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The impacts of climate change on the habitat distribution of the vulnerable Patagonian-Fueguian species *Ctenomys magellanicus* (Rodentia, Ctenomyidae)

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ABSTRACT

The ongoing climate change could intensify endangerment of species with a restricted distribution and small population size, such as rare or endemic species. Magellanic tuco-tuco (*Ctenomys magellanicus*) is the southernmost Patagonian-Fueguian fossorial caviomorph rodent with a small distribution. This species has been categorized as vulnerable due to a strong population decline caused by over-exploitation and habitat loss and degradation produced by sheep grazing. This study aims to estimate suitable habitat distribution for *C. magellanicus* and predict suitable habitat distribution and potential range shifts under near-future climate change. For these, we used the method of maximum entropy distribution modeling, using 116 occurrence records from literature and, most importantly, direct species surveys. Seven climatic variables, associated with the water regime and with various aspects of the temperature variation between seasons of Patagonia, were the most important for the species' distribution. Under the major part of future climate change scenarios, the suitable habitat for *C. magellanicus* will likely be severely and negatively affected. Specifically, it would decrease mainly in its continental present distribution, with a drastic loss and fragmentation of suitable habitats. Our results can be useful for design evidence-based conservation and management policies.

1. Introduction

The geographical distribution of species is an important trait for biodiversity conservation and management policies because contains relevant and meaningful information regarding the requirements for species' ecological success (Margules and Pressey, 2000; Bozinovic et al., 2011). The development of species distribution models (SDMs, or ENMs: ecological niche models), an increasingly important statistical predictive tool (Araújo and Peterson, 2012; Warren, 2012), has been successfully applied in numerous fields of biological sciences, such as ecology, biogeography, invasive species and conservation biology, estimating the distribution of species and suitable habitat (Elith and Leathwick, 2009; Franklin, 2010; Guisan and Zimmermann, 2000; Peterson et al., 2011). This modeling approach establishes relationships between the occurrence of species and environmental variables, aiming to predict the potential suitable habitat where the species' niche requirements are satisfied (Soberón and Nakamura, 2009; Wiens et al., 2009). Interestingly, the usefulness of these models is even wider. For instance, once identified the species' current climatic niche it allows estimating the potential impacts of future climate change (McMahon et al., 2011; Pearson and Dawson, 2003; Thuiller et al., 2005).

Disruption of connectivity among populations, reconfiguration of community structure, extinction of species, and severe disturbance of ecosystems are the most common consequences of global climate change (Chen et al., 2011; Parmesan and Yohe, 2003; Root et al., 2003). Under climate change, the ecological niche changes or contracts. Populations of species can respond in different ways to climate change; moving to a habitat that conserves the characteristics of their niche, or adapt to the new conditions, but if they do not follow any of these responses, they can be locally extinct (Berg et al., 2010). The vulnerability of a species to climate change is a function of both the exposure to the change and the species sensitivity (Pacifici et al., 2015). The

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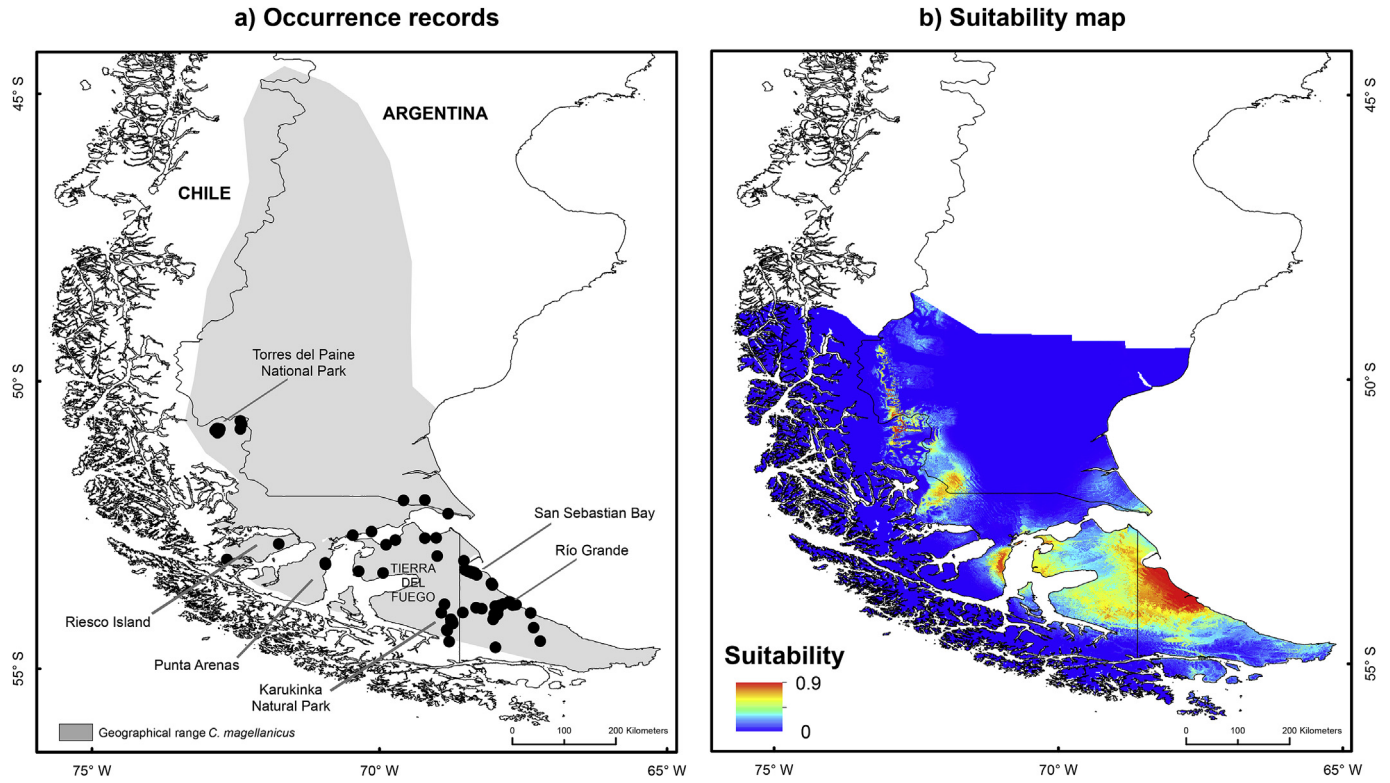

Fig. 1. Occurrence records and present-day habitat suitability (expressed as probability of presence) for Magellanic Tuco-Tuco. a) Map of occurrence records used in this study. The polygon shows the species' distribution *sensu* Patton et al. (2015). b) Map of habitat suitability under current conditions using Maxent.

exposure corresponds to the extent of climate change experienced by a species, which depends on the rate and magnitude of climate change in the species' habitat (Dawson et al., 2011). Sensitivity refers to the degree to which species' persistence or survival is dependent on the prevailing climate (Dawson et al., 2011). Sensitivity depends on several species' traits: life history, dispersal capacity, ecophysiology, and microhabitat preferences. Then, the future climate change could intensify endangerment of species with a narrow distribution and small population size, such as rare or endemic species, increasing the extinction risk (Convention on Biological Diversity, 2010). Accordingly, for those species prone to extinction, the direct survey for new records aiming to enhance the predictive power of ENMs should be a powerful tool for decision making, as it establishes an updated temporal framework for the distribution of the species.

Magellanic tuco-tuco, *Ctenomys magellanicus* (Bennett, 1836) is the southernmost Patagonian and Fueguian Caviomorpha species in Argentina and Chile (Fig. 1a), distributed from Aysén province to Última Esperanza and Magallanes provinces toward Tierra del Fuego in Chile, and from San Sebastian bay to northern shore of Fagnano Lake in Argentina (Fasanella, 2012; Iriarte, 2008, but see Materials and Methods). This species also is the southernmost subterranean rodent and the only of its group inhabiting the Isla Grande de Tierra del Fuego (Gallardo, 1979; Patton et al., 2015). *C. magellanicus* inhabits patagonic steppes, grasslands, and shrubland (e.g. genera *Festuca*, *Hordeum*, *Poa*, *Senecio,* and *Baccharis*), with 5 subespecies; *C. m. osgoodi* and *C. m. magellanicus* inhabit cold grass steppes; *C. m. fueginus* inhabits cold steppes under 150 m a. s. l. and *C. m. obscurus* inhabits grasslands and shrubland, while *C. m. dicki* used to inhabit forests and shrublands (Osgood, 1943; Cabrera, 1961; Texera, 1975; Patton et al., 2015). *C. magellanicus* has been categorized as vulnerable by IUCN (Bidau et al., 2008) due to a population decline (around 30% over the past 10 years) caused by grazing of livestock, that has led to a shrinkage in this species distribution due to the habitat loss and degradation. In Argentina, Magellanic tuco-tuco was categorized as vulnerable by the Red Book of Argentine Mammals (Diaz and Ojeda, 2000). Likewise, in Chile, the Chilean Red List assessment categorized the subspecies *C. magellanicus dicki* as extinct and, *C. m. osgoodi*, *C. m. magellanicus*, *C. m. fueginus* and *C. m. obscurus* as vulnerable (http://especies.mma.gob.cl). Taking this background together, our objectives aim to: (1) estimate suitable habitat distribution for vulnerable *Ctenomys magellanicus*, using 116 occurrence records, from literature and direct species surveys, to inform conservation planning in southernmost South America; (2) identify the environmental factors associated with *C. magellanicus* habitat distribution, and (3) predict suitable habitat distribution and potential range shifts for Magellanic tuco-tuco under several climate change scenarios projected to the year 2080. For these, we used species occurrence records, GIS (geographical information system) environmental layers (bioclimatic), and the maximum entropy distribution modeling algorithm (Phillips et al., 2006), to estimate current suitable habitat distribution for *C. magellanicus* and project potential impacts of climate change for this important caviomorph of southernmost Patagonia.

2. Materials and Methods

2.1. Occurrence database and environmental variables

We obtained 116 occurrence records of *Ctenomys magellanicus* from Chile and Argentina (Research Data Table 1) which correspond to 84 points in a grid of 30″ of spatial resolution (Fig. 1a). These records where obtained from two sources: (a) exhaustive literature search (e.g Fasanella, 2012, http://especies.mma.gob.cl) and (b) field observations. For these, we established two transects inside Torres del Paine National Park. These were established in areas where the presence of the species was reported in literature and currently confirmed by park rangers (Iriarte, 2008). Specifically, these transects were deployed in the Laguna Azul sector surrounding the valley of this lake (50°52′55.00"S, 72°46′30.00"W). The first had an orientation from east to west bordering Laguna Azul to Laguna Cebolla, with a length of

9.71 km. The second transect was the largest with a length of 14 km, oriented north to south, from Laguna Azul to Laguna Smock. Along these transects the presence of burrows was georeferenced (Research Data Table 1).

These occurrence records were refined according to two relevant criteria. First, we worked only with those data that are contemporary with the bioclimatic database and/or with those records that are prior to the time range of the explanatory variables but that present more recent occurrences in the same area. Then, we did not incorporate the occurrence records of the subspecies *C. magellanicus osgoodi* into the analyses. The data for this subspecies dates back to the work of Allen (1903; n = 23, one Argentinean locality) and since then, the only new records came from Osgood (1943; n = 4, from one Argentinean and one Chilean locality). In addition, there is a remarkable geographic gap between these historical records and the remainder subspecies of *C. magellanicus* (Osgood, 1943; Cabrera, 1961; Bidau, 2006). Taking these antecedents together, the occurrence records for *C. magellanicus osgoodi* could have a negative influence during the posterior analyses by producing an overestimation of the ENM (Fig. S1). Second, given the potential sampling bias in occurrence records caused by oversampling in some areas of the known species' distribution, we generated a random background points using a mask based on the Kernel density of the actual records. This density mask was used to represent the magnitude per unit area of the points generating a surface that indicates where there are higher densities of point entities. The Kernel density allows to adjust a uniform curved surface on each point. A surface value is high at the location of the point and decreases as distance increases (Silverman et al., 1986). Then, a relevant number of cells was sampled and the probability of each cell was weighted by the values of the Kernel density layer. The background points were generated on this mask using the randomPoints function of the "dismo" R package (Hijmans et al., 2017. R core team, 2018), and selecting the Probability argument, in which the values of the mask represent probability weights.

For species distribution modelling we used nineteen bioclimatic variables, which are biologically meaningful to define ecophysiological limits of a species (Graham and Hijmans, 2006). These variables were obtained from WorldClim dataset, with 30" (~1 × 1 km) spatial resolution (Hijmans et al., 2005; Hijmans and Graham, 2006, http://www.worldclim.org/).

2.2. Climatic niche model

To establish the proportion of suitable habitat for *C. magellanicus* on the Patagonian landscape, we used Maxent 3.3.3k (Phillips et al., 2006; Phillips and Dudík, 2008, http://biodiversityinformatics.amnh.org/open_source/maxent/), a machine-learning technique based on maximum entropy algorithm. Maxent uses presence points (from incomplete information) to estimate the likelihood of a species being present by finding the distribution of maximum entropy based on the environmental conditions spread over the study area (Phillips et al., 2006). The probability of presence, associated with habitat suitability, of a species is represented by values between 0 and 1.

We selected the bioclimatic variables through an exploratory analysis which allowed those strongly related variables to be eliminated. We used the variance inflation factor (VIF) to evaluate the collinearity among predictors. A VIF greater than 19 is a signal that model has collinearity problems (Quinn and Keough, 2002). We tested 120 different models (Research Data Table 2), these models were generated by considering seven uncorrelated predictors (selected variables), configuring the parameters features class and the regularization multipliers (RM; see Elith et al., 2011; Shcheglovitova and Anderson, 2013). The best model was selected through the Akaike information criterion (AIC) which is a measure of relative adjustment, proportional to the likelihood of the model and the number of parameters used (Akaike, 1974; Burnham and Anderson, 2002). The selection of models was made through the package ENMeval (Muscarella et al., 2014). Once the best model was selected, we implemented it on Maxent to predict suitability of habitat (i.e. potential distribution) under current climate and future projections. This was performed with a Jackknife test of variable importance to identify the variables with important individual effects (Elith et al., 2011). Performance of fitted model was evaluated using the Area Under the Curve test (AUC), with the criterion of values for AUC > 0.8 representing more adequate fit.

For future climate projections, we selected two relevant scenarios (A1B and B1) for the year 2080 from the GCM data portal (http://ccafs-climate.org/data_spatial_downscaling). Scenario A1B assumes a very rapid economic growth, and a rapid introduction of efficient technologies. By another side, scenario B1 assumes the storyline of "reductions in material intensity and, clean and efficient technologies". From these scenarios, we selected six future climate models to project: cccma cgcm31 A1B; cccma cgcm3 B1; csiro mk30 A1B; csiro mk30 B1; ukmo hadcm3 A1B; and ukmo hadcm3 B1 (http://www.ipcc-data.org/sim/gcm_clim/SRES_AR4/index.html). Then, we use the same seven bioclimatic variables selected by the modeling of habitat distribution under current climate, but according to each future model, in the software Maxent, using the same procedure for present-day modeling. To characterize the changes on bioclimatic variables between current and future models, we used ArcGis 10.2 (Environmental System Research Institute, Inc., Redlands, CA) to estimate descriptive statistics (mean, standard deviation) from the raster of selected variables, restricted to the study area (Table 1).

2.3. Area estimation

To quantify geographic distribution changes under future climate change scenarios, we compared current model with future projected models. Each model was converted from a continuous logistic output to a binary classification (presence/absence) using the minimum training presence threshold (Pearson et al., 2007). In this structure, cells with values over the threshold were classified as suitable habitat and cells with values below the threshold were classified as no suitable habitat. Then, we used SDMtoolbox module (Brown, 2014) implemented in

Table 1
Description of the climate change scenarios used in this study. In Celsius degrees for temperature variables and in mm for precipitation (mean value ± standard deviation).

MODEL	SCENARIO	BIO1	BIO3	BIO6	BIO8	BIO9	BIO12	BIO15
Present-day		5.567 ± 1.910	4.795 ± 0.185	−2.508 ± 2.038	6.078 ± 2.647	4.913 ± 2.736	950.174 ± 1143.913	16.537 ± 5.031
cccma cgcm3	A1B	8.037 ± 1.960	3.785 ± 0.583	1.642 ± 1.903	6.024 ± 2.296	9.704 ± 3.644	959.483 ± 1128.495	29.195 ± 20.049
	B1	7.485 ± 1.936	4.177 ± 0.498	0.747 ± 1.910	5.38 ± 2.354	9.007 ± 3.157	961.835 ± 1134.539	28.275 ± 19.578
csiro mk30	AIB	6.97 ± 1.950	4.816 ± 0.198	−1.255 ± 1.986	4.845 ± 2.628	8.244 ± 3.571	955.625 ± 1147.863	28.17 ± 19.918
	B1	6.594 ± 1.941	4.806 ± 0.190	−1.594 ± 1.998	4.343 ± 2.49	8.204 ± 3.916	955.864 ± 1143.835	25.969 ± 19.826
ukmo hadcm3	A1B	7.266 ± 2.116	4.935 ± 0.208	−0.577 ± 2.024	4.804 ± 2.409	2.409 ± 3.781	1092.935 ± 1135.731	34.125 ± 19.731
	B1	6.871 ± 2.059	5.134 ± 0.189	−1.41 ± 2.032	4.364 ± 2.381	8.404 ± 3.515	1036.623 ± 1133.496	32.431 ± 18.323

BIO1: Annual Mean Temperature; BIO3: Isothermality; BIO6: Min. Temperature of Coldest Month; BIO8: Mean Temperature of Wettest Quarter; BIO9: Mean Temperature of Driest Quarter; BIO12: Annual Precipitation; BIO15: Precipitation Seasonality.

ArcGis 10.2 (Environmental System Research Institute, Inc., Redlands, CA) to calculate the areas of expansion range, contraction range and the distribution without change between present and future models.

3. Results

3.1. Description of climatic change scenarios and models

The bioclimatic variables selected using the VIF approach were "Annual Mean Temperature" (BIO1), "Isothermality" (BIO3), "Minimum Temperature of Coldest Month" (BIO6), "Mean Temperature of Wettest Quarter" (BIO8), "Mean Temperature of Driest Quarter" (BIO9), "Annual Precipitation" (BIO12) and "Precipitation Seasonality" (BIO15). The best model had an AICc value of 2807.6 (Research Data Table 2). For subsequent analyses, the model with features Hinge and RM = 1 was used to obtain predictions of suitability habitat distribution of *Ctenomys magellanicus*. Table 1 shows mean values (± standard deviation [SD]) of these seven bioclimatic variables for current distribution model and for future climate change projections. The modeled current suitable habitat distribution shown a mean (± SD) annual temperature (BIO1) of 5.567 ± 1.910 °C, a mean (± SD) isothermality (BIO3) of 4.795 ± 0.185 °C, a mean (± SD) minimum temperature of coldest month (BIO6) of −2.508 ± 2.038 °C, a mean (± SD) temperature of wettest and driest quarter of 6.078 ± 2.647 °C and 4.913 ± 2.736 °C respectively, while the mean (± SD) annual precipitation (BIO12) was 950.174 ± 1143.913 mm and mean (± SD) precipitation seasonality (BIO15) was 16.537 ± 5.031 mm. Regarding future climate change scenarios, ccma cgcm3 under both scenarios, A1B and B1, shown the highest increase on BIO1, while the models that shown the lower increase were csiro mk30 under both scenarios, A1B and B1. With respect to BIO3, ccma cgcm3 A1B model projected a decline on isothermality (3.785 ± 0.583 °C), while the remainder of the models were more conservative, with the exception of ukmo hadcm3 B1 which shown an increase. For BIO6, BIO8 and BIO9 cccma cgcm3 under both scenarios, A1B and B1, shown the highest temperatures, been cccma cgcm3 A1B the model that exhibit higher temperatures than cccma cgcm3 B1. By another side, the models that shown an increase on precipitation (BIO12 and BIO15) were ukmo hadcm3 under both scenarios, A1B and B1. Whereas, the models that projected less variation in comparison to current model were csiro mk30 A1B and csiro mk30 B1. However, the standard deviation in all the models was wide.

3.2. Current suitable habitat distribution

The Maxent model predicted that the potentially suitable habitat distribution for *C. magellanicus* is continuous and narrow in its continental portion; and a slightly wider in its southern part, toward the Isla Grande de Tierra del Fuego (Fig. 1b). The areas with the high suitability of habitat for Magellanic tuco-tuco are Torres del Paine National Park (and northwards of this location), Punta Arenas in Chile, and Isla Grande de Tierra del Fuego, especially nearby to San Sebastian Bay and Río Grande in Argentina (Fig. 1b). The jackknife test shown that BIO9, BIO12 and BIO15 were the most important variables of *C. magellanicus* habitat distribution (Table 1). Model performance is acceptable according to AUC > 0.8 value (Table 2).

3.3. Projection to future

According to the results of Maxent models, the most benign model was cccma cgcm3 under A1B scenario, where the predicted suitable habitat distribution at the year 2080 will show an increase moderately to highly suitable areas in the center and south of Tierra del Fuego, but low and fragmentated presence in the continent (Fig. 2a and b). Furthermore, cccma cgm3 A1B was the model with less contraction range (Fig. 2c, Table 3). Habitat loss was mainly concentrated in continental areas (Fig. 2c, Table 3). Additionally, cccma cgcm3 A1B projects ~8503km^{2}of stables areas with respect to current distribution modeling, with an expansion range over 16564km^2 and ~23289 km^2 of contraction range (Table 3).

By another hand, the model cccma cgcm3 under B1 scenario predicted a fragmentation with a drastic shrinkage on Magellanic tuco-tuco's habitat distribution. The prediction to the future shown two small areas of high suitability, one in Torres del Paine National Park in Chile, and the second nearby to Río Grande in Tierra del Fuego, Argentina (Fig. 2d and e). Also, this model, cccma cgcm3 B1, predicted the greatest contraction range of 99751 km^2 (Fig. 2f, Table 3).

The four remaining tested models predicted a strong decline of suitable habitats for *C. magellanicus*. The model csiro mk30 under A1B scenario shown a decline of habitat suitability in Tierra del Fuego, with a small area of high suitability nearby to Rio Grande location, but a increase of habitat suitability nearby Punta Arenas, in the continent (Figs. S2a and S2b). This model predicted a range expansion ~5217 km^2, but a contraction range over 52291 km^2 (Fig. S2c, Table 3). The csiro mk30 model under B1 scenario predicted a fragmented suitable habitat distribution for the Magellanic tuco-tuco, where the most area in its continental current distribution was predicted to be no longer suitable for this species (Fig. S2d, Fig. S2e). This model predicts 59792 km^2 of stable area, losing ~72763 km^2 with respect to the current model, and a expansion range of only 402 km^2 (Fig. S2f, Table 3).

For the model ukmo hadcm3 the projection to the future under A1B scenario shown high habitat suitability for Magellanic tuco-tuco in Punta Arenas and Río Grande (Fig. S3a, Fig. S3b), with 15328 km^2 reduction range, especially in the northern continental current distribution and nearby to San Sebastian Bay in Tierra del Fuego (Fig. S3c, Table 3). By the other hand, under B1 climate scenario the projection shown high Magellanic tuco-tuco's habitat suitability only in Tiera del Fuego, but projected the presence of the specie in the continent with low habitat suitability (Fig. S3d, Fig. S3e), This scenario predicted aa drastic shrinkage in habitat distribution (range contraction ~79776 km^2), a expansion range of 3615 km^2 and maintaining over 52778 km^2 of species' current distribution (Fig. S3f, Table 3).

4. Discussion

4.1. Current suitable habitat distribution

Our results estimated that *Ctenomys magellanicus,* the southernmost fossorial rodent, has a narrow and restricted current distribution, which, under the major part of future climate change models, will likely be severely and negatively affected. It is not surprising that the bioclimatic variables that more contributed to the present model are those associated with water availability (annual precipitation and precipitation seasonality), isothermality, annual mean temperature, and those related to temperature of the coldest, wettest and driest period of the year due to characteristics of Patagonia. The Patagonian steppe is a cold, large, arid and semiarid region, with a west to east precipitation gradient. This feature is related to the Southern Andean Rain Shadow: west winds lose humidity toward the western Andes slope, producing very moderate precipitations in the eastern flank of the Andes (Jobbágy et al., 2002). Then, the major part of annual precipitation (> 70%) is concentrated in fall and winter, thereby generating that most of the region has a marked water deficit during spring and summer (Paruelo et al., 1998). In Patagonia, plants use this water throughout the growing season, which is controlled by temperature (Aguiar et al., 1996). Although subterranean ecotope provides advantages to fossorial species, giving protection from predators and environmental fluctuations (Begall et al., 2007), Magellanic tuco-tuco appears frequently to the surface to forage and coping roots, bulbs, etc. Therefore, precipitation and temperature patterns should influence the suitable habitat of this species indirectly through constraining the resources availability. This has been also proposed for other *Ctenomys* species, where climatic

Table 2
AUC - value, threshold - value (p-value), percentage of contribution, permutation importance, and training gain (with and without the respective variable) for the selected bioclimatic variables.

Variable	AUC (test)	Threshold (p-value)	BIO1	BIO3	BIO6	BIO8	BIO9	BIO12	BIO15
	0.937	0.562(< 0.001)							
contribution (%)			1.5	18.4	5.5	0.8	11.7	33.9	28.2
Perm. Importance			6.8	8.2	4.1	0	24	40.5	16.3
Training gain without			13.417	12.356	13.377	13.693	12.031	10.916	11.763
Training gain with only			0.2511	0.0431	0.1259	0.0483	0.1302	0.8155	0.3188

BIO1: Annual Mean Temperature; BIO3: Isothermality; BIO6: Min. Temperature of Coldest Month; BIO8: Mean Temperature of Wettest Quarter; BIO9: Mean Temperature of Driest Quarter; BIO12: Annual Precipitation; BIO15: Precipitation Seasonality.

change, specially precipitation patterns, trigger relevant changes on suitable habitats, that may could led to a decline of populations of the species (Tammone et al., 2018).

4.2. Projections to the future and relevance to conservation

The first response of species to climate change would be a shift in the distribution allowing to track geographic areas with the preferred environmental conditions (Pecl et al., 2017). Usually, species shift their distributions moving poleward and to higher elevations (Chen et al., 2011; Pecl et al., 2017). According to our results, the predicted future range of habitat for the vulnerable Magellanic tuco-tuco are likely to be negatively affected by future climate change and will concentrate on the southernmost portion of its present distribution. Under four of the six tested future models, the suitable habitat for *C. magellanicus* would decrease mainly in its continental present distribution, with a drastic loss and fragmentation of suitable habitats (cccma cgcm3, csiro mk 30 and ukmo hadcm3 models under B1 scenario). Therefore, the suitable future habitat distribution under climate change scenarios may be limited to Tierra del Fuego. These species' responses could be due to tuco-tucos have limited dispersal capacity (Busch et al., 2000) and small population demes (Kittlein and Gaggiotti, 2008; Lacey and Patton, 2000; Wlasiuk et al., 2003), attributes that would constrain the distribution range change, by colonizing new habitat, and increasing extinction risk.

These results can be used for design conservation policies. Protected

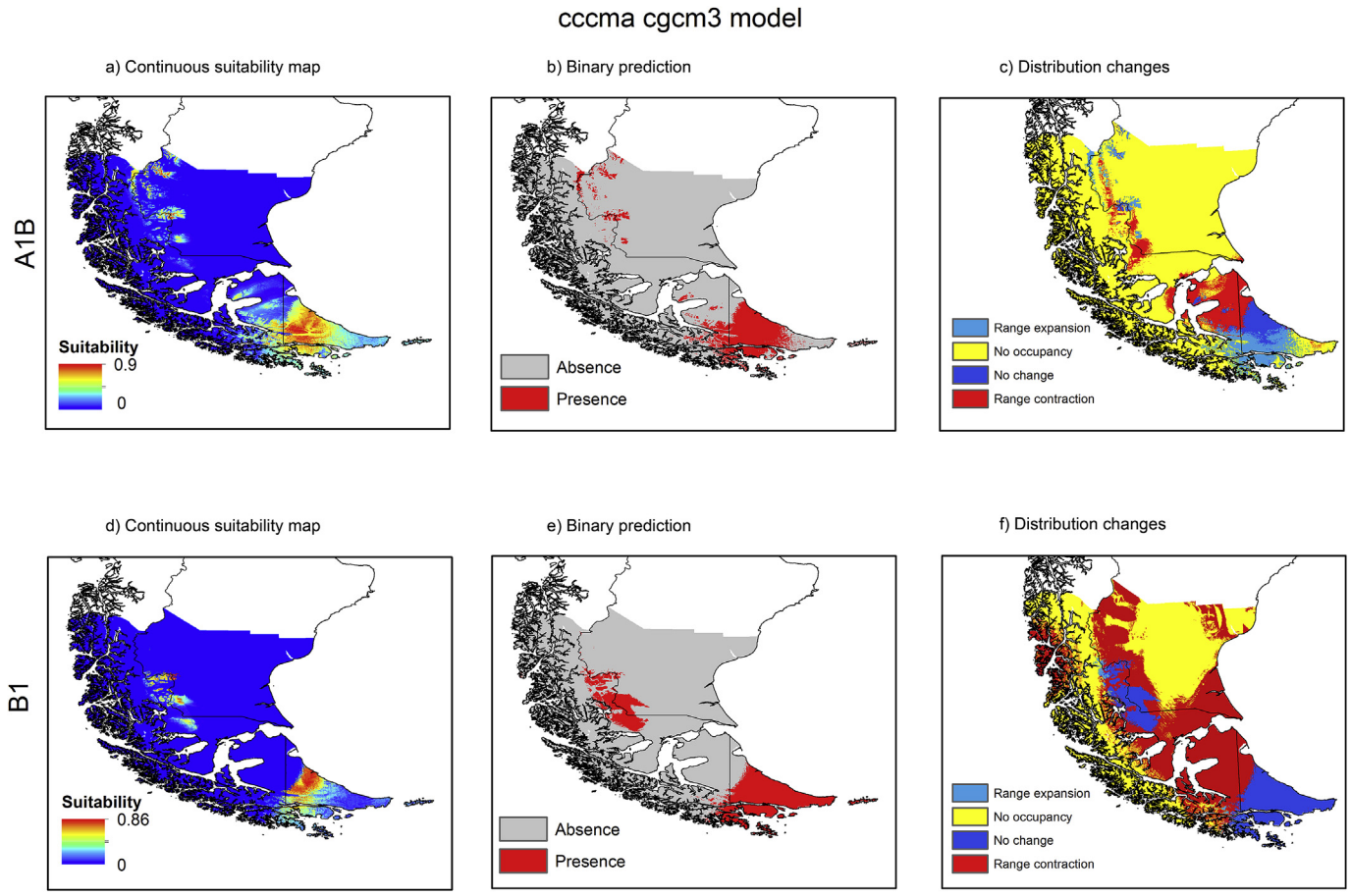

Fig. 2. Maps of habitat suitability and expected future distribution changes for Magellanic tuco-tuco under predicted climate conditions for 2080 under cccma cgcm3 model for A1B and B1 scenarios. a) Map of habitat suitability under cccma cgcm3 A1B (the most benign scenario). b) Binary prediction for cccma cgcm3 A1B. c) Distribution changes, map of expected future contraction, expansion, and areas of no change under cccma cgcm3 A1B. d) Map of habitat suitability under cccma cgcm3 B1 (the harsh scenario). e) Binary prediction for cccma cgcm3 B1. f) Distribution changes, map of expected future contraction, expansion, and areas of no change under cccma cgcm3 B1.

Table 3
—Predicted contraction, expansion, and areas of no change (km^2) for the distribution of *Ctenomys magellanicus*.

MODEL	SCENARIO	NO OCCUPANCY	RANGE CONTRACTION	NO CHANGE	RANGE EXPANSION
cccma cgcm3	A1B	193024	23289	8503	16564
	B1	107514	99751	32803	1311
csiro mk30	A1B	103608	52291	80263	5217
	B1	108423	72763	59792	402
ukmo hadcm3	A1B	93496	64387	68168	15328
	B1	105209	79776	52778	3615

areas planning and management would be focused in areas where present and future ranges overlap to meet the minimum range requirements for species (Midgley et al., 2003). In this venue, the continental Chilean portion of the species distribution, the most vulnerable area according to our results, it is mainly under the strong protection of the Chilean government. In fact, Torres del Paine National Park preserves an important amount of species' occurrences (Fig. 1a). Also, the insular distribution of *Ctenomys magellanicus* on the Chilean territory is under private preservation efforts of World Wildlife Fund at Karukinka Park. This provides a favorable scenario for long-term close monitoring of this species and the consequences of climate change on it, in order to be able to apply real-time remediation actions. However, an important part of the projected distribution was predicted between national borders. Accordingly, we stress the urgent need of increasing cooperation and governance between the Argentinean and Chilean wildlife technical units.

4.3. Caveats and future directions

There is a major criticism to bioclimatic approach, which establishes that these variables are not the key predictors for the occurrence of a species in a geographic area, but other factors are more important structuring species' distributions (Guisan and Thuiller, 2005). Without entering into such dichotomy, we suggest other environmental variables, potentially significant to *C. magellanicus,* to be considered in future modeling studies, in accordance with its fossorial habitus and present-day habitat threat: soil type, vegetation type, human footprint, and biotic interactions. However, these variables are difficult to use in future climate change projections.

Limitation in occurrence data, unsuitable spatial resolution and weak selection of predictor variables may increase bias for modeling the spatial distribution of a species (Guillera-Arroita et al., 2015). To minimize these uncertainties, we use > 80 occurrence points distributed throughout of Magellanic Tuco-tuco's known historical distribution. In addition, we used a spatial resolution of 30" (1 km × 1 km) which was adequate for our focal species due to its restricted vagility and home range. By another hand, the selected bioclimatic variables make sense in the light of the ecological traits of the modeled species.

5. Conclusion

This study provides the first predicted habitat suitability for *Ctenomys magellanicus*. Our results supported a severe decrease of suitable habitat for *C. magellanicus* under future climate change projections. These results can be used for more effective, evidence-based, conservation policies. However, it is required to increase the knowledge about species' biology. The poor knowledge that we have until now of Magellanic Tuco-tuco could have negative impacts for management purposes. For instance, population parameters are unknown for the species. In addition, an important trait for the success of small mammals facing a changing environment is their social system. However, for *C. magellanicus* this is unknown.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaridenv.2019.104016.

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