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# Spatial priorities for agricultural development in the Brazilian Cerrado: may economy and conservation coexist?

Larissa Lemes<sup>1,4</sup> · André Felipe Alves de Andrade<sup>1</sup> · Rafael Loyola<sup>2,3</sup>

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# Abstract

The ever-increasing requirement of land for food production causes habitat loss and biodiversity decline. Human activities like agriculture are responsible for increases in global temperature, which may preclude species' survival if they cannot adapt to new climatic conditions or track suitable ones. Although negative impacts of climate change may act in synergy with agriculture when dispersion routes are blocked by croplands, agriculture is important to local economies. Therefore, the demand for land conversion causes conflict among stakeholders and decision makers. But can we benefit both economy and environment? Here we propose an approach to help find a balance between agriculture expansion and biodiversity conservation. We used suitable areas for agriculture to identify priority places to implement monocultures. We modeled species distributions to avoid sites with high conservation value and used species dispersal ability to minimize the distance between present-day and future suitable areas for species persistence. We used a decision-support tool to find a balance between economic development and species conservation, and we conclude that land use conversion is a threat for species persistence given that negative impacts caused by crops could be exacerbated by climate change. Unguided agriculture expansion into future species distribution areas is possible due to severe decreases in the areas for species to persist in the future. Facing this scenario, applying ecological knowledge to guide agriculture expansion is urgent if we want to spare species future distribution area in the Cerrado.

Keywords Agriculture  $\cdot$  Brazil  $\cdot$  Conservation policy  $\cdot$  Mammals  $\cdot$  Spatial conservation planning  $\cdot$  Tropical savanna

Larissa Lemes larissapereiralemes@gmail.com

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# Introduction

The ever-increasing trend in human population growth imposes great demands on land use for agriculture (Polasky et al. 2008; FAO 2010; Li et al. 2015). Nearly 13 million hectares of forest are converted into croplands every year (FAO 2010), negatively impacting the environment through habitat degradation and fragmentation and, consequently, biodiversity loss (FAO 2010; Jackson and Fahrig 2013). Intensifying the threats biodiversity have been suffering due to habitat degradation and fragmentation, agriculture does also aggravate another threat for species: climate change. The deforestation that precedes agriculture implementation leads to emission of high levels of carbon dioxide to the atmosphere, which is linked to rising global temperatures (Pereira et al. 2010).

As temperature increases, suitable areas for species survivalchange in space (Chen et al. 2011; Hannah et al. 2013; Lemoine 2015) and may expose them to climatic conditions that are beyond their fundamental niche (Jezkova and Wiens 2016). If species phenotypic plasticity is not sufficient to smooth the effects of these new climatic conditions, they will only persist through time if they adapt to new environmental conditions (Charmantier et al. 2008; Bell and Gonzalez 2009; Bellard et al. 2012) or are capable to disperse and track new suitable areas (Schloss et al. 2012). Further, the effects of land-use and climate change are synergistic, given that changes in landscape structure and composition may preclude species dispersal to future suitable areas (Asner et al. 2010; Mantyka-pringle et al. 2012). Moreover, species are predicted to have a small proportion of their distribution protected in the future if agriculture continues to expand (see Pereira et al. 2010; Dobrovolski et al. 2011a, b, for global analysis and Strassburg et al. 2017 for a Cerrado study case). Therefore, there is an urgent need to identify species future suitable areas, include them in spatial conservation planning and protect them against land use change (Hannah et al. 2007; Faleiro et al. 2013; Vieira et al. 2018).

Despite the threats that agriculture impose to biodiversity, this activity is important for economic purposes. This duality based on negative and positive impacts of agriculture gave rise to a trade-off between agricultural development and species conservation (Srivastava and Alderman 1993; Dobrovolski et al. 2014). That trade-off causes conflict among stakeholders, making it difficult to choose between economic development and environmental conservation. Conflicts caused by the economy-conservation trade-off are intense in Brazil due to the importance of agriculture to national economy (Dobrovolski et al. 2011b; Faleiro et al. 2013). Agriculture is the most important activity in the Brazilian economy, corresponding to 27% of the national gross domestic product (GDP) and 37% of the employed population (Buainain and Garcia 2015). Also, the emergence of agribusiness contributed to a scenario of external investments in the country (Buainain and Garcia 2015). With these strong investments, agriculture is mostly expanding in a central Brazilian biome, known as Cerrado (Brazilian tropical woodland savanna). Due to soil attributes and topography, the Brazilian Cerrado is under implementation of intensive agricultural mechanization (Buol 2009). However, despite the importance of agriculture to national economic development, cropland expansion has threatened species conservation. Agribusiness has already converted half of native vegetation into anthropogenic land uses in the Cerrado (MMA 2015). In the last years, threats to Cerrado's biodiversity increased due to the expansion of agriculture toward northern and most preserved region of the biome, known as MATOPIBA (Salvador and de Brito 2018).

The Cerrado is important for both biodiversity and national economy in Brazil. Hence, disagreement between decision makers is unavoidable and scientific knowledge is essential to bring a balance for both economic development and environmental conservation. Notwithstanding, is there a way to benefit economy with simultaneous protection of species? Some systematic conservation plans were built aiming to avoid sites of social and economic value in an attempt to promote agreement between stakeholders (Sala et al. 2000; Faleiro et al. 2013; Devillers et al. 2015). This technique has the advantage of promoting the understanding and agreement between stakeholders, but fails to avoid the loss of areas with high conservation value to land use changes and facilitates the creation of residual areas for conservation (see Devillers et al. 2015).

Here, we propose a new approach based on systematic conservation planning to help find a balance between agriculture expansion and biodiversity conservation in the Cerrado. We use spatial prioritization methods to balance between agriculture and conservation importance of the sites along the biome, and identify productive, but least ecologically valuable areas to direct future agriculture expansion. The aims of our study are: (1) to model and infer if species may persist simultaneously with agriculture expansion and a changing climate; (2) to verify if the application of spatial planning tools for economic purposes can spare biodiversity from agriculture; and (3) to prioritize high conservation value land in the Cerrado from land use change with the purpose of guaranteeing species' persistence in the face of climate and land use changes.

To accomplish our aims, we used both present-day and future suitable areas for the implementation of soybean and sugarcane plantation, which are the two most important crops in the Brazilian savanna and predicted to have the most significant area in the future (Brasil 2018). We used this data to identify potential areas for economic development in the region. Further, we modeled species distributions and measured and mapped model uncertainties to identify the most valuable areas for conservation that should be avoided while targeting economic development. We also calculated species dispersal capacity to minimize the distance between species present-day and future suitable areas. The information about local suitability for agriculture implementation, local suitability for species persistence and species dispersal capacity was used as input data on a software for spatial prioritization. Further, we used a future scenario of agriculture expansion based on present-day expansion trends to compare with our expansion scenario based on spatial prioritization and verify if the gains in environmental conservation are factual. Details are explained below.

#### The case study

We used non-flying mammals and the Brazilian Cerrado as our case study. We used these species as surrogate for biodiversity because the amount of data available for this group enables us to calculate dispersal capability and build robust distribution maps. The Cerrado has heterogeneous and complex vegetation, including savanna, grassland and forest, and a highly threatened biodiversity (Klink and Machado 2005). Only 3.2% of the Cerrado's area is under strict protection (Françoso et al. 2015). Hence, species survival depends not only on the few existing protected areas, but mostly on the suitable areas currently maintained in private lands. This is problematic because large species' range shifts induced by climate change and high rates of habitat loss may impede species dispersion to new suitable areas (Diniz-Filho et al. 2009; Loyola et al. 2012).

# Materials and methods

### Species distribution models

#### Occurrence data

We updated previous lists of non-flying mammals occurring in the Cerrado (species sources are listed in Table S1) and obtained occurrence records for 183 species from two online databases: SpeciesLink (splink.cria.org.br/) and GBIF (www.gbif.org/occur rence). We conducted additional search on species records at the literature, but the records coming from individual researches overlaid the records from online databases. *Mus musculus* and *Rattus rattus* were excluded from our analysis because these species are not targets for conservation. We checked species occurrence records based on species extents of occurrences maps made available by the International Union for Conservation of Nature (IUCN; available at www.iucnredlist.org/) to avoid typing errors concerning latitude and longitude, and used only geo-referenced records. We only produced species distribution models (SDM) of species with five or more records after removing duplicated records (see Bean et al. 2012 for more details), resulting in 122 SDMs.

#### Environmental variables, extent definition and future scenarios

To model species distributions, we obtained current bioclimatic variables from the WorldClim database at a resolution of 2.5 arc minutes (Hijmans et al. 2005), which are related to temperature and precipitation mean, minimum, maximum and fluctuation. We also obtained two topographic variables (terrain elevation and slope) from EarthEnv database at the same resolution (Amatulli et al. 2018).

To deal with collinearity issues that are present in environmental variables and reduce the dimensionality of our models (Silva et al. 2014), we ran a principal component analysis (PCA) on the coupled WorldClim and EarthEnv variables. We selected seven principal components (PCs), which explained up to 95.94% of the total variance from the original variables, and used the scores as predictors. We used the same linear relation between PCs and environmental variables in the present to create the PCs for the future scenarios.

We used the same bioclimatic variables for the year 2030 according to four Atmosphere–Ocean General Circulation Models (AOGCMs: CSIRO-MK3.6, GISS-E2-R, MIROC-5, HADGEM2-AO) of the Representative Concentration Pathways 8.5 (RCP8.5) emission scenario, downloaded from WorldClim (http://www.worldclim.org/cmip5\_5m; Fig. 1). Representative Concentration Pathways are scenarios for greenhouse gas concentrations at the end of the century and are estimated based mostly on scenarios of population and economic growth, and targets for climate mitigation (Riahi et al. 2011). The main consequence of a growing population and a growing economy is the loss and degradation of native habitats (Lambin and Meyfroidt 2011). In many RCPs, the emission of greenhouse gases peaks several decades after the loss of native vegetation, and decreases on the emission of greenhouse gases on these scenarios are gradual (Intergovernmental Panel on Climate Change 2000). We selected RCP8.5 based on our tendency to expand agribusiness, what will cause the loss of land cover and a delay on peaks of greenhouse gases emission. Future topographic variables were the same ones used for the current period models.



**Fig. 1** A schematic representation of the methods used to identify priority areas for agricultural development. We modeled species distributions (SDMs) based on seven algorithms and projected them into the future (2030) based on four Atmosphere–Ocean General Circulation Models (AOGCMs) to obtain current and future distribution maps of each species. We quantified the uncertainty associated to AOGCMs for each site and modeled the maximum dispersal distance as proportional to the diet and body weight of species. We also used the International Union for the Conservation of Nature (IUCN) categories and endemism to attribute weights for each species. Finally, we used the distributions maps, the dispersal distance, model uncertainty, species weight, agricultural suitability data and the current network of protected areas to generate present-day and future spatial economic plan and quantify ongoing and future threats for species

SDM projections are sensible to the area defined as background or available for pseudoabsence allocation (Barve et al. 2011; Acevedo et al. 2017). In theory, this area must be representative of all areas a species had access during its evolutionary time (Soberón and Peterson 2005); however, this is not an easy task. Nevertheless, carefully delimiting this area is a crucial step for any SDM. We grounded our choice on the ecoregions (WWF's Terrestrial Ecoregions of the World; Olson et al. 2001) in which a species is known to occur, and selected those ecoregions as the accessible area for a species.

#### Modelling procedures and ensemble models

We built SDMs using seven algorithms: Maximum Entropy (MaxEnt; Phillips et al. 2006), Support Vector Machine (SVM; Cortes and Vapnik 1995), Generalized Linear Model (GLM; Guisan et al. 2002), Generalized Additive Model (GAM; Hastie and Tibshirani 1986), Random Forest (RDF; Breiman 2001), Maximum Likelihood (MLK; Royle et al. 2012) and Gaussian (GAU; Golding and Purse 2016). These algorithms were chosen to represent a variety of modelling strategies and, as such, require different input data. Our algorithms encompass methods that require presence/pseudo-absence and presence/background data. Therefore, we had to create both pseudo-absence and background data.

For pseudo-absence data, we generated the same number of pseudo-absences as the number of presences for each species. The allocation of those points was random but with and environmental profiling (RSEP; Iturbide et al. 2015) and restricted to the species' accessible area (defined as stated above; VanDerWal et al. 2009; Anderson and Raza 2010).

This strategy is used to avoid pseudo-absence allocation in locations in which a species is not recorded but has a high likelihood of occupying (Jiménez-Valverde et al. 2008; Wisz and Guisan 2009; Lobo et al. 2010). For background data, we randomly selected 10,000 points along the ecoregion.

As different algorithms may have different performance with different modelling conditions and are, therefore, one of the major sources of variation in models' results, we created ensemble models to reduce the uncertainty in our predictions (Diniz-Filho et al. 2009; Zhu and Peterson 2017). We created species ensemble by selecting those algorithms with a value of TSS greater than or equal the arithmetic average of the TSS of all algorithms. Models' development and data analysis were done in the R software v. 3.5.1. (The R Core Development Team 2008), we used the packages stats v. 3.4.1, *maxnet* (Phillips 2017), *dismo v. 1.1-4* (Hijmans et al. 2017), *randomForest v. 4.6-12* (Liaw and Wiener 2002), *kernlab v. 0.9-25* (Karatzoglou et al. 2004), *maxlike* (Royle et al. 2012), and *GRaF v.0.1-12* (Golding 2014) to fit GLM, GAM, MXS, RDF,SVM, MLK and GAU models, respectively. For pseudo-absence creation and models' predictions, we also used the *dismo* package. The whole modelling routine was performed using the *ENM\_TheMetaLand* package (available at: https://github.com/andrefaa/ENM\_TheMetaLand).

#### Model evaluation and data partition

Ideal SDM evaluation involves using an independent dataset, which is rarely possible. Therefore, the most common way for model evaluation goes through data partition and cross-validation (Roberts et al. 2017). While the most common way to partition the data is by randomly allocating occurrences to training or testing subsets, there are serious issues with the autocorrelation of those subsets (Muscarella et al. 2014; Roberts et al. 2017; Val-avi et al. 2018). To minimize these issues, when a species had enough data (>15 occurrence points) we geographically split subsets similar to the checkerboard partition in Muscarella et al. (2014). In this method, both subsets are used for fitting and evaluating the models and the final result is an average of both. For species with less than 15 occurrence points, we resorted to random split to create training-test subsets. We randomly partitioned the data into 75% for fitting (the training subset) and 25% for validation (the testing subset) and repeated this process 10 times. Again, the final result is an average, but this time of the 10 replicates.

We used True Skill Statistics (TSS) and the Boyce index to measure model accuracy. Both metric values range from -1 to +1, where a value equal to +1 indicates perfect model performance, minimum over-prediction and omission error rates, and values equal to zero or less indicate predictions no better than random (Boyce et al. 2002; Hirzel et al. 2006; Allouche et al. 2006). We only used the distribution models for species with TSS value equal or higher than 0.4 (see Allouche et al. 2006 for more details), resulting in 109 models. As TSS is a threshold-dependent metric, we used the maximum sensitivity and specificity values as threshold to convert the continuous predictions of suitability into presence/absence maps (Liu et al. 2013). In spite of being one of the most commonly used metrics for SDMs, there are intrinsic issues related to the effect of species prevalence and TSS values (Leroy et al. 2018). Therefore, we also calculated the independent-threshold Boyce index as evaluation metric. This metric is less sensitive to the effects of species prevalence and, is, therefore, more robust to variations in species range (Boyce et al. 2002; Hirzel et al. 2006; Leroy et al. 2018). After species distributions were modeled and projected into the future, we calculated, for each species, the standard deviation among suitability values arising from models that used different AOGCMs as input. We used this measure as the uncertainty related to the occurrence of species in a given grid cell (Fig. 1). Standard deviation values were projected onto the grid covering the Cerrado, revealing areas with higher/lower model uncertainty. This procedure allowed us to avoid areas with high uncertainty during the spatial prioritization process.

#### Suitable areas for agriculture

We used the global data for land suitability to agriculture modeled by Zabel et al. (2014). These authors estimated the suitability of the sixteen most important crops to global economy, biofuel issues and food security. Data on temperature, precipitation, proximity to rivers, soil features (pH, organic carbon, sodicity and salinity), topography and forested areas were used to identify the most suitable areas to implement agriculture (see Zabel et al. 2014 for more details). From their models, we used only the most import crops for agribusiness in the Cerrado: soybean and sugarcane. We used crop suitability data from Zabel et al. (2014) on its original resolution (30 arc seconds or  $0.008 \times 0.008$  degrees of latitude/longitude or approximately nine hundred meters at the Equator line) and cropped to the Cerrado's extent.

#### Spatial conservation planning

We used Zonation (version 4.0; Lehtomäki and Moilanen 2013), a decision-support software to prioritize areas for agricultural expansion in the Cerrado, also aiming to safeguard the persistence through time of non-flying mammal species (Fig. 1). To achieve this purpose, we used suitable areas for agriculture development together with suitable areas for mammal species occurring in Cerrado's area, estimated by species distribution models. From 183 species included in the list of non-flying mammals of the Cerrado, 59 species were excluded from the study due to lack of records, two species were excluded due to lack of records in the Cerrado (*Philander frenatus* and *Sphiggurusspinosus*), two other species were excluded due to lack of conservation purpose, and 12 species were excluded due to low model accuracy. After all filtering process, we included 108 mammal species in final the prioritization analyses (Table S1 shows information about species status, included or excluded, in the analyses for each one of the 183 species and exclusion criteria). We cropped species distributions data to the Cerrado extent and downscaled them from their original resolution of 2.5 arc minutes to the resolution of the crop suitability data (Fig. 1).

Zonation compares each cell in our grid with all other cells to calculate the loss in conservation value if that cell was converted into agricultural land. The result of this process is that each cell in our grid will have a conservation value (the contribution of the area to maintain biodiversity) following a rank of importance (Lehtomäki and Moilanen 2013). We used the additive benefit function as our method to calculate the marginal loss of a cell (see details in Lehtomäki and Moilanen 2013). We built our conservation planning analyses using the existent protected areas in the Cerrado as a mask layer to modulate the importance of those sites, so the results of our analyses necessarily indicate the complementary areas for the current network of protected areas (Faleiro et al. 2013).

Kelt and Van Vuren (2001) proposed a model to estimate species' home ranges based on information about species diet and body mass. Further, Bowman et al. (2002) described a new model to estimate species maximum dispersal distance assuming proportionality between species' home range and their dispersal capability. Owing to the development of these two models for species' home range and dispersal capability estimation, spatial conservation plans could be improved through the implementation of species dispersal information. Spatial priorities for species conservation could be selected aiming to enable species movement between areas with conservation purposes. We used species maximum dispersal distance previously estimated by Faleiro et al. (2013), which encompassed 106 species of our species pool. We obtained the home range of *Dasyprocta prymolopha* and *Herpailurus yagouaroundi* from the literature (Jorge 2005; Giordano 2016, respectively), and estimated their maximum dispersal distance using the model described by Bowman et al. (2002). We used species dispersal capability (maximum dispersal distance) to minimize the distance between their present-day and future distributions.

We used the classification of species extinction risk by the International Union for Conservation of Nature (IUCN) and information about endemism level to attribute weights to species, so we could attribute higher conservation value to cells with more threatened and endemic species. We attributed weights as follows: Least Concern (LC) and Near Threatened (NT) species equal to 1, Vulnerable (VU) and Data Deficient (DD) equal to 1.25, Endangered (EN) equal to 1.5, Critically Endangered (CR) equal to 2 (see Loyola et al. 2012), Non-endemic species equal to 1, and Endemic species equal to 2 (Fig. 1). We also attributed an initial weight to all species, reflecting their value regardless of endemism or vulnerability. This initial weight was calculated as one (or one hundred percent: the importance value summed for all species) divided by the number of species in the analysis (108). Species weight regardless of endemism or vulnerability was set as 0.009 for all species. We multiplied species weight due to vulnerability, species weight due to endemism and species initial weight to estimate species final weight. This final weight influences the priority ranking of the landscape, in which areas containing several non-threatened and non-endemic species are located at lower position in the priority rank, while areas containing threatened and endemic species have higher priority for conservation (Moilanen et al. 2014).

We also linked species final weights to their uncertainty information, so we could reduce the conservation value of a cell when it contained threatened and endemic species, but the uncertainty related to their presence was high. We conducted the prioritization for the present-day and 2030 periods considering a scenario of 30% of agriculture expansion in the Cerrado, according to projections of the Brazilian Ministry of Agriculture, Livestock and Food Supply (MAPA; Brasil 2018).

#### Testing the need to guide agriculture

To verify if the application of spatial planning tools for economic purposes can spare biodiversity from agriculture, we estimated the loss of species distribution areas due to unguided agriculture and compared to the loss in species distribution areas when agriculture expansion is guided by spatial planning tools, such as Zonation. We obtained data about Brazilian land use in 2030 (Soares-Filho et al. 2016; available at maps.csr.ufmg.br/) and cropped the data into Cerrado's extent. Brazilian land use in the future was estimated for several different crops. Notwithstanding, we considered only soybean and sugarcane area occupied in 2030 (what represents an expansion of 10% into Cerrado's area).

We used Soares-Filho et al. (2016) future expansion of soybean and sugarcane as our scenario of future unguided agriculture. Further, we calculated total distribution area for

each species in the future and the loss in distribution area for unguided scenario. We also estimated the loss in future species distribution areas when agriculture is guided by Zonation in a scenario of 10 percent of agriculture expansion. Finally, we did an analysis to verify if the loss of area on a guided expansion scenario is lower than the loss of area on an unguided expansion scenario.

# Results

In general, SDMs had high values of TSS ( $TSS \pm SD = 0.78 \pm 0.13$ ) and Boyce index (Boyce  $\pm SD = 0.76 \pm 0.14$ ), indicating good predictive accuracies (TSS and Boyce values for each species is available at Table S2).Twelve SDMs presented low accuracy and were discarded, resulting in 108 final SDMs to be used in our prioritization analysis. Further, we used these 108 SDMs to make projections for 2030.

A total of 102 species (94% out of 108 species) were predicted to have a smaller distribution area in the future due to climate change, while only six species would have larger distributions (Fig. 2). Table S3 shows the information about which species would have their distributions increased or decreased and the remaining area in km<sup>2</sup> in 2030. Through species-specific representation loss curves estimated by Zonation, we predicted a gain of more than 60% of the suitable areas for soybean and sugarcane with a conversion of 30% of the Cerrado's area into croplands in both periods, and still, we can represent more than 70% of all species distributions in both present-day and future periods (Fig. 3; Table 1). Species would maintain about 34% of their present-day suitable areasin the future if we



**Fig. 2** Number of species that gained or lost distribution area in the future due to climate change (2030). The majority of species lost distribution area, but some species had their area increased by climate change. Therefore, the x-axis ranges from negative values (species losing distribution area—in percentage) to positive values (species acquiring distribution area—in percentage)



**Fig. 3** Performance curves for the prioritization of agriculture for the present-day (**a**) and 2030 periods (**b**). Graphs show the gain of suitable areas for soybean and sugarcane according to the conversion of landscape, and the species distribution remaining, separated by mammal order according to the loss (conversion) of habitat

Table 1 Amount of the suitable area converted to soybean and sugarcane in both present-day and future periods, and the remnant mammal distribution area if the land is converted	Period	Soy (%)	Sugarcane (%)	Species distribu- tion remaining (%)
	Present-day 2030	73 73	61 62	70 34
	-			

Mammal distribution area at present-day is the percentage of area remaining from present-day distribution area after agriculture expands in present-day period. Mammal distribution area at 2030 is the percentage of area remaining from present-day distribution area after the climate changes and agriculture expands

account for the areas lost due to climate change and the areas lost to land-use conversion (Tables 1 and S3).

In a scenario of 10% of agriculture expansion, species can retain about four percent more of their distribution areas when agriculture is guided by spatial planning tools compared to an unguided scenario (P < 0.01; t = 4.03; df = 102). Present-day and future priority areas for agriculture in the Cerrado are concentrated in the center, extreme north and south-west of the biome, leading to an overlap of 28.6% between the present-day and 2030 priority areas (Fig. 4). Areas harboring the largest number of non-flying mammals in the Cerrado are in the south, south-east and center of the biome (Fig. 5).

# Discussion

Science-informed policies for agriculture expansion can alleviate the conflicts between agriculture and biodiversity conservation (Kennedy et al. 2016; Strassburg et al. 2017; Vieira et al. 2018). Our results show that it would be possible to use a great portion of all suitable area for soy and sugarcane production and still protect a great portion of non-flying mammal distribution area in the Cerrado if land-use conversion was the unique anthropic impact. Given the large overlap among priority areas for agricultural



**Fig. 4** Priority areas for agricultural development for current (**a**) and 2030 (**b**) periods, and the overlap area between these periods (**c**). Owing to the congruence between priority areas in present-day and future periods, most of Cerrado's area (almost 70 percent) will be agriculture-free in the future



**Fig. 5** Spatial pattern of non-flying mammal species richness for current (**a**) and future (**b**) climates in the Cerrado. Species richness of non-flying mammals in the Cerrado was calculated through binary maps estimated by ensembling species distribution models

expansion for present-day and future time periods, it would be feasible to conserve a great portion of species distributions in the biome even in the future. Further, our approach based on crop suitability and not on present-day opportunity costs indicated not only a great portion of Cerrado's area for food production, but the areas where farmers would need to spend less in cropping. The natural suitability of those areas decreases the need for complex irrigation systems and soil improvement techniques, such as the use of fertilizers, manure and liming (Mcsorley and Gallaher 1996; Meng et al. 2005; Manna et al. 2007; Brar et al. 2015), ground leveling or the acquisition of more expensive machines for cropping in uneven terrain. Opportunity costs could also be minimized given that our analyses bypass the capability to improve soil quality, which increases with technological development (Tester and Langridge 2010).

Identifying priority areas to agriculture implementation is also important owing to the economic opportunities those areas offer. For instance, the areas used to crop soybean are also used to crop other cultures during the soybean inter-crop period (FAO 2010). Cornis one of the most inter-crop cultures in the country and its production is projected to increase by 26.3% until 2025, but with only 2.9% of additional area (FAO 2010). That rise in corn production without wide land extension is possible due to the release of soybean plantation land to corn production during the inter-crop period. It allows a greater income for farmers and growth opportunity for Brazilian GDP. The prioritization of suitable areas for agricultural development based on types of monocultures does also provide economic development through other types of monocultures.

Notwithstanding, agriculture does also intensify the impacts of climate change. As we observed, climate change will promote loss of suitable areas for many species (102 out of 108 species), and it seems to be a consistent pattern reported in the literature (Maiorano et al. 2011; Langham et al. 2015; Brown and Yoder 2015). A total of 37 species will lose more than 70% of their suitable areas in the future only because of the changes in climate. In a study made by Thomas and Williamson (2012) on species extinction risk from climate change, these authors concluded that most species losing more than 70% of its suitable area will be extinct in the next years after 2050 due to the near-linear change in temperature. We found that even when species do not lose a large amount of area, many of them are threatened in the future because their area in the present is already small, leading to an also small suitable area in the future. If this pattern holds, based on our results and Thomas and Williamson's (2012), we can assume that about half of the non-flying mammals of the Cerrado are under high risk of being extinct in the future (see similar results for plants and other animal groups in Strassburg et al. 2017; Vieira et al. 2018, respectively).

We could spare about 70% of species distribution areas in both current and future periods if we guide agriculture expansion. However, 37 species will lose more than 70% of their present-day distribution area in the future due to a changing climate only (Table 2). Hence, to preserve 70% of species distribution area may not be an optimistic scenario for conservation because species future distribution area may be severely lost. Therefore, land-use or climate change impacts must not be seen separately owing to their complex interaction (García-Valdés et al. 2015; Mantyka-Pringle et al. 2015). If we consider the amount of area lost by species due to both climate change and agriculture expansion, a total of 62 species will have lost more than 70% of their distribution area (Table 2). The losses in species distribution area

Table 2 Number of species   inside each category of habitat loss owing to climate change   only and owing to agriculture expansion in a changing climate   scenario scenario	Category	Climate change	Climate change and agriculture
	>90	4	5
	70–90	33	62
	50-70	38	21
	30-50	10	13
	< 30	23	7

Number of species with severe loss in their distribution area (more than 70 percent) increases drastically if climate change and agriculture impacts are analyzed together

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are severe, but unguided agriculture will promote an even bigger loss. If agriculture expands based only on expansion trends, the loss in species distribution areas will be about four percent higher in a scenario of 10 percent of agriculture expansion into Cerrado's area. We argue that increasing agriculture expansion will promote a bigger difference between the areas preserved on a guided agriculture expansion scenario and unguided agriculture expansion scenario. Therefore, facing drastic decreases in species distribution areas due to climate change, the differences in distribution area loss due to guided and unguided agriculture expansion are meaningful.

Further, to look only for the decrease in species suitable area, due to agriculture expansion or habitat contraction, does not show the real threat species may face in the future. We must look at the extent of species future suitable area. Many species that we analyzed will occur in a very small portion of the Cerrado in the future (Table S3), and even a little loss of this area must affect species survival, emphasizing the threats to species. If we look at the remaining suitable area in square kilometers for each species (Table S3), we will see that for many of them, even the lowest expansion scenario for agricultural development negatively affect species persistence through time. Moreover, these negative impacts of agriculture expansion into small area species may be more intense when agriculture is not guided by scientific knowledge. Unguided agriculture can easily expand into entire species distribution areas in the future if these areas are small ones. Once more, to guide agriculture expansion in the Cerrado proves to be an urgent need.

Areas harboring higher species richness are concentrated on the southern portion of the biome (Fig. 5). However, such a species richness pattern is partially explained by bias on the records as mammal occurrences are spatially aggregated near major research centers or near existing protected areas. This bias leads to consequences in our priority areas for agriculture: they are pushed to central and northern areas of the biome. Nevertheless, as previously exposed, the northern areas of the Cerrado are extremely important for biodiversity conservation.

Cerrado's northern areas are known as MATOPIBA (an area composed by part of the states of MAranhão, TOcantins, Plauí and BAhia). MATOPIBA is the region with the largest area of native vegetation preserved and is the place for the most recent discoveries of new species (i.e., for lizards: Rodrigues et al. 2007; Teixeira et al. 2013; for rodents: Bonvicino et al. 2003; Gonçalvez et al. 2003; for fishes: Costa 2017).MATOPIBA is rapidly being occupied by agriculture due to the land low prices and is already known as the new Brazilian agricultural frontier. The deforestation rate in MATOPIBA increased 61.6% in the last years (MMA 2015) and is predicted to increase in the next years, since the Cerrado will undergo the majority of soybean expansion in the next decade (Strassburg et al. 2017). Although our prioritization analysis for agriculture development selected huge portions of central and northern areas of the biome, we emphasize that direct conservation efforts (such as the creation of areas destined for conservation) must advance in such areas. Further, some places with high predicted species richness (south and southwest Cerrado) are currently the most devastated and occupied region within the biome and conservation efforts are extremely expensive in these areas. Hence, to create areas for conservation in northern Cerrado is more feasible due to lowest land prices and is also a need to protect the areas with high conservation value.

# **Final considerations**

With scientific knowledge, we can identify the lands in which agriculture can expand and simultaneously sparing species distribution areas. Deforestation preceding the implementation of crops is an intensifier of climate change, and rising temperatures will cause severe losses in future species distribution areas. In the face of the threat climate change presents for species, spatial economic plans aiming to minimize overlap with species future suitable areas seem to be urgent and useful to safeguard species persistence through time. Agriculture is rapidly occupying land not only in the Cerrado, but in many other biomes and many other countries, threatening biodiversity. Losing species future suitable areas for land use change is easy, mainly when these areas are small and agriculture expansion is not guided by scientific knowledge, but with expansion trends only. We must use knowledge to avoid biological losses, and it is easier when we look at the two sides of the coin. As we are able to show that both economic development and biological conservation can be achieved in a biome, designing spatial economic plans can minimize conflicts between stakeholders. Indicating to farmers places they can crop with high productivity and less costs, instead of showing them where they cannot crop, makes the communication and understanding between stakeholders possible. Also, this strategy withdraws financial interests from lands with low outcomes for agriculture but with high conservation value, making the creation of areas for conservation purposes at these lands more feasible.

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1697

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# Affiliations

### Larissa Lemes<sup>1,4</sup> · André Felipe Alves de Andrade<sup>1</sup> · Rafael Loyola<sup>2,3</sup>

- <sup>1</sup> Programa de Pós-graduação em Ecologia e Evolução, Universidade Federal de Goiás, Goiânia, Brazil
- <sup>2</sup> Laboratório de Biogeografia da Conservação, Departamento de Ecologia, Universidade Federal de Goiás, Goiânia, Brazil
- <sup>3</sup> Fundação Brasileira para o Desenvolvimento Sustentável, Rio de Janeiro, Brazil
- <sup>4</sup> Departamento de Ecologia, Universidade Federal de Goiás, Avenida Esperança s/n, Campus Samambaia, Goiánia, Goiás CEP 74.690-900, Brazil