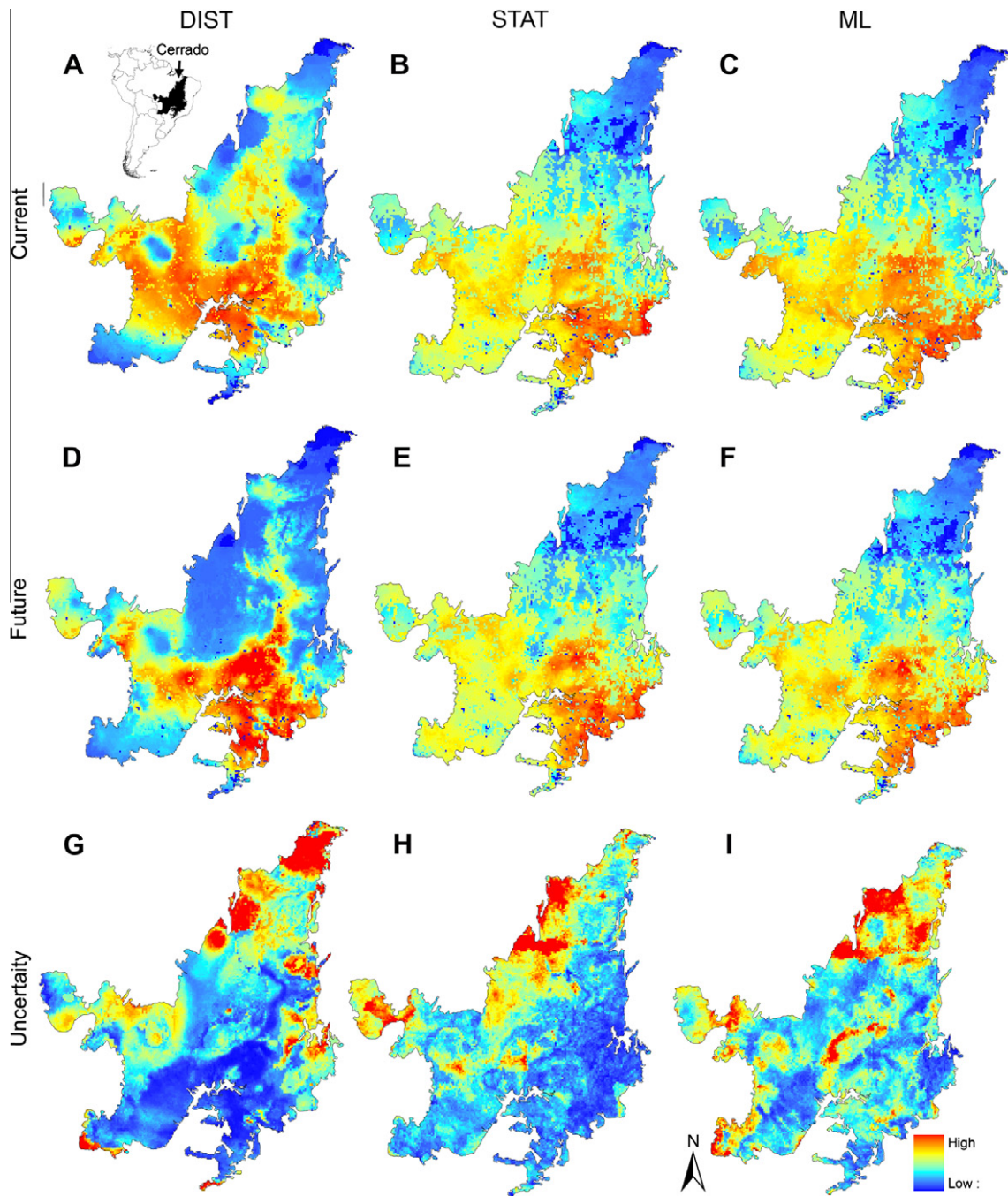


Fig. 3. Average frequency of projections of non-flying mammals in the Cerrado, both for current time (A–C) and for the future (D–F). Color legend is not absolute, and do not necessarily represent the same values in all maps. Grid cells have a $0.1^\circ \times 0.1^\circ$ spatial resolution. In (G–I), the level of uncertainty associated to different modeling methods and climate models (AOGCMs) found in each set of models: the distance set (DIST), the statistical set (STAT), and the machine learning set (ML). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

suitable areas (Parmesan, 2006). As shown here, it is possible to take advantage of this species-specific trait in conservation planning (see also Dawson et al., 2011). Hence, proper conservation plans can adapt species range shift to climate change considering the dispersal abilities of each species (Williams et al., 2005; Phillips et al., 2008; Dawson et al., 2011). Note that the spatial pattern of priority sites showed in our scenarios favored the expansion, formation of corridors and stepping stones among protected areas depending on their spatial location and surrounding matrix. All this will be ultimately a consequence of the tradeoffs among the variables used to build the spatial plan (i.e. species distribution, uncertainty, dispersal distance, land-use change and SDM set).

Although our approach cope with the interaction between land use and climate changes in spatial conservation, our study has its own caveats. First, we used extent of occurrence maps to model the species' distribution and these data overestimate the distribution of species and increase the false positive rate (Rondinini et al., 2006). Therefore, it is likely that the same error will be in our SDM predictions. One way to minimize this is to apply a habitat filtering approach, as we did, to remove unsuitable sites from the distribution of species, reducing the number of false positive projections (Rondinini et al., 2011). We could have used points of occurrence from museums, but the sampling bias (e.g. collected along roads, proximity of cities), purposive sample (sampling based in expert

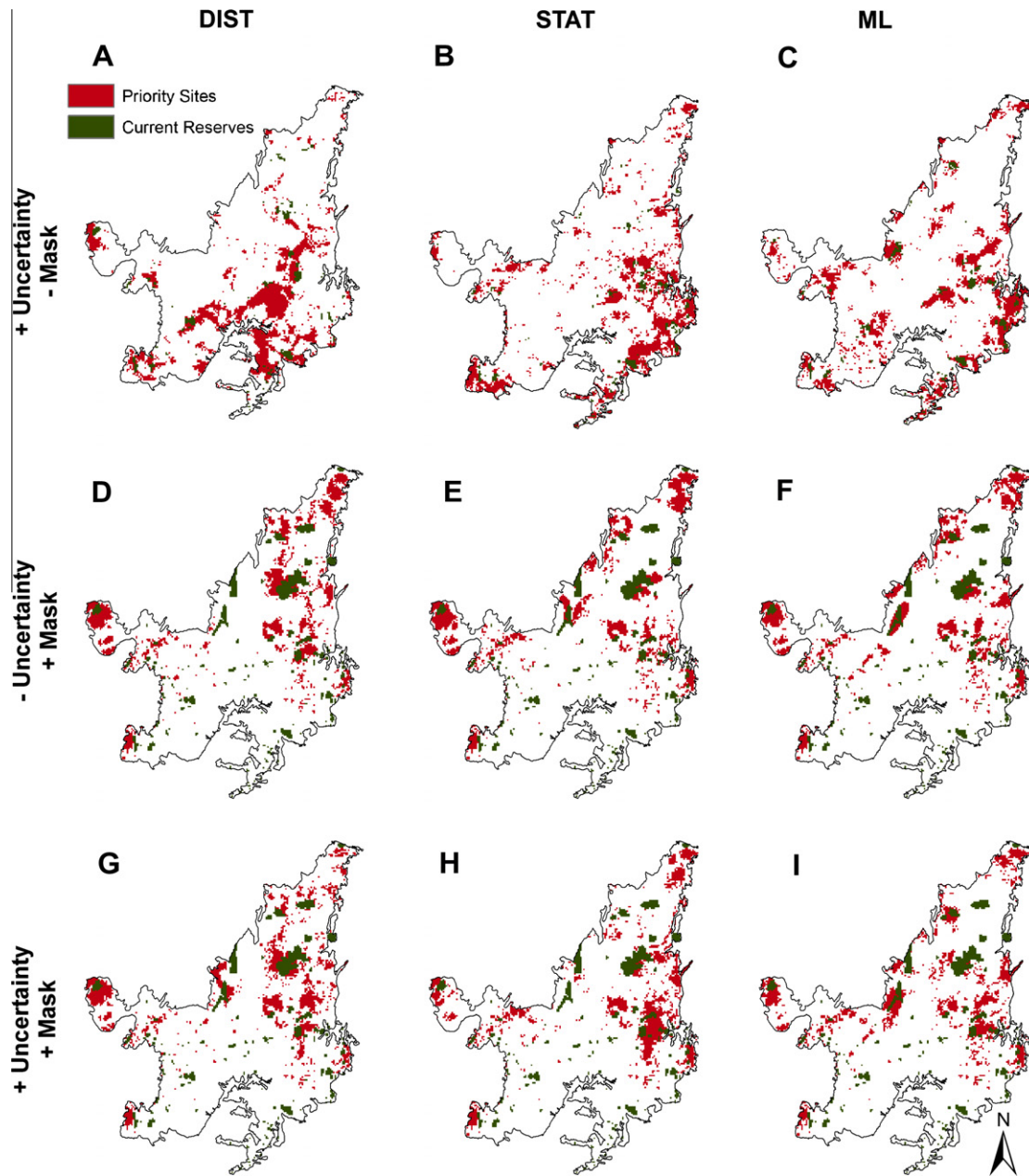


Fig. 4. Spatial distribution of priority sites (red/black) that should be protected to reduce the impacts of land-use and climate change on non-flying mammals of the Cerrado. Color legend is not absolute, and do not necessarily represent the same values in all maps. Grid cells have a $0.1^\circ \times 0.1^\circ$ spatial resolution. (A–C) shows the scenario considering the costs of uncertainties in species distribution models; (D–I) shows the scenario considering land-use changes, but the combined effects of land-use changes and uncertainties were considered only in (G–I). Spatial solutions are separated according to the distance set (DIST), statistical set (STAT) and machine learning set (ML) of species distribution modeling methods. The location of currently established protected areas are shown in green/gray. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

knowledge), and low sample size of these data underestimate real species occurrences, and have serious consequences to model accuracy and interpretability (Rondinini et al., 2006; Loiselle et al., 2008; Franklin, 2009).

Second, we predicted future land use changes assuming that vegetation types and that the Cerrado will remain in the same regions they are currently established, but they can change (Salazar et al., 2007). This assumption can affect our habitat filtering and SDM predictions. Species' range shifts outside current limits of the Cerrado or preferential habitats cannot be measured by our method. Nevertheless, we believe that this assumption will have little effect in our predictions because these changes would be a real problem only for narrow-ranged species that are habitat spe-

cialists, which is not the case of mammals occurring in the Cerrado (Marinho-Filho and Juarez, 2002).

To sum up, we believe our scenarios are a scientific support to the planning and decision-making process regarding the conservation of Cerrado biodiversity. However, it is obviously necessary to account for other socioeconomic and cultural forces and the process of negotiation with all stakeholders to implement on-the-ground conservation actions (Margules and Pressey, 2000; Ferrier and Wintle, 2009). Equally the coordination of global efforts is necessary considering that the climatic changes are global, although better solutions would be found across the national borders. Finally, our spatial plans have the important function to avoid current and future extinctions by human impacts, but others actions like

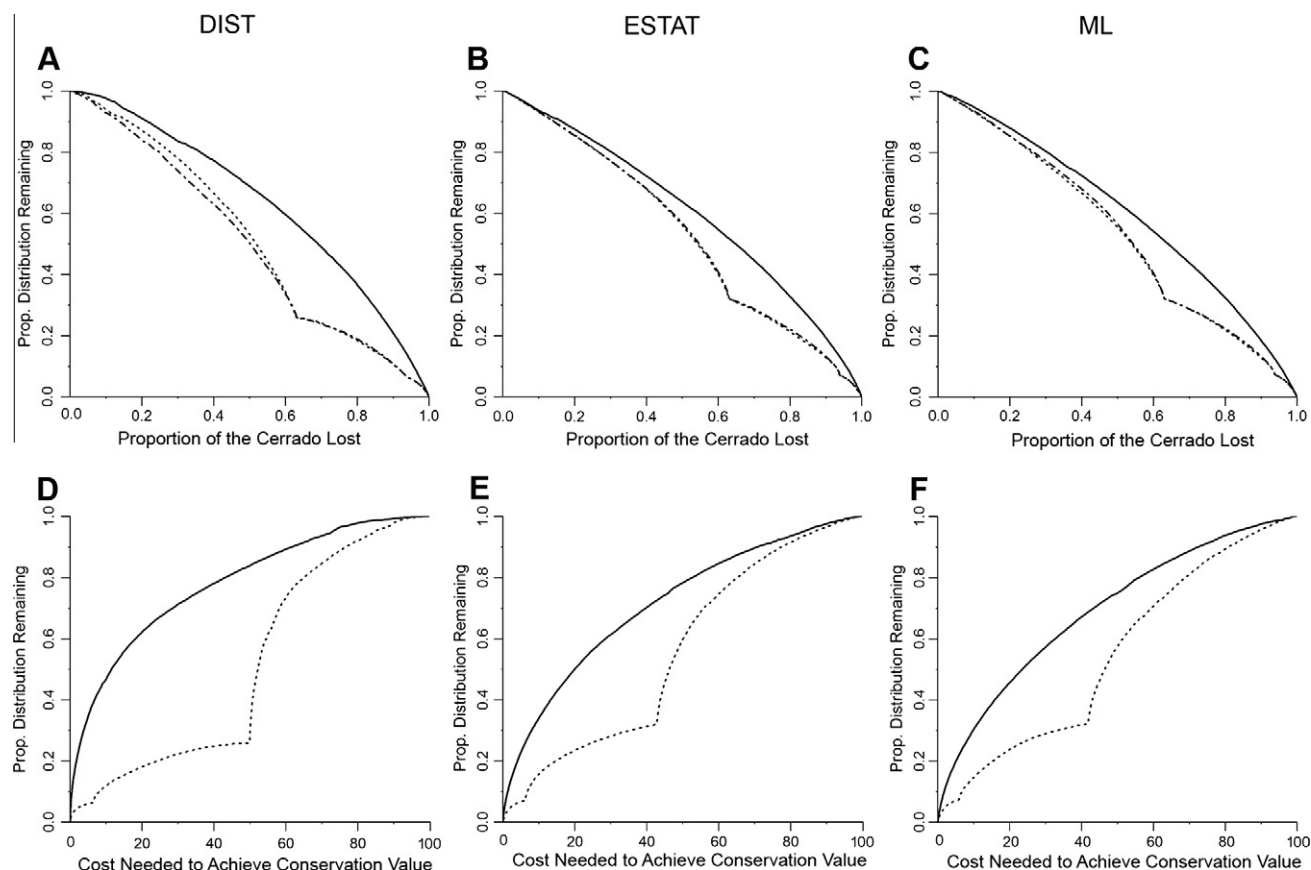


Fig. 5. Performance curves for our different conservation scenarios. (A–C) Graphs show the proportion of the Cerrado lost and their correspondent average proportion of species distribution remaining (frequency of projections). (D–F) Graphs show the costs of considering uncertainty in conservation planning and their correspondent average proportion of distribution remaining. The full line stands for the scenario considering the costs of uncertainty; dot-dash line stands for the scenario considering land-use changes; and the dotted line represents the a comprehensive scenario considering both uncertainties and land-use changes. Results are shown for the distance set (DIST), statistical set (STAT) and the machine learning set (ML) of species distribution modeling methods.

landscape management, assisted migration, population management (Dawson et al., 2011; Redford et al., 2011) should also be considered to achieve effective conservation in this region.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.biocon.2012.09.020>.

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