

Identification of limiting climatic and geographical variables for the distribution of the tortoise *Chelonoidis chilensis* (Testudinidae): a baseline for conservation actions

Alejandro Ruete, Gerardo C Leynaud

Background. Just as for most other tortoise species, the once common Chaco tortoise, *Chelonoidis chilensis* (Testudinidae), is under constant threat across its distribution in Argentina, Bolivia and Paraguay. Despite initial qualitative description of the species distribution and further individual reports of new locations for the species, there is no description of the species distribution in probabilistic terms. With this work we aim to produce an updated predictive distribution map for *C. chilensis* to serve as a baseline management tool for directed strategic conservation planning.

Methods. We fitted a spatially expanded logistic regression model within the Bayesian framework that accounts for uncertainty on presence-only and generated pseudo-absence data into the parameter estimates. We contrast the results with reported data for the national networks of protected areas to assess the inclusion of the species in spatial conservation strategies.

Results. We obtained maps with predictions of the occurrence of the species and reported the model's uncertainty spatially. The model suggests that potential suitable habitats for the species are continuous across Argentina, West Paraguay and South Bolivia, considering the variables, the scale and the resolution used. The main limiting variables were temperature-related variables, and precipitation in the reproductive period.

Discussion. Given the alarming low density and coverage of protected areas over the distribution area of *C. chilensis*, the map produced provides a baseline to identify areas where directed strategic conservation management actions would be more efficient for this and other associated species.

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2 **distribution of the tortoise *Chelonoidis chilensis* (Testudinidae): a baseline for**
3 **conservation actions**

4

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13

14 **ABSTRACT**

15 **Background.** Just as for most other tortoise species, the once common Chaco tortoise,
16 *Chelonoidis chilensis* (Testudinidae), is under constant threat across its distribution in Argentina,
17 Bolivia and Paraguay. Despite initial qualitative description of the species distribution and
18 further individual reports of new locations for the species, there is no description of the species
19 distribution in probabilistic terms. With this work we aim to produce an updated predictive
20 distribution map for *C. chilensis* to serve as a baseline management tool for directed strategic
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25 of protected areas to assess the inclusion of the species in spatial conservation strategies.

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27 model's uncertainty spatially. The model suggests that potential suitable habitats for the species
28 are continuous across Argentina, West Paraguay and South Bolivia, considering the variables,
29 the scale and the resolution used. The main limiting variables were temperature-related variables,
30 and precipitation in the reproductive period.

31 **Discussion.** Given the alarming low density and coverage of protected areas over the distribution
32 area of *C. chilensis*, the map produced provides a baseline to identify areas where directed
33 strategic conservation management actions would be more efficient for this and other associated
34 species.

35

36 **INTRODUCTION**

37 Globally, turtles and tortoises are the most threatened group of vertebrates, with over half of all
38 their species threatened with extinction (van Dijk, Stuart & Rhodin, 2000; Turtle Conservation
39 Fund, 2002). Exploitation and unregulated trade are the primary causes for sharp declines in
40 many turtle species, with habitat loss and degradation also being major factors in widespread
41 declines (Gibbon et al., 2000; van Dijk, Stuart & Rhodin, 2000; Turtle Conservation Fund,
42 2002). Therefore, without directed strategic conservation planning, a significant portion of turtle
43 diversity could be lost over the next century (Buhlmann et al., 2009).

44 The common Chaco tortoise, *Chelonoidis chilensis* (Testudinidae, Gray 1870), is mainly
45 found in Argentina, but also in Bolivia and Paraguay (Ceï, 1993; Cabrera, 1998). Although we
46 still lack demographic evidence of population decline, *C. chilensis* is severely threatened by
47 habitat degradation, poaching and illegal trade (Chebez, 2009). Thus, persistent threats and
48 continuous habitat transformation lead to its categorization as Vulnerable by the IUCN (Tortoise
49 & Freshwater Turtle Specialist Group, 2010) and its inclusion in the Appendix II of CITES.

50 An updated and refined distribution map of the species is required to serve as baseline for
51 future conservation measures. Specifically, it is important to evaluate the contribution of the
52 protected area network to the conservation of *C. chilensis*. However, despite initial qualitative
53 and coarse descriptions of the species distribution (e.g. Waller, 1986; Buskirk, 1993; Richard,
54 1999) and further individual reports of new locations for the species (e.g. Ceï, 1993; Gonzales,
55 Muñoz & Cortéz, 2006; Fritz et al., 2012), there is no description of the distribution of the
56 species in probabilistic terms. Species distribution models (SDMs) are a way of linking species
57 occurrence data to environmental variables explaining and limiting the species distribution
58 (Cassini, 2011). SDMs can further provide a spatial depiction of probabilities of occurrence

59 rather than deterministic presence-absence maps. Because of the lack of systematic surveys at a
60 national scale, the only data available for this species are presence-only records from museums
61 and other literature. Given the great uncertainty inherent to this kind of data, state of the art
62 Bayesian modelling techniques are required to account for this uncertainty and present it as part
63 of the resulting species distribution map (Lobo, Jiménez-Valverde & Hortal, 2010).

64 With this work we aim to produce an updated predictive distribution map for *Chelonoidis*
65 *chilensis*, based on geographical and bioclimatic explanatory variables and accounting for data
66 uncertainty, as a baseline management tool for the conservation of the species. We aim to i)
67 gather as many records as possible for the species in Argentina, Paraguay and Bolivia; ii)
68 develop a probabilistic species distribution model using presence-only data that accounts for data
69 uncertainty and spatial autocorrelation of the explanatory variables; and iii) determine the
70 inclusion of the species on protected areas by comparing model predictions to independent
71 presence-absence datasets for the protected areas.

72

73 **METHODS**

74 *Data collection*

75 In the current study the species is defined following Fritz et al. (2012), who concluded that
76 *Chelonoidis chilensis* (Gray, 1870), *C. donosobarrosi* (Freiberg, 1973) and *C. petersi* (Freiberg
77 1973) are the same species (i.e. *C. chilensis*). *C. chilensis* is a burrow-nesting species, found on
78 sandy soils in scrublands or dry forests in the ecoregions of Monte and Chaco (Fig. 1; Cei, 1993;
79 Cabrera, 1998), up to 1200 m.a.s.l. (Cerro Nevado, Mendoza; Richard, 1988). We collected
80 confirmed observations of the Chaco tortoise dated 1950-2012 from the EMYSsystem World
81 Turtle Database (<http://emys.geo.orst.edu/>), and from scientific literature (Waller, 1986; Buskirk,

82 1993; Ergueta & Morales, 1996; Cabrera, 1998; Ernst, 1998; Richard, 1999; Gonzales, Muñoz &
83 Cortéz, 2006; Fritz et al., 2012). We merged all reported observations in a GIS vector layer using
84 QuantumGIS 1.8 (Quantum GIS Development Team, 2012). In case of overlap within 5 km we
85 kept only the latest observation to avoid duplicated reports, and oversampling in densely
86 populated areas. We also excluded three observations located close to Buenos Aires city because
87 based on previous descriptions of the species distribution they most likely belong to translocated
88 individuals. For a complete list of the 244 observations and corresponding sources, see Table S1
89 in Supporting Information. We arbitrarily defined the study area (Fig. 1) larger than the observed
90 species distribution to include surrounding areas where the species is known to be absent. We
91 excluded Chile from the study area because the Andean Mountain Range is a physical barrier the
92 species cannot pass (i.e. highest observation at 1200 m.a.s.l.; Richard, 1988).

93 We obtained geographic and bioclimatic data from raster layers with 5 km resolution
94 from two world databases (Hijmans et al., 2005; Hengl, 2009). The complete list of variables
95 included in the study is presented in Table S2. We did not included land-use variables in the
96 analysis because the data collected covers a wide temporal range (1950-2012), and the landscape
97 has changed dramatically over this time period.

98

99 *Modelling the species distribution*

100 We implemented a Bayesian spatially expanded logistic (BSEL) model (Casetti, 1997; Congdon,
101 2003) to obtain the probability of occurrence at non-visited locations. Non-visited locations were
102 randomly located with the same density as the observed locations ($\sim 0.0004/\text{km}^2$). Given the
103 nature of presence-only data, predicted probabilities combine the probability of the species being
104 at the location, the probability of an observer being at the same location, and the probability of

105 the observer finding the species (Lobo, Jiménez-Valverde & Hortal, 2010). The Bayesian
106 approach allows us accounting for all three uncertainty sources on each observation, and
107 displaying the model's uncertainties spatially. We assume that occurrences at every non-visited
108 location i are distributed according to a Bernoulli distribution $Obs_i \sim \text{Bernoulli}(p^*_i)$, where p^*_i is
109 an *a priori* probability distribution generated from confirmed observations (Fig. 1b). We
110 generated the *a priori* probability distribution as a quadratic density kernel raster layer using the
111 R package “*splancs*” (Rowlingson et al., 2013). By generating a prior distribution from the
112 observations, we assume that the entire study region has been sampled for the species with the
113 same intensity, which is a fair assumption given the map resolution and the time span of the
114 study.

115 We then modelled observations Obs_i according to a logistic model, $Obs_i \sim \text{Bernoulli}(p_i)$,
116 The spatially expanded model (Casetti, 1997; Congdon, 2003) assumes that the effect of an
117 explanatory variable on the response variable p_i can vary among the observed locations. This
118 assumption is particularly convenient when fitting species distribution models along large
119 ranges, where the species can be locally adapted to e.g. temperature ranges (Turchin & Hanski,
120 1997; Nilsson-Örtman et al., 2013). The model was fitted using JAGS 3.0 (Plummer, 2012)
121 through R (R Development Core Team, 2014). For further details on the modelling approach see
122 Appendix S1.

123 The final model presented (Table 1) is the result of a forward stepwise selection
124 procedure based on the deviance information criterion (DIC), an information-theoretic criterion
125 similar to Akaike's information criterion (a.k.a. AIC), that is appropriate for Bayesian
126 hierarchical modelling (Spiegelhalter et al., 2002). For further details on the selection procedure
127 and all tested variables see Appendix S1 and Table S2.

128 Once the final model was obtained, we generated maps for the occurrence probability.
129 We predicted occurrence probabilities for regularly distributed locations with the same resolution
130 as the raster images for environmental variables (i.e. 5 km). We generated raster layers for the
131 mode and for the length of the 95% credible interval (95% CI). The length of the 95% CI is a
132 measure of precision ranging from 0 (precise) to 1 (imprecise).

133

134 *Model evaluation*

135 We calculated the AUC index with the *SDMtools* package for R (VanDerWal et al., 2012),
136 contrasting predictions (Fig. 2a) against the *a priori* probability distribution (Fig. 1b). Then, we
137 contrasted model predictions with two independent datasets of observations of Chaco tortoises in
138 Argentinean and Bolivian protected areas (a similar dataset for Paraguay was not available). The
139 first data set is mainly based on park rangers reports, and includes 144 Argentinean protected
140 areas in the study area (Sistema de Información de Biodiversidad, SIB; Administración de
141 Parques Nacionales, 2012). The second data set was put together in the framework of a doctoral
142 thesis (Embert, 2007), and includes museum and field systematic collections for 38 Bolivian
143 protected areas in the study area. The species was reported as present in 14 Argentinean and 3
144 Bolivian protected areas (Table S3).

145

146 **RESULTS**

147 The final species distribution model obtained for *Chelonoidis chilensis* was mainly driven by
148 temperature-related variables, but also included water availability in the reproductive period (i.e.
149 precipitation in warmest quarter; Table 1). From this model we generated maps displaying the
150 probability of occurrence (Fig. 2a) and the model's uncertainty. The model suggests that

151 potential suitable sites of the species are continuous across Argentina, West Paraguay and South
152 Bolivia, considering the variables, the scale and the resolution used. The model's predictions
153 generally overlap with published distribution maps for the species (Waller, 1986; Ernst, 1998;
154 Richard, 1999; Administración de Parques Nacionales, 2012; Fritz et al., 2012) and with the
155 ecoregions where the species has been described from (Fig. 1a). The model predictions' accuracy
156 is relatively high (AUC = 0.92). The uncertainty of the model was generally low (i.e. 95% CI
157 length < 0.5, Fig. 2b) and is lower in areas where the occurrence probability is close to either 0 or
158 1 (Fig. S1). However, uncertainty is highest in areas with low density of observations (e.g.
159 Bolivia).

160 The model has very low omission error (i.e. false negatives). In Argentina, the model
161 predicts low occurrence probabilities ($p < 0.5$) for only one out of 14 protected area where the
162 species has been reported ($p = 0.45$; Table S3.1). However, although the model predicted $p < 0.3$
163 for all protected areas in Bolivia (Fig. S2, Table S3.2), there were confirmed observations in
164 three protected areas. Conversely, the commission error is high. That is, there is large
165 discrepancy between positive predictions and the validation dataset, indicating potential false
166 positives. Out of a total of 25 Argentinean protected areas where the model predicted $p \geq 0.5$ the
167 species was not reported in 12 of them.

168

169 **DISCUSSION**

170 The model predicts a large and continuous area where *Chelonoidis chilensis* may be found,
171 taking into account the selected variables, the scale of the study area and the resolution used. In
172 general terms, temperature-related variables constrain the latitudinal and altitudinal range of the
173 species, as it is expected for ectothermic species like amphibians and reptiles (Araújo, Thuiller &

174 Pearson, 2006). Even more, precipitation-related variables constrain its range longitudinally.
175 Altitude is certainly correlated to annual mean temperature, and this may be the reason why
176 altitude did not improve the model fit when added to the full model. In the same way, leaf area
177 index is expected to be highly correlated to precipitation in summer (i.e. the reproductive
178 season), a variable that explains the adaptation of the species to dry environments (Waller, 1986;
179 Buskirk, 1993; Ernst, 1998). However, correlation among variables *per se* was not a deterrent to
180 test for variables together in a model because the aim of a predictive model is to capture and
181 explain as much variability in the response variable as possible (Reichert & Omlin, 1997).

182

183 *Model uncertainty and usage of predictions*

184 An honest display of model uncertainties is crucial to evaluate and validate model predictions.
185 We observed that higher uncertainty is expected on transition areas between high and low
186 estimated probabilities or on poorly sampled areas (Figs. 2b and S1). In general, probabilities
187 obtained for each pixel on the map have uncertainties associated to the observation events (Lobo,
188 Jiménez-Valverde & Hortal, 2010), as well as to the model that generated those probabilities
189 (Congdon, 2003; Clark & Gelfand, 2006). Model uncertainty maps complement the information
190 contained on point estimate predictions, and should be displayed as yet another SDM result.
191 Species distribution maps generated with low quality data (e.g. presence-only data) could be
192 dangerously misleading if not accompanied with the corresponding uncertainty map. Too high or
193 too widely spread uncertainty would also question the accuracy of the model, suggesting that
194 more observations or alternative explanatory variables should be considered in the study. Also,
195 uncertainty maps can be a valuable tool for designing field work efficiently. The researcher can

196 then decide to focus future sampling effort either on areas with high uncertainty to validate the
197 model or on areas with high probabilities of occurrence and low error to sample more efficiently.

198 For many practical applications it is necessary to transform continuous maps to binary
199 presence-absence maps assuming a (more or less) objective detection threshold (Liu et al., 2005;
200 Jiménez-Valverde & Lobo, 2007). It is the researcher's task to decide on which side of the
201 detection threshold he/she wants the most of the model's uncertainty. Liu et al. (2005) and
202 Jiménez-Valverde and Lobo (2007) previously discussed that a threshold $t = 0.5$ is not always the
203 best option, although it is often used. We observed that our model predictions have the highest
204 uncertainty (widest 95% CI range) on regions where predicted occurrence probabilities are close
205 to 0.5 (Fig. S1). Choosing $t = 0.4$ would leave higher uncertainties on values interpreted as
206 presences. The opposite is also true for $t = 0.6$.

207 There are a few considerations to take into account when comparing the model
208 predictions with the presence of the species on protected areas. First, it is important to consider
209 the bias present on the distribution of protected areas. For example, commission error (i.e. false
210 positive rate) is probably underestimated on the east of the species distribution (Espinal and
211 Pampas ecoregions, <1% protected) if compared to the cover on the core distribution area
212 (Monte and Chaco ecoregions, 3.7% protected)(Chebez, 2009) because of a heavily unbalanced
213 distribution of protected areas (Fig. S2). Second, there are no data on the probability of detection
214 or in the completeness of observation reports within the protected areas. *Chelonidis chilensis* is
215 declared a "species of interest" by the National Parks Administration Office, requiring from its
216 entire field staff to report observations of the species to the National Biodiversity Information
217 System (Administración de Parques Nacionales, 2012). However, this is not necessarily the case
218 for provincial, municipal or private protected areas. Therefore, the discrepancy between high

219 predicted probabilities of occurrence with low uncertainty on protected areas where the species
220 was not reported could be simply due to lack of reports or local extinction instead of model
221 commission error.

222

223 *Implications for conservation in protected areas*

224 An important aspect for the conservation of *C. chilensis* that emerges from this study is the low
225 density and total area of protected areas within the distribution of the species. Only 3.7% of
226 Monte and Chaco ecoregions are under some form of protection (“Secretaria de Ambiente y
227 Desarrollo Sustentable”). This value is far from the Aichi Biodiversity Target 11: 17% of
228 terrestrial areas [...] are conserved through [...] systems of protected areas and other effective
229 area-based conservation measures (Convention on Biological Diversity, 2010). The current
230 situation is particularly alarming because of the continuous expansion of the agricultural
231 activities on these ecosystems (Chebez, 2009; Grau et al., 2014).

232 At a smaller scale than the one used on this study it is likely to find greater heterogeneity
233 and fragmentation of suitable habitats. The probability of occurrence of the species is likely to be
234 much lower in some sites after considering the effect of local variables describing the species
235 microhabitat (e.g. availability of favorable nesting sites), barriers to dispersal, human impact and
236 biotic interactions. For example, despite high and homogenous probabilities of occurrence
237 predicted for Sierra de las Quijadas National Park (which emblem depicts a Chaco tortoise), the
238 populations in the park are confined to restricted areas (personal observation). This local
239 heterogeneity is likely due to the wide variability in habitat types and geographic accidents as
240 well as due to the pressure of uncontained grassing activity by neighbor’s cattle. Conversely, in

241 Santiago del Estero Province (at the core of the species distribution) the rate of extraction from
242 unprotected areas does not seem to have decline over time (Prado et al., 2012).

243 This study does not aim to identify healthy populations but to guide the search for them.
244 Also, the predictive maps produced provide a baseline to identify areas where directed strategic
245 conservation management actions (e.g. creation or expansion of protected areas) would be more
246 efficient for this and other associated species. However, before new protected areas or
247 management plans could be delineated, more research is required to better understand what
248 variables drive local habitat selection within areas where the species is expected to be present.

249

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252

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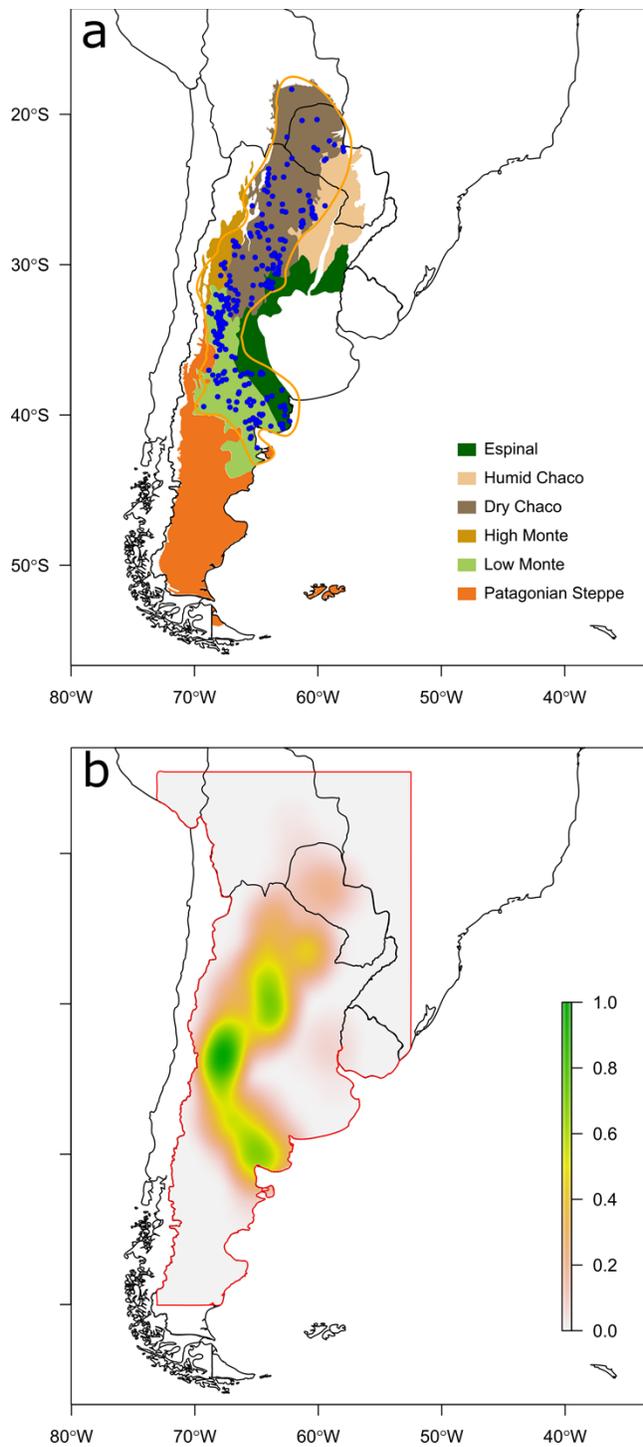
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- 347
348

349 **Table 1:** Explanatory variables included in the final model. Deviance Information Criterion
 350 (DIC) are calculated stepwise from the null model (Table S2). Estimates of the effect parameters
 351 (δ) are extracted from the final model.

	DIC	$\bar{\delta}^a$	$\bar{\delta}$ 95% CI	
355 Mean annual temperature	930.4	0.56	-4.68	5.14
357 Max. temperature of warmest month	869.4	1.61	-2.05	5.86
359 Temperature annual range	853.7	0.03	-2.25	2.12
361 Precipitation of warmest quarter	824.5	-1.57	-2.35	-0.80

363 ^a: mode of the effect parameter.
 364

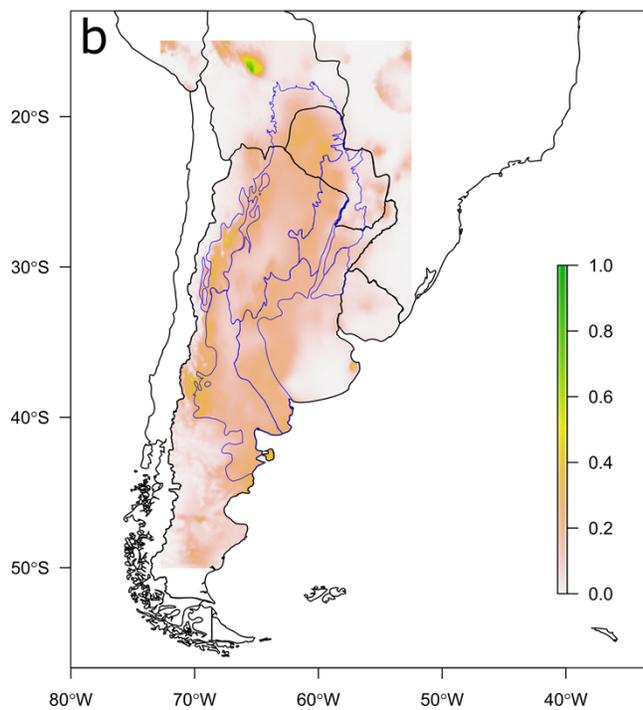
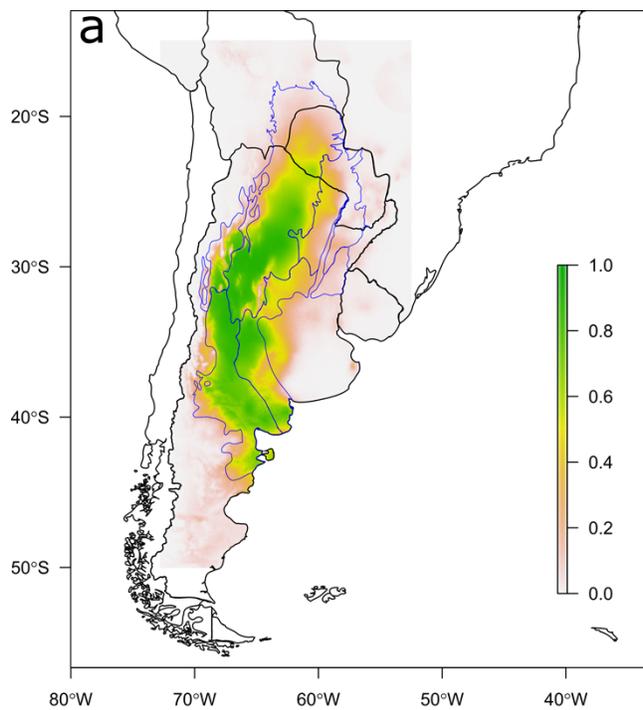
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368 **Figure 1:** Map of austral South America, showing a) sites of confirmed observations of
 369 *Chelonoidis chilensis* (blue dots) and ecoregions where the species has been observed (coloured

370 polygons); b) *a priori* probability distribution of observations (colour scale) estimated from
371 observation densities.



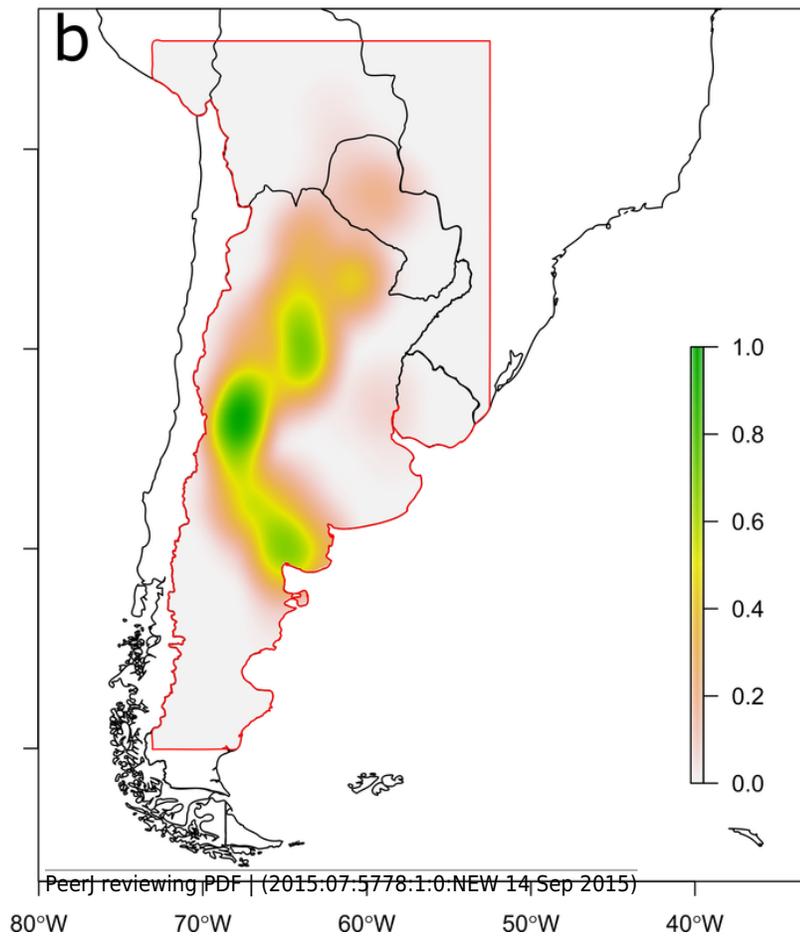
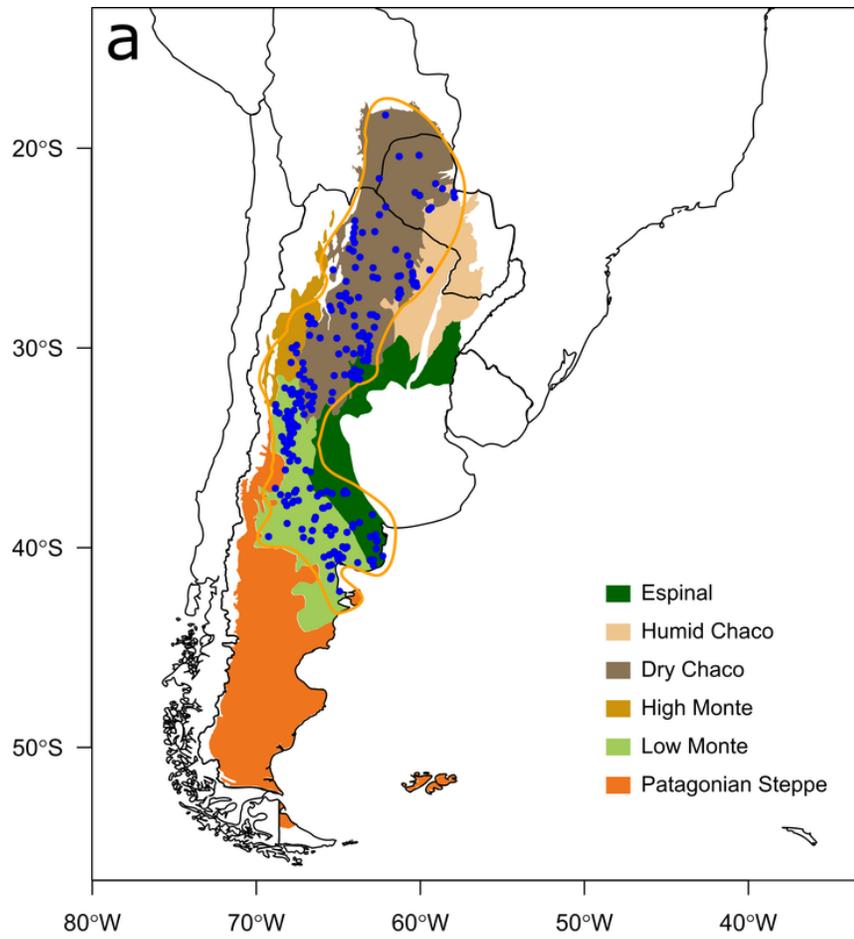
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373 **Figure 2:** Maps showing a) mode and b) length of the 95% Credible Interval (CI) of probabilities
374 of occurrence generated with the Bayesian Spatially Expanded Logistic model (BSEL). Blue
375 lines show ecoregions delimitation for comparison with Figure 1a.

1

Observations and *a priori* probability distribution of *Chelonoidis chilensis*.

Figure 1: Maps of observations and a *priori* probability distribution of *Chelonoidis chilensis*. Map of austral South America, showing a) sites of confirmed observations of *Chelonoidis chilensis* (blue dots) and ecoregions where the species has been observed (coloured polygons); b) *a priori* probability distribution of observations (colour scale) estimated from observation densities.



2

Predictions of the species distribution model.

Figure 2: Predictions of the species distribution model. Maps showing a) mode and b) length of the 95% Credible Interval (CI) of probabilities of occurrence generated with the Bayesian Spatially Expanded Logistic model (BSEL). Blue lines show ecoregions delimitation for comparison with Figure 1a.

