1 **Here be dragons: important spatial uncertainty driven by climate data in**

2 **forecasted distribution of an endangered insular reptile**

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4 Heading title: High uncertainty driven by climate data in SDMs

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21 Abstract

22 The effect of future climate change is poorly documented in the tropics, especially in mountainous areas. Yet,
 23 species living in these environments are predicted to be strongly affected. Newly available high-resolution
 24 environmental data and statistical methods enable the development of forecasting models. Nevertheless, the
 25 uncertainty related to climate models can be strong, which can lead to ineffective conservation actions.
 26 Predicted studies aimed at providing conservation guidelines often account for a range of future climate
 27 predictions (climate scenarios and global circulation models). However, very few studies considered
 28 potential differences related to baseline climate data and/or did not account for spatial information (overlap)
 29 in uncertainty assessments. We modelled the environmental suitability for *Phelsuma borbonica*, an
 30 endangered reptile native to Reunion Island. Using two metrics of species range change (difference in overall
 31 suitability and spatial overlap), we quantified the uncertainty related to the modelling technique ($n = 10$),
 32 sample bias correction, climate change scenario, global circulation models (GCM) and baseline climate
 33 (CHELSA *versus* Worldclim). Uncertainty was mainly driven by GCMs when considering overall suitability,
 34 while for spatial overlap the uncertainty related to baseline climate became more important than that of
 35 GCMs. The uncertainty driven by sample bias correction and variable selection was much higher when
 36 assessed based on spatial overlap. The modelling technique was a strong driver of uncertainty in both cases.
 37 We eventually provide a consensus ensemble prediction map of the environmental suitability of *P. borbonica*
 38 to identify the areas predicted to be the most suitable in the future with the highest certainty. Predictive
 39 studies aimed at identifying priority areas for conservation in the face of climate change need to account for
 40 a wide panel of modelling techniques, GCMs and baseline climate data. We recommend the use of multiple
 41 approaches, including spatial overlap, when assessing uncertainty in species distribution models.

42

43 Keywords: Baseline climate, CHELSA, *Phelsuma borbonica*, Reunion Island, Schoener's D overlap, Species
 44 distribution models, Uncertainty, Worldclim

45

46

47 **Introduction**

48 Predictive studies of climate change effects are poorly documented in the tropics, especially in rare and
 49 endangered species (Pearson et al., 2014). Yet, tropical species are predicted to be more severely impacted by
 50 climate change than temperate species because they live closer to their thermal limit (Tewksbury, Huey, &
 51 Deutsch, 2008; Jiguet et al., 2010; Dubos et al., 2019). This is particularly true for species with a narrow
 52 distribution, a narrow niche, or living in highly heterogeneous environments such as mountainous areas
 53 (Raxworthy et al., 2008; Freeman & Class Freeman, 2014; Platts et al., 2014; Tang et al., 2018; Ahmadi et
 54 al., 2019; Cordier et al., 2020; Manes et al., 2021). Those species are difficult to model mostly because of
 55 data scarcity and statistical constraints related to low sample sizes and the lack of spatial coverage in
 56 environmental gradients. The recent availability of high-resolution environmental data along with
 57 methodological advances help filling this gap of knowledge (e.g., Dubos et al., 2021; Lannuzel et al., 2021).
 58 Forecasting models are useful to anticipate conservation management in the face of climate change.
 59 Specifically, species distribution models (SDMs) can be used to identify priority areas for protection (Leroy
 60 et al., 2014; Lannuzel et al., 2021), suitable conditions for habitat restoration and species (re)introductions
 61 and translocations (Minteer & Collins, 2010; Wilson, Roberts, & Reid, 2011; Adhikari, Barik, & Upadhaya,
 62 2012; Draper, Marques, & Iriando, 2019; Bellis et al., 2020; Butt et al., 2020; Westwood et al., 2020; Zhong
 63 et al., 2021).
 64 A range of climate data is available for species distribution models, including several baseline climate data,
 65 some of which are used to predict climate change (e.g., Worldclim and CHELSA; Fick & Hijmans, 2017;
 66 Karger et al., 2017). Future climate predictions include multiple emission gas scenarios (Shared Socio-
 67 economic Pathways, SSP; as known as Representative Concentration Pathways, RCP) and global circulation
 68 models (GCMs). Both gas emission scenarios and GCMs can produce highly heterogeneous results in terms
 69 of predicted future distributions (Buisson et al., 2010; Baker et al., 2016). Most predictive studies included a
 70 range of scenarios and GCMs, but very few have considered potential uncertainties related to baseline
 71 climate data (Baker et al., 2016; Morales-Barbero & Vega-Álvarez, 2019; Datta, Schweiger, & Kühn, 2020;
 72 Ocon, 2020; Dubos, et al., 2021). This can induce a risk of misidentification of suitable environments, which
 73 can affect conservation prioritisation (Kujala et al., 2013; Baker et al., 2016; Muscatello, Elith, & Kujala,
 74 2020) and subsequently lead to ineffective conservation actions (Converse & Sipe, 2021). Despite recent
 75 studies emphasising the need to account for multiple baseline climates (Morales-Barbero & Vega-Álvarez,

2019; Datta, Schweiger, & Kühn, 2020; Ocon, 2020), most studies aimed at providing conservation guidelines do not assess the uncertainty related to bioclimatic input data.

Uncertainty assessments in SDMs can be made by comparing a range of modalities in model settings or data. These comparisons can be based on differences in performance metrics such as the area under the receiving operating characteristic curve (AUC) or the true skill statistic (TSS; Tassarolo et al., 2021). However, such performance comparisons require independent data to be reliable. In absence of independent data, uncertainty can be assessed based on differences in predicted species range change between model input parameters, climate scenarios or climate data (e.g., Kujala et al., 2013; Baker et al., 2016; Muscatello, Elith, & Kujala, 2020). Species range change can be estimated using the difference between current and future summed suitability. This approach enables to identify which parameter drives the highest uncertainty in terms of overall suitability across a region. However, it ignores the spatial component in suitability differences. For instance, a difference in shift in distribution with no change in overall suitability would remain undetected. Another approach is to discount the variation between model replicates from mean suitability scores (Kujala et al., 2013). This method is highly relevant for conservation purposes since it provides a spatially explicit map of the most consistently identified suitable areas but prevents from disentangling the sources of uncertainty. A possible approach to assess each source of uncertainty while accounting for spatial information is the use of overlap metrics such as Pearson's coefficient or similarity indices (Muscatello, Elith, & Kujala, 2020; Dubos, Montfort, et al., 2021). To date, no study has tested for potential differences in uncertainty assessments between these approaches.

In our study we generate a set of SDMs for the two subspecies of the Reunion Island day gecko, *Phelsuma borbonica borbonica* and *P. borbonica mater* (subsequently referred to as *P. borbonica*), and test potential differences in uncertainty assessments between the different approaches. Reunion Island is located in the western Indian Ocean and has faced a number of alterations over the last century related to agricultural practices (mostly sugarcane cultivation) and invasive species (Strasberg et al., 2005; Dubos, 2013; Fenouillas et al., 2021; Irl et al., 2021). Its herpetofauna has already been strongly modified after multiple local extinctions events and the arrival of allochthonous species (Cheke, 1987; Cheke & Hume, 2010; Sanchez & Probst, 2016). Today only two native reptile species remain, the indigene *P. borbonica* and the endemic *P. inexpectata*, while five reptile species having faced extinction in the recent past (Cheke & Hume, 2010).

Climate change can facilitate biological invasions and alters habitat suitability for locally adapted species

(Mainka & Howard, 2010; Gillard et al., 2017). To date, very few studies have focused on the potential effects of climate change on the future of Reunion Island's biodiversity (but see Legrand et al., 2016). Dubos et al. (2021) predicted the potential extinction of the endemic Reunion Island reptile, *P. inexpectata*, driven by climate change.

The Reunion Island day gecko, *P. borbonica* is classified nationally as endangered due to its narrow distribution. With high rates of land use change in Reunion Island, fire hazards and high pressure related to introduced species (Macdonald & Cedex, 1991; Strasberg et al., 2005; Lagabriele et al., 2009; Sanchez & Probst, 2016), many populations are isolated and are exposed to local extinctions. This calls the urgent need to identify priority areas for habitat conservation and restoration.

We assess for the first time the climatic niche of *P. borbonica* and the potential effects of climate change on its future distribution. We quantify the uncertainty in species range change (SRC) driven by the statistical methods (modelling technique, sample bias correction, variable selection) and climate data (RCPs, GCMs and baseline data) using two approaches (difference in summed suitability and spatial overlap) in the predicted future distribution of *P. borbonica*. We eventually provide a consensual map accounting for uncertainty to guide conservation actions.

120

121 **Methods**

122 *Occurrence data*

Phelsuma borbonica is mostly distributed in the forested areas of the eastern, southern, and northern parts of Reunion Island, from sea level to 2800 m (Meier, 1995; Mickaël Sanchez & Probst, 2017). Most observations are made in intermediate altitudes, near trails, on artificial structures or at the edge of pristine or disturbed forested areas (Augros et al., 2017). We obtained 5922 occurrence data (2648 after removing redundancies) from the Système d'information de l'inventaire du patrimoine naturel (SINP) provided by the Direction de l'Environnement, de l'Aménagement et du Logement (DEAL) and the Parc National de la Réunion (PNRun) and some additional unpublished occurrence data from various sources (Biotope Océan Indien, Cynorkis, Eco-Med Océan Indien, Nature Océan Indien). We removed 171 observations corresponding to single observations with no evidence of persistence (presumably corresponding to individuals transported out of their native range; Deso, 2001), translocated individuals, inaccurate coordinates, or indices of past presence (e.g., subfossil clutches). To limit spatial autocorrelation, we

134 resampled one occurrence per occupied pixel at the resolution of the environmental data (3 arc seconds,
135 approximately 100m). The final sample included 1050 points when sampled from the Worldclim data, 1056
136 with CHELSA.

137

138 *Land use data*

139 We accounted for the habitat requirements of our model species by applying a filter to the climate data. We
140 obtained very high-resolution land cover categories (Urban, agricultural, natural, water) at 1.5m resolution
141 (resampled at 100m for computing purposes) derived from remote sensing (Dupuy, Gaetano, & Le Mézo,
142 2020; Fig. Sx). We removed agricultural and urbanised areas, because *P. borbonica* is only found in natural
143 and semi natural habitats, which enabled to minimise model complexity while remaining biologically
144 realistic and relevant for conservation applications.

145

146 *Climate data*

147 We used 19 bioclimatic variables for 30 arc sec (approximately 900m) resolution of the current climate data
148 and of the 2070 projections from CHELSA (Karger et al., 2017) and from Worldclim global climate data
149 (Fick & Hijmans, 2017). We removed isothermality (bio2) from the analysis because of a lack of variability
150 in Reunion Island. We decided to include all the remaining variables because both temperature and
151 precipitation are related to the species' biology, including those referring to indices of variability. We used
152 three Global Circulation Models (GCMs; i.e., BCC-CSM1-1, MIROC5 and HadGEM2-AO) and two
153 greenhouse gas emission scenarios (the most optimistic RCP26 and the most pessimistic RCP85; Fig. S3,
154 S4). To enable the filtering of unsuitable habitats, we downscaled the climate data to fit the resolution of the
155 land cover variables (3 arc sec) using bilinear interpolation.

156

157 *Distribution modelling*

158 We modelled and projected species distributions in R (version 4.0.3; R Core Team, 2020) with the Biomod2
159 R package (Thuiller et al., 2009), using 10 modelling techniques: generalised linear and generalised additive

models (GLM and GAM; Guisan, Edwards, & Hastie, 2002), classification tree analysis (CTA; Prasad, Iverson, & Liaw, 2006), artificial neural network (ANN; Manel, Dias, & Ormerod, 1999), surface range envelop (SRE, also known as BIOCLIM; Booth et al., 2014), flexible discriminant analysis (FDA; Manel, Dias, & Ormerod, 1999), random forest (RF; Prasad, Iverson, & Liaw, 2006), multiple adaptive regression splines (MARS; Leathwick et al., 2005), generalised boosting model (GBM; Elith, Leathwick, & Hastie, 2008) and maximum entropy (MaxEnt; Phillips & Schapire, 2006). We generated five different sets of 1050/1056 pseudo-absences (to equal the number of presences) and ran a first set of models using a random pseudo-absence selection (Wisz & Guisan, 2009).

To accounting for sample bias, we reperformed all calculations using a non-random pseudo-absence selection. Following Phillips et al. (2009), we produced five sets of pseudo-absences selected around the presence points to reproduce the spatial bias of the sample. We used a geographic null model generated with the dismo R package (Hijmans, 2012) and used it as a probability weight for pseudo-absence selection. Since no independent data is available to assess the effect of sample bias correction, we used the relative overlap index (ROI; Dubos, Préau, et al., 2021) based on Schoener's D overlap. The ROI enables to assess whether the effect of correction is significant compared to the variability between model runs. It computes (1) the mean overlap between the uncorrected and the corrected predictions (i.e., the absolute effect of correction), and (2) the overlap between every pair of model replicate (between each pseudo-absence and cross validation runs, individually for each modelling technique, i.e. model stochasticity). We computed the ROI as follows:

$$ROI = \frac{\bar{D}_0 - \bar{D}(p_x, p_y)}{\bar{D}_0}$$

Where $\bar{D}_0$ is the mean overlap between model runs of the corrected group and $\bar{D}(p_x, p_y)$ is the mean overlap between runs of the uncorrected and the corrected models. A value close to 0 represents a perfect match between predictions (i.e. no effect of sample bias correction). The overlaps between uncorrected and corrected groups tend to be significantly smaller than the overlaps between runs when the ROI approaches 1 (i.e. strong effect of sample bias correction).

For each individual baseline climate data, we selected one variable per group of inter-correlated variables to avoid collinearity (Pearson's $r > 0.7$, Dormann et al., 2013) and assessed the relative importance of each

187 variable kept with 10 permutations per model replicate (total = 500 for each baseline data). The variables
188 included in the final models were those with a relative importance > 0.2 across at least 50% of model runs.
189 To determine whether variation in future predictions was driven by baseline climate *per se* or by differences
190 in the selected variables, we swapped the selected variables between baseline climates and repeated the
191 whole process.

192 Model evaluation—We spatially partitioned the data into five folds, with three runs of block cross-validation
193 (i.e., k-fold cross-validation; Fig. S1). We assessed model performance using the Boyce index, assumed to be
194 the best evaluation metric with pseudo-absence data (Leroy et al., 2018). A value of 1 means the models
195 reliably predicted the presence points while a value of 0 means that models did not perform better than
196 random. For ensemble models, we excluded models for which the Boyce index was below 0.5 (Gillard et al.,
197 2017). We verified that models are well informed for predictions on novel (future) data using clamping
198 masks.

199 Uncertainty analysis—We assessed the uncertainty in species range change (SRC) related to the modelling
200 technique, sample bias correction, climate scenarios, GCMs, baseline climate and variable selection. We
201 quantified SRC following two approaches. Firstly, we computed SRC as the difference between the summed
202 suitability scores of the baseline climate and the future predictions. Then we used linear models (LM,
203 assuming Gaussian errors), with SRC as a response variable, and the aforementioned sources of uncertainty
204 as explanatory variables, following Baker et al. (2016). We then assessed the proportion of deviance
205 explained by each source of uncertainty f as follows:

206
$$Pf = \frac{Df - D0}{D1}$$

207 where, Pf = proportion of deviance explained by factor f , $D1$ = deviance of full model, Df = deviance of full
208 model minus factor f , and $D0$ = deviance of null model.

209 Secondly, we quantified SRC using an overlap metric. We computed the Schoener's D overlap between
210 baseline projections and future projections using the ENMTools R package (Warren, Glor, & Turelli, 2010).
211 We eventually repeated the assessment of the proportion of deviance explained by the five aforementioned
212 sources of uncertainty using beta-regression GLM instead of LM, since overlap measures range continuously
213 between 0 and 1 (glmmTMB R package; Brooks et al., 2019).

214 In total, we computed 2000 models (10 modelling techniques * 5 pseudo-absence runs * 5 block cross-
 215 validation runs * 2 modalities of sample bias correction * 2 baseline climate data * 2 modalities for variable
 216 selection) for the current distribution, and 12000 projections on future climate data (2000 models * 3 GCMs
 217 * 2 emission scenarios). To provide the most certain conservation guidelines, we built a consensus map of
 218 the mean predictions across all simulations (of the corrected group and with the original selected variables)
 219 after removing poorly performing models, discounted with the standard deviation (Kujala et al., 2013).

220

221 **Results**

222 *Current distribution*

223 Models predicted well the presence of *P. borbonica* (median Boyce index (Worldclim) = 0.81; median Boyce
 224 index (CHELSA) = 0.78; Fig. S2, S3). A few points, corresponding to isolated populations, fell into areas
 225 predicted as moderately suitable. Sample bias correction slightly increased the predictions of suitable areas,
 226 but its effect on projections was not significant compared to within-model variation (ROI = 0.08; Fig. S4).
 227 With the Worldclim baseline climate, the selected variables were mean annual temperature (Bio1) and winter
 228 precipitation (Bio19; Fig. 1). With the CHELSA baseline climate, the selected variables were mean annual
 229 temperature (Bio1) and summer precipitation (Bio18; Fig 2).

230

231 Fig. 1 Response of *Phelsuma borbonica* to the selected Worldclim bioclimatic variables. The black lines
 232 represent the individual response curves for each iteration. The blue line represents the smoothed response
 233 across iterations. Bio1: annual mean temperature (°C); Bio19: precipitation of coldest quarter (mm).
 234

235 Fig. 2 Response of *Phelsuma borbonica* to the selected CHELSA bioclimatic variables. The black lines
 236 represent the individual response curves for each iteration. The blue line represents the smoothed response
 237 across iterations. Bio1: annual mean temperature (°C × 10); Bio18: precipitation of warmest quarter (mm).
 238
 239 *Future distribution*

240 Predictions differed strongly between modalities. Predictions derived from Worldclim baseline data indicated
 241 a dramatic decline in climate suitability across the entire island, regardless of the scenario or GCM (Fig. 3).
 242 The best predicted areas would shift upslope, but remain largely suboptimal. When based on CHELSA
 243 baseline data, predictions were more optimistic but highly variable between GCMs (Fig. 4). The ‘BCC-
 244 CSM-1-1’ GCM predicted little effect of climate change. The ‘MIROC5’ GCM indicated a slight decrease in
 245 climate suitability in the north-western part of the current distribution area, while the HadGEM2-AO
 246 predicted a strong decline in the eastern part.

247 Fig. 3 Current (a) and future (b) environmental suitability of *Phelsuma borbonica* in Reunion Island based
 248 on Worldclim baseline climate data.

249 Fig. 4 Current (a) and future (b) environmental suitability of *Phelsuma borbonica* in Reunion Island based
250 on CHELSA baseline climate data.

251

252 *Effect of variable selection*

253 After swapping the selected variables between baseline climate data, model performances decreased only
254 slightly (median Boyce index (Worldclim) = 0.71; median Boyce index (CHELSA) = 0.70). The predicted
255 current distribution was overestimated with Worldclim, and slightly underestimated with CHELSA.

256 The differences between Worldclim and CHELSA in predictions of future climate suitability persisted.

257 Predictions based on Worldclim strongly differed between GCMs (Fig. 5) but were consistent when based on
258 CHELSA (Fig. 6).

260 Fig. 5 Current (a) and future (b) environmental suitability of *Phelsuma borbonica* in Reunion Island based
 261 on Worldclim baseline climate data using the selected variables from the CHELSA models.
 262

264 Fig. 6 Current (a) and future (b) environmental suitability of *Phelsuma borbonica* in Reunion Island based
 265 on CHELSA baseline climate data using the selected variables from the Worldclim models.
 266

267 *Uncertainty analysis*

268 The highest source of uncertainty differed according to the metric of species range change considered (Fig.
 269 7). Overall change in suitability scores were the most variable between the modelling technique (SDM),
 270 followed by the GCM and the baseline climate. Uncertainty related to sample bias correction and variable
 271 selection were of lower magnitude. Regarding the amount of spatial information shared between current and
 272 future predictions (overlap), the highest source of uncertainty was the modelling technique, followed by
 273 variable selection and baseline climate. The uncertainty related to the GCM was lower than that of baseline
 274 climate when considering overlaps. Sample bias correction was the lowest source of uncertainty.
 275 The consensus maps indicate that the areas with the most consistent suitable conditions will be located at
 276 several places throughout the island (Fig. 8). The mean prediction maps also indicates that the best
 277 conditions will be largely suboptimal, from a maximum suitability score of 797 under current conditions to
 278 362 by 2070.

280 Fig. 7 Proportion of deviance explained by five sources of uncertainty, quantified with two metrics of species
 281 range change (SRC). SDM: modelling technique (species distribution model); GCM: global circulation
 282 model; Correction: sample bias correction (non-random pseudo-absence selection); Baseline: baseline
 283 climate data (Worldclim versus CHELSA); Overlap: Schoener's D overlap between current and future
 284 projections; Suitability scores: difference between summed suitability scores of current and future
 285 predictions.

Fig. 8 Consensus maps of current (a) and 2070 (b) priority areas for conservation for *Phelsuma borbonica*, derived from predicted climate suitability. Current and future predictions (bottom) are the result of mean projections (top left of each panel) discounted with inter-model variability (top right of each panel).

Discussion

We predicted the future climate suitability of *P. borbonica* while accounting for multiple climate models and found a strong disagreement between future predictions derived from Worldclim and CHELSA baseline climate data. The uncertainty related to both methodological aspects and input climate data depended on the approach used to quantify species range change (summed suitability *versus* overlap). Mean projections indicate an important decline in climate suitability by 2070.

Drivers of species distribution

The effect of temperature is consistent between simulations, with an optimal suitability estimated around 20°C on average throughout the year (mostly between 15 and 25°C, with a second peak near 10°C). The identified temperature window corresponds to the overall thermal tolerance of tropical reptiles (Sunday, Bates, & Dulvy, 2011).

Phelsuma borbonica is more present in areas with high precipitation, mostly corresponding to native remnant rainforests. We presume that *P. borbonica* benefits from a higher availability of specific native tree

species (e.g., Arecaceae and Pandanaceae), which provide shelter, food and oviposition sites, as it is also found in other *Phelsuma* species from the Comoros and Seychelles (Noble et al., 2011; Augros et al., 2018; Augros, 2019). *P. borbonica* may also be adapted to cyclone activity, as this might be the case in Madagascar or in the Pacific islands (e.g., fallen trees used as hatching sites or open areas for thermoregulation; Ineich, 2010; Dubos et al., 2020). However, the species is mainly found in intact forests and may therefore use them as shelter to reduce cyclone impact instead.

Overall, *P. borbonica* can persist in very different habitats and environmental conditions, from cold and dry rocky slopes near the summits of the island (above 2.000 meters; Sanchez & Probst, 2017) to warm lowland and midland humid forests. We found a bimodality in the response curves to temperature and precipitation for several iterations. These were likely caused by the presence of isolated populations on mountain ridges and reflect the local adaptations to these specific environments. In Reunion, two subspecies were described, i.e. *P. borbonica borbonica* and *P. borbonica mater* (Meier, 1995; Probst & Deso, 2001). However, the two modalities we found do not correspond to these subspecies, which seem to share the same climatic niche instead. Preliminary unpublished genetic analyses suggest a strong isolation between these populations (Sanchez et al., 2015; unpubl. data). Further genetic analyses are needed to quantify the degree of isolation between populations.

Occurrence data which corresponded to isolated observations with no evidence of established populations (i.e., with no individual was observed after further surveys) were from areas that were predicted as unsuitable, a sign that our models identified well the species climatic niche.

Predictions based on Worldclim indicated that suitable conditions can be met around the island at intermediate altitudes. It is possible that *P. borbonica* once occupied this whole area, but was extirpated because of intensive agriculture and habitat fragmentation in the western part of the island. A local extinction of the *P. borbonica* was already documented in Cheke (1987). This depletion was associated with the severe deforestation that occurred in the 18th century at the intermediate and lower belt of the island, and a high pressure from invasive alien species (i.e., the introduced wolf-snake *Lycodon aulicus*; Cheke & Hume, 2010). These combined factors may have dramatically decreased habitat suitability and habitat availability for *P. borbonica* in the past centuries, which may explain its absence in some of the predicted climatically suitable areas. The former presence of *P. borbonica* in the western part of the island is supported by the

332 presence of isolated remnant populations in the southwest (near Les Makes & Le Tampon) and recently
 333 extinct populations in the northern lowlands (Cheke, 1987).

334 As shown by the response curves, *P. borbonica* persists over a relatively wide range of climatic conditions.
 335 However, its presence remains localised throughout the island. To fully understand and explain the current
 336 distribution patterns of *P. borbonica*, there is a need to also consider additional key factors such as micro-
 337 habitat use and behaviour (Kearney, Shine, & Porter, 2009; Porter & Kearney, 2009). For instance, cold-
 338 blooded species can respond to climate change by altering their period of activity and thermoregulation time
 339 (Kearney, Shine, & Porter, 2009). Moreover, the availability of suitable oviposition sites, thermoregulation
 340 sites with specific exposure to wind, sun or rain is a strong determinant of gecko occupancy (Ineich, 2010;
 341 Bungard et al., 2014; Augros et al., 2017, 2018). Habitat structure is provided in native forests by tree species
 342 from the Arecaceae and Pandanaceae families and abiotic features (e.g. sunny-exposed rocks, cliffs, man-
 343 made structures; Petren & Case, 1998; Augros et al., 2017). In additions to climate change, habitat
 344 modifications, such as further urbanisation and deforestation will strongly influence the future distribution of
 345 *P. borbonica* in Reunion Island.

346 Biotic interactions play an important role in shaping species distributions (Araújo et al., 2007). The current
 347 distribution of *P. borbonica* is strongly influenced by the occurrence of invasive alien species. The wolf
 348 snake *Lycodon aulicus* is presumed to be the cause of historical local extinctions through predation (Cheke,
 349 1987). The introduced Giant Madagascar day gecko *P. grandis* and the Gold-dust day gecko *P. laticauda* are
 350 present throughout the island. Both species were reported from areas within the distribution of *P. borbonica*.
 351 To date, there is no evidence of local extirpation of *P. borbonica* by these two species. However, *P. grandis*
 352 was suspected to be the cause of local extinctions of *Phelsuma* species in Mauritius, presumably through
 353 competitive exclusion and/or predation (Buckland et al., 2014). It is also the case for *P. laticauda* in French
 354 Polynesia (Lund, 2015). *Phelsuma laticauda* is a rising cause of concern in the south of Reunion Island
 355 where it possibly threatens the persistence of the critically endangered *P. inexpectata* (NOI, unpubl. data; but
 356 see Porcel et al., 2021). Other introduced species may also affect *P. borbonica* through predation and/or
 357 habitat alterations, including other reptiles (*Agama agama*, *Calotes versicolor*, *Furcifer pardalis*), rodents
 358 (*Rattus rattus*, *Mus musculus*), ants (*Solenopsis geminata*), birds (*Pycnonotus jocosus*, *Acridotheres tristis*)
 359 and plants (*Lantana camara*). The rate of invasion is increasing in Reunion Island (Fenouillas et al., 2021).

360 Further studies will need to account for biotic interactions to better understand the key drivers of the
361 distribution of *P. borbonica* and refine forecasted predictions.

362

363 *Sources of uncertainty*

364 We found a strong uncertainty driven by the modelling technique and GCMs. This is consistent with the
365 findings of Buisson et al. (2010) and Baker et al. (2016) and advocates the use of a wide range of modelling
366 techniques and GCMs for conservation planning. However, the uncertainty related to the baseline climate
367 data was stronger than that of GCM when considering the spatial overlap between current and future
368 predictions. When considering overall suitability, the importance of the baseline climate was probably
369 underestimated because it affected the suitability scores in a lower extent than GCMs, however, resulted in
370 higher discrepancies in spatial distribution of the future suitable conditions. The mismatch caused by the
371 baseline climate data can be due to the differences in temporal coverage, with Worldclim representing the
372 conditions of the 1960–1990 period while CHELSA was computed for 1979–2013. However, temporal
373 coverage cannot fully explain these discrepancies because future predictions (both for 2070) also strongly
374 differed, even when using the same predictors. Another factor potentially affecting these differences in
375 predictions is the higher accuracy in predictions for precipitation of the CHELSA climatic data, with more
376 topographic factors accounted for (Karger et al., 2017). This difference in accuracy may be exacerbated in
377 mountainous environments such as Reunion Island. These results suggest that the spatial component of
378 species range change should not be neglected when the aim is to identify priority areas for conservation.
379 More generally, the importance of drivers of uncertainty may be downplayed when ignoring spatial
380 information. We recommend the use of multiple approaches, including overlap estimations, in uncertainty
381 assessments of species range change.

382

383 *Conservation considerations*

384 The current distribution of *P. borbonica* is generally consistent with the predicted future suitable areas (see
385 Fig8b, ‘Mean prediction’ panel). We recommend that the areas identified with the highest certainty should be
386 prioritised for conservation and habitat restoration. In the context of Reunion Island, conservation actions are
387 drastically limited by land use policy as the available land is strongly disputed for by urbanisation and
388 agriculture planning. Overall, conservation efforts should be intensified in the forested uplands, where

389 predictions are favourable and anthropogenic pressure is the least. Nevertheless, the conservation of the
390 small, isolated populations of *P. borbonica* along some of the mountain ridges and in the west of Reunion
391 Island is of paramount importance, as these represent remnant populations that possibly form genetically
392 isolated entities (Sanchez et al., 2015; unpubl. data). Being supposedly more adapted to colder conditions,
393 mountain ridge populations may also be at even greater risk due to climate change (Raxworthy et al., 2008;
394 Freeman et al., 2018). We recommend the close monitoring of these populations for early detection of
395 potential signs of population declines.

396 Conservation actions should encompass a range of management strategies, including the protection of native
397 forests, restoration of degraded habitats, creation of artificial oviposition sites and the implementation of
398 sustainable agricultural practices. The control of invasive species represents an additional challenge, for
399 instance with *P. grandis* and *P. laticauda* currently in expansion throughout the island (Dubos, 2013; Porcel
400 et al., 2021).

401 This study stresses the need for proactive conservation actions given the high risk of extinction predicted by
402 some of our models. *Phelsuma borbonica* is already threatened by habitat loss and fragmentation, which will
403 likely increase in the future with human population. Future conservation actions will need to consider socio-
404 economic factors to prevent potential land use conflicts (Lagabrielle et al., 2011). This can be achieved by
405 involving stakeholders from urban and agricultural sectors and conservation practitioners into public
406 decision-making processes.

407 Depending on the climate data considered, our models predicted either a strong decline throughout the entire
408 island, upward, westward, or eastward shifts, or almost no change. Despite the high uncertainty, we
409 identified the areas with the most consistent predictions of suitable climate by 2070. In a context of urgent
410 decision making, we advocate the use of all the available tools to prevent possible extinctions in spite of the
411 apparent uncertainty. Forecasting models need to consider a wide range of methods and data, and assess the
412 variability between them in order to identify and mitigate potential sources of uncertainty and provide
413 relevant conservation guidelines.

414

415 **Aknowledgements**

416 We thank Boris Leroy for useful discussions. We are thankful to all the field workers that collected the data
417 used in this study. We thank Biotope Océan Indien and Cynorkis for providing additional data.

418

419 Data accessibility statement

420 All the occurrence data and the R scripts used in this study are available in online supporting information.

421

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423

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