Are narrow-ranging species doomed to extinction? Projected dramatic decline in future climate suitability of two highly threatened species

Nicolas Dubos, Frederique Montfort, Clovis Grinand, Marie Nourtier, Gregory Deso, Jean-Michel Probst, Julie Hanta Razafimanahaka, Raphali Rodlis Andriantsimanarilafy, Eddie Fanantenana Rakotondrasoa, Pierre Razafindraibe, et al.

1   **Are narrow-ranging species doomed to extinction? Projected dramatic decline in future climate**

2   **suitability of two highly threatened species**

3

4   Running title: Narrow-ranging species and climate change

5

6   Nicolas Dubos[1, 2], Frederique Montfort[3], Clovis Grinand[3], Marie Nourtier[3], Gregory Deso[4], Jean-Michel

7   Probst[5], Julie Hanta Razafimanahaka[6], Raphali Rodlis Andriantsimanarilafy[6], Eddie Fanantenana

8   Rakotondrasoa[6], Pierre Razafindraibe[6], Richard Jenkins[6,7] and Angelica Crottini[8]

9

10

11   1 Centre d'Ecologie et des Sciences de la Conservation (CESCO UMR 7204), Sorbonne Université, MNHN,
12   55 rue Buffon, 75005 Paris, France.

13   2 INRAE (UMR TETIS), Maison de la télédétection, 500 rue Jean-François Breton 34093 Montpellier Cedex
14   5, France.

15   3 N'Lab, Nitidæ, Maison de la télédétection, 500 rue Jean-François Breton 34093 Montpellier Cedex 5

16   4 Association Herpétologique de Provence Alpes Méditerranée, Maison des Associations, 384 route de
17   Caderousse, F-84100 Orange, France.

18   5 Association Nature and Patrimoine, 1 rue des amarantes résidence Valeriane 2, Bat C appartement 15.
19   97490 Sainte Clotilde, Île de La Réunion, France.

20   6 Madagasikara Voakajy, B.P. 5181, Antananarivo (101), Madagascar.

21   7 Durrell Institute of Conservation and Ecology, School of Anthropology and Conservation, Marlowe
22   Building, University of Kent, Canterbury, CT2 7NR ; Current address: IUCN Global Species Programme,
23   219c Huntingdon Road, Cambridge, CB3 0DL, UK.

24   8 CIBIO, Research Centre in Biodiversity and Genetic Resources, InBIO, Universidade do Porto, Campus

25   Agrário de Vairão, Rua Padre Armando Quintas, No 7, 4485-661 Vairão, Portugal.

26

27 **Abstract**

28 Narrow-ranging species are usually omitted from Species distribution models (SDMs) due to statistical

29 constraints, while they are predicted to be particularly vulnerable to climate change. The recently available

30 high-resolution environmental predictors, along with recently developed methods enable to increase the

31 eligibility of narrow-ranging species for SDMs, provided their distribution is well known. We fill a gap of

32 knowledge on the effect of predicted climate change on narrow-ranging species. We modelled the

33 distribution of the golden mantella frog *Mantella aurantiaca* and the Manapany day gecko *Phelsuma*

34 *inexpectata,* for which the distribution of their occurrence records is well documented. Our modelling

35 scheme included a range of processes susceptible to address statistical issues related to narrow-ranging

36 species. We predict an alarming decline in climate suitability in the whole current distribution area of both

37 species by 2070, potentially leading to a complete extinction in most scenarios. We identified the areas with

38 the best climate suitability in the future, but these remain largely suboptimal regarding species climatic niche.

39 The high level of habitat fragmentation suggests that both species likely need to be at least partly

40 translocated. Climate change may not only drive range contractions or distribution shifts in narrow-ranging

41 species, but may lead to the complete extirpation of suitable environments across their entire region. This

42 study suggests that the level of threats of narrow-ranging species already identified as threatened may be

43 underestimated, especially in heterogeneous tropical areas. We stress the need to develop sampling

44 campaigns and implement proactive actions for narrow-ranging species in the tropics.

45

46 Keywords: Climate change, Ensemble of Small Models, Jackknife, Madagascar, *Mantella aurantiaca*,

47 *Phelsuma inexpectata*, Reunion Island, Species distribution models, Translocation

Introduction

Climate change is predicted to become the main driver of biodiversity loss it in the next decades (Bellard *et al.*, 2012). Species Distribution Models (SDMs) are probably the most common approach used to predict the impact of future climate change on species. They are used to predict current and future environmental suitability, and provide guidelines for the identification of priority areas for protection (Leroy *et al.*, 2014), habitat restoration and species (re)introduction/translocations (e.g., Bellis et al., 2020; Draper et al., 2019; Butt et al., 2020; Westwood et al., 2020). Habitat restoration and translocations are two ecological engineering techniques enabling the restoration of depleted populations. Translocation programs will become increasingly needed in the face of climate change, especially for species with small distribution ranges (Thomas, 2011). In this regard, SDMs help identifying suitable receptor sites that meet the species' habitat requirements while accounting for climate suitability (Bellis et al., 2020). In highly degraded environments a combination of habitat restoration and translocation may be needed to avoid species extinctions. This may be the case in highly fragmented tropical systems, where the number of narrow-ranging species is higher and where climate change effects are expected to be stronger (Tewksbury et al., 2008).

The impact of future climate change is largely understudied in endangered narrow-ranging species. This is mainly due to the difficulty to model their current distribution and project their future because of low sample sizes and subsequent little spatial replicates when fitted on climate data (Botts *et al.*, 2013; Platts et al., 2014; Breiner et al., 2015; Galante et al., 2018). Both these factors lead to statistical constraints that withdraw these species from eligibility for SDMs. However, the omission of narrow-ranging species in SDMs may be problematic in terms of conservation planning, because the area encompassing their distribution may be downplayed (Platts *et al.*, 2014). Although narrow-ranging species are known to be more vulnerable to climate change (Pearson *et al.*, 2014), few studies have provided quantitative assessment of climate change impacts on these (but see Alamgir *et al.*, 2015; Zhang *et al.*, 2020).

The recent availability of high-resolution climatic data (e.g., Fick & Hijmans, 2017; Karger et al., 2017), along with high-resolution land cover data (e.g., Vieilledent et al., 2018) is offering new opportunities for modelling the distribution of these species (Lannuzel et al., 2021). However, despite a probable increase in

74 statistical power, there is still the possibility for SDMs to produce misleading results due to spatial sampling

75 bias (Phillips *et al.*, 2009). The effect of sample bias may be particularly strong in rare (or poorly known)

76 species with small sample sizes, because models are more influenced by each occurrence data that is used

77 (Pearson *et al.*, 2007). A number of techniques were recently developed for data-poor species. For instance,

78 jackknife procedures (i.e. leave-one-out; Pearson et al. 2007) improves model assessments and Ensemble of

79 Small Models (ESMs) enable to deal with model complexity while keeping sufficient explanatory power

80 (Breiner et al. 2015). Other techniques are dedicated to sampling bias correction, often implying the filtering

81 of occurrence or environmental data (Gábor *et al.*, 2019) or non-random pseudo-absence selection (Phillips

82 *et al.*, 2009). However, data filtering can become problematic for species with low sample sizes (Vollering et

83 al., 2019), especially when species distribution is highly localised (Inman et al., 2021) and is not

84 recommended in absence of evidence of bias in occurrence data (Gábor et al., 2019). Similarly, non-random

85 pseudo-absence selection is not always effective (Dubos et al., 2021) and tends to make predictions worse in

86 narrow-niche species (Inman et al., 2021). However, the restriction of the background area (where pseudo-

87 absences are generated), i.e. background thickening, can be advantageous for sample bias correction when

88 data is scarce without discarding presence records (Acevedo et al. 2012; Vollering et al. 2019). On the other

89 hand, the reliability of an SDM is more driven by the quality of the data than the implementation of models

90 (Araùjo et al., 2019). Therefore, the best option for narrow-ranging SDMs may be to (1) use all the available

91 methodological tools to deal with statistical issues, and (2) select species for which the distribution is well

92 known.

93 Given the predicted magnitude of climate change, along with the narrow thermal tolerance of tropical species

94 (Tewksbury et al., 2008), we may not only expect a reduction or a geographical shift in suitable conditions

95 for narrow-ranging species, but the extirpation of suitable conditions across the entirety of their distribution

96 range. Here we fill a gap of knowledge regarding the impact of future climate change on narrow-ranging

97 species using two species for which the distribution is particularly well documented. These were the

98 Manapany day gecko *Phelsuma inexpectata,* classified as Critically Endangered (IUCN & MNHN, 2010)

99 and the golden mantella frog *Mantella aurantiaca* formerly classified as Critically Endangered (Vences &

100   Raxworthy, 2008), now classified as Endangered after the inclusion of one locality record which increased its

101   extent of occurrence (IUCN SSC Amphibian Specialist Group 2020). Both species are in continued decline

102   (Probst & Turpin, 1997; Crottini et al., 2019), live in highly fragmented areas (respectively in Reunion Island

103   and central Madagascar) and are in urgent need for conservation actions. Given the important, long-term

104   efforts invested to document their distribution, we assume that the geographic information for these species

105   is nearly comprehensive and unbiased. We tested whether climate change will 'only' drive range

106   reductions/shifts, or lead to a total extirpation of their suitable areas. We eventually identify the most suitable

107   candidate areas for habitat restoration and translocation across their respective regions.

108

109   **Methods**

110   *Occurrence data*

111   *Phelsuma inexpectata* – The Manapany day gecko is endemic to the south of Reunion Island. We retrieved

112   31 occurrence data from literature (Bour *et al.*, 1995). Since then, the surroundings of the known distribution

113   range of the species were regularly visited (an 11 km-long coastal band; Fig. 1). Two localities corresponding

114   to introduced populations were identified west of the current range, which we added to the data (Deso, 2001;

115   Porcel *et al.*, 2021). Recent sampling campaigns enabled to find additional occupied habitats (Dubos 2010)

116   but did not add any occurrence point after aggregation at the resolution of the environmental variables (30

117   arc seconds). Therefore, we assume that the sample occurrence of the species is nearly comprehensive. The

118   total number of 30 sec. occupied pixels resulted in 15 presence points.

119   *Mantella aurantiaca* – The golden mantella frog is distributed in central-Eastern Madagascar (region of

120   Moramanga; Fig. 1). We obtained 131 occurrence data from Piludu *et al.* (2015). Those included compiled

121   published data from surveys conducted between 2001 and 2007 (Bora *et al.*, 2008; Randrianavelona *et al.*,

122   2010) and new locations from additional surveys conducted between 2008 and 2013. More recent surveys

123   conducted between 2014 and 2019 enabled to add 39 occurrences. The region has been extensively surveyed

124 and it is very likely that most occupied habitats were identified. After aggregation to match the resolution of

125 environmental data, sample size resulted in 101 occurrence points.
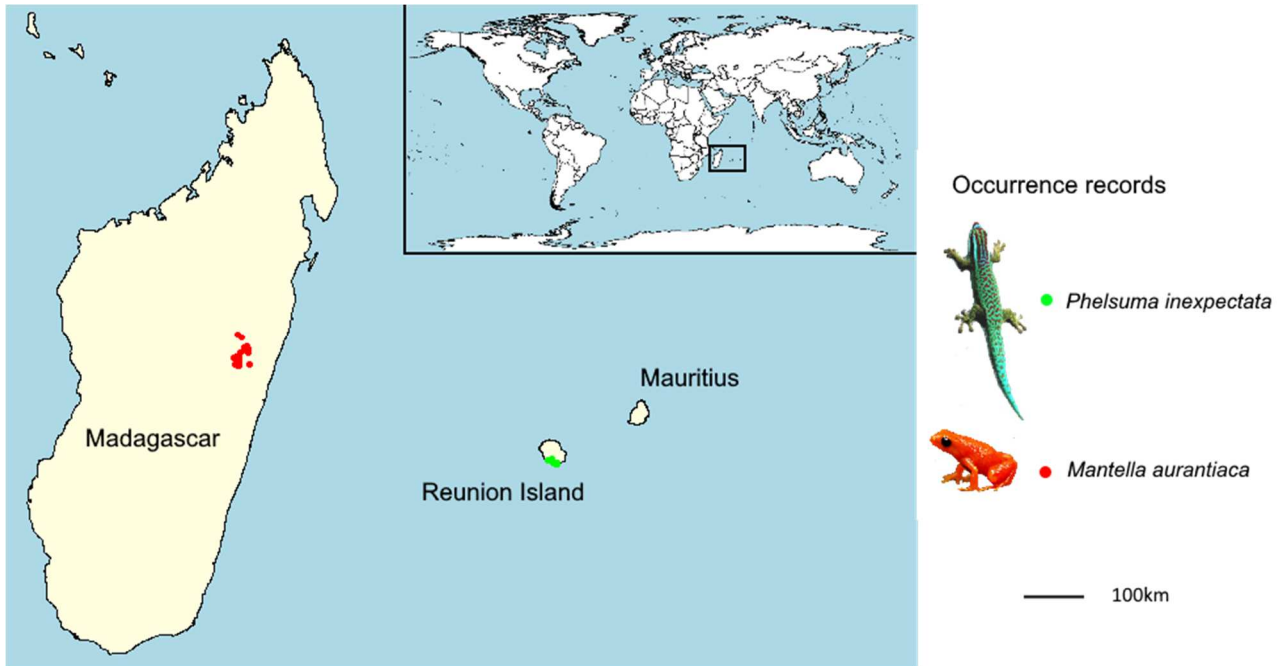
126 Fig. 1 Study area and species, with occurrence points.

127 *Climate data*

128 We used the 19 bioclimatic variables for 30 arc sec (approximately 900m) resolution of the current climate

129 data and of the 2070 projections from CHELSA (Karger et al., 2017; Fig. S1, S2). We decided to include all

130 the 19 variables because both temperature and precipitation are related to the species' biology, including

131 those related to indices of variability (e.g., cyclones drive mortality in *Phelsuma* and heavy rains drive

132 reproduction in *Mantella*; Vinson, 1975; Randrianavelona et al., 2010). We used three Global Circulation

133 Models (GCMs; i.e., BCC-CSM1-1, MIROC5 and HadGEM2-AO) and two greenhouse gas emission

134 scenarios (the most optimistic RCP26 and the most pessimistic RCP85; Fig. S3, S4). We also ran sets of

135 models using the WorldClim Global Climate Data (Fick & Hijmans, 2017), with the same GCMs and

136 scenarios to account for potential effect of the baseline data in our predictions.

137

138 *Distribution modelling*

139 We modelled and projected species distributions with the biomod2 R package (Thuiller et al. 2009), using 10

140 modelling techniques: generalised linear model (GLM), generalised additive model (GAM), classification

141 tree analysis (CTA), artificial neural network (ANN), surface range envelop (SRE, as known as BIOCLIM),

142 flexible discriminant analysis (FDA) and random forest (RF), Multiple Adaptive Regression Splines (MARS),

143 Generalised Boosting Model (GBM) and Maximum Entropy (MaxEnt). For machine learning modelling

144 techniques, hyperparameters were set to their default values implemented in biomod2 (see

145 https://www.rdocumentation.org/packages/biomod2/versions/3.5.1/topics/BIOMOD_ModelingOptions). We

146 generated five different sets of randomly-selected pseudo-absences (random generation is recommended for

147 rare and specialised species; Inman et al., 2021). We selected one variable per group of inter-correlated

148 variables to avoid collinearity (Pearson's r > 0.7) and assessed the relative importance of each variable kept

149 with 10 permutations per model replicate (total = 500). The variables included in the final models were those

150 with a relative importance > 0.2 across at least 50% of model runs (these varied with the baseline climate and

151 the background extent; Table 1). We show the fitted predicted values for each individual model, and a mean

152 smoothed response curve. We predicted species distributions with an ensemble of small models approach

153 (ESM; Breiner et al., 2015). We ran sets of bivariate models, i.e. including all pairwise combinations of the

154 selected variables, and produced an ensemble model with the mean predictions across all models weighted

155 by their respective AUC (see below). This method is advocated for rare species and enables to reduce model

156 complexity without reducing the explanatory power. We set three runs of cross validation (except for the

157 jackknife procedure; see below). We ran a first set of models (1), hereafter referred to as 'Base' setting, with

158 1000 pseudo-absences selected from a background covering the entire respective island of each species (i.e.

159 all island cells). We ran a second set (2) where the 1000 pseudo-absences were down-weighted to equal

160 presence data (setting prevalence to 0.5) referred to as 'equal total weight' (ETW; Liu et al. 2019). We

161 reperformed the first two model sets but with a background covering the southern part of Reunion Island and

162 the eastern forested part of Madagascar (see 'Land use data' section), without, and with pseudo-absence

163 down-weighting, respectively referred to as (3) 'Restricted background' and (4) 'ETW-Restricted

164 background'. Eventually, we ran a (5) Base model set with the Worldclim baseline climate instead of Chelsa,

165 referred to as 'Worldclim baseline'. For both species we present five ensemble models of current distribution

166 (of varying background, prevalence and baseline climate), and 30 ensemble models of projected future

167 distribution (of varying background, prevalence, baseline climate, GCM and RCP). We did not account for

168 species dispersal ability, because the purpose was not to predict potential shifts, but to assess how suitable

169 will be the climate in the future in order to identify candidate sites for restoration and translocation.

170

171 *Model evaluations* – Ideally, performance evaluations are based on block-cross validation to limit spatial

172 autocorrelation at large scales. In our case, species distributions are highly localised and the use of spatial

173 splits would result in strong unbalances between blocks. We therefore used a random partitioning for *M.*

174 *aurantiaca* and a jackknife for *P. inexpectata*. The jackknife procedure is appropriate for small sample sizes

175 (Pearson *et al.*, 2007; Galante *et al.*, 2018). This approach consists in running n iterations corresponding to

176 the number of occurrence data, removing one occurrence for each run of calibration. Models are evaluated

177 with the withheld occurrence. We did not used it for *M. aurantiaca* given that the number of occurrence data

178 was sufficient for a standard procedure, and used an 80% calibration subset (random partitioning). We

179 assessed model performance using the Area Under the Operative Curve (AUC), the True Skill Statistics (TSS)

180 and the Boyce index (the latter was not computed for the jackknife procedure, because this index is based on

181 Spearman's coefficients and cannot be estimated on the basis of a single location). Poorly performing models

182 could result from calibration subsets falling into different conditions than evaluation subsets. For ensemble

183 models (mean predictions), we excluded models for which the AUC was below 0.9 and for which the Boyce

184 index was below 0.5 (Gillard et al., 2017).

185 We performed a multivariate environmental similarity surfaces analysis (MESS) to determine whether

186 models are well informed for projections on novel (future) data. We eventually quantified the uncertainty

187 related to model input parameters (modelling technique, pseudo-absence distribution, number of pseudo-

188 absences generated, pseudo-absence down-weighting, GCMs, RCPs and baseline climate data) by computing

189 the standard deviation of the suitability scores between model predictions.

190

191 *Land use data*

192 We accounted for the habitat requirements of our model species by applying a filter to the projected climate

193 suitability based on land use and land cover data (e.g., Gillard *et al.*, 2017). This enabled to minimise model

194 complexity while remaining biologically realistic and relevant for conservation applications.

195 Reunion Island – We used very high-resolution land cover categories (Urban, agricultural, natural, water) at

196 1.5m resolution (resampled at 15m for computing purposes) derived from remote sensing (Dupuy and

197 Gaetano, 2019; Fig. S5). Since *P. inexpectata* can be found in both urbanised and natural areas and avoids

198 agricultural areas (Probst & Turpin, 1997), we excluded the latter land use type only. This is relevant also for

199 conservation applications because habitat restoration is more difficult to implement in agricultural areas.

200 Madagascar – *Mantella aurantiaca* is exclusively found in swampy forested areas (Randrianavelona *et al.*,

201 2010). We filtered our suitability maps to include only cells corresponding to rainforests. We obtained forest

202 cover data for two periods (1990 and 2017) from a study that combined global tree cover loss data with

203 historical national forest (resolution 30m; Vieilledent et al., 2018; Fig. S6). We used forest cover of the year

204 1990 for current distribution models because it corresponds approximately to the period of the oldest

205 occurrence data (some areas were deforested since then). For future projections, we used the latest forest

206 cover data available, i.e. 2017.

207

208 **Results**

209 *Variable selection and model performance*

210 Three to four variables were selected in every cases (no change between prevalence settings; see details in

211 Table 1; Fig. S7, S8). The current distribution of both species was well predicted (across five model sets: *P.*

212 *inexpectata*: mean AUC = 0.96, mean TSS = 0.91; *M. aurantiaca*: mean Boyce = 0.82, mean AUC = 0.97,

213 mean TSS = 0.94; Fig. S9, S10). We excluded 5076 poorly performing models out of 18750 for *P.*

214 *inexpectata*, and 343 out of 4140 for *M. aurantiaca*. The median suitability score at the presence points for *P.*

215 *inexpectata* was 836 (911 when removing the two introduced populations) and 783 for *M. aurantiaca*.

216 Models consistently identified the current distribution range between all runs for both species, as shown by

217 the uncertainty map (SD intermodel suitability scores at the presence points of 168 for *P. inexpectata* and 113

218 for *M. aurantiaca*; Fig. S11, S12).

219 Table 1. Selected variables for two narrow-ranging species in Reunion Island and Madagascar. Variables

220 were obtained from CHELSA (Karger et al., 2017) and Worldclim (Fick & Hijmans, 2017), and selected on

221 the basis of 10 permutations per modelling technique and pseudo-absence set (total = 500).

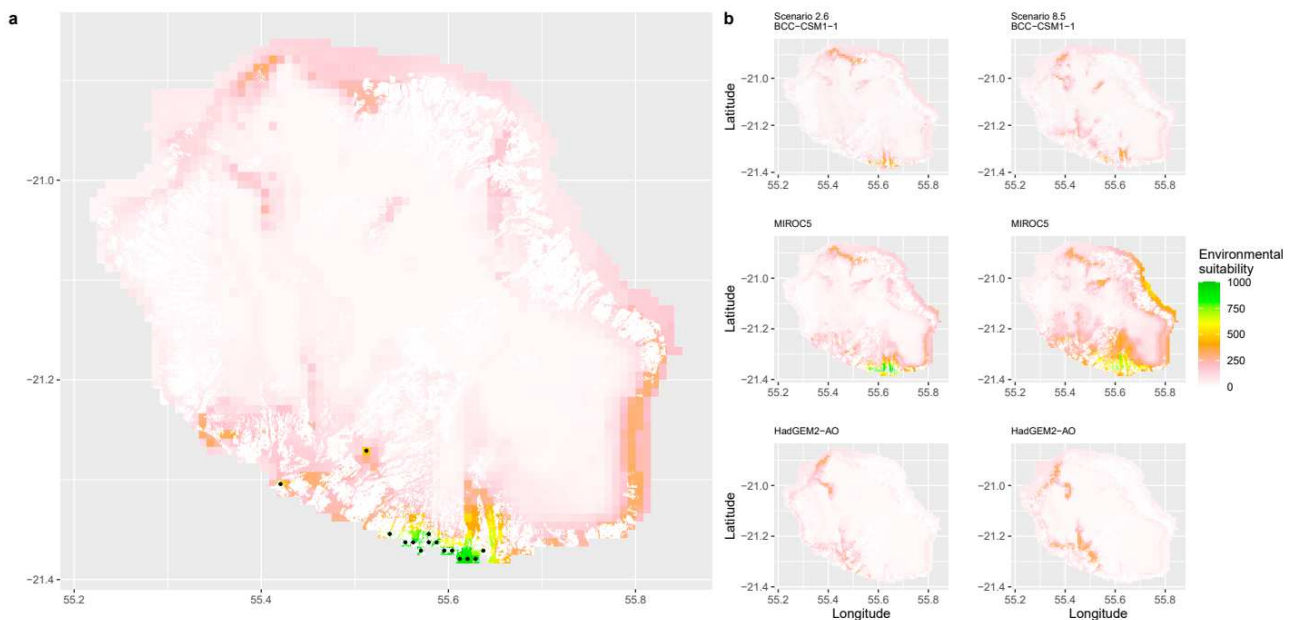| Species	Model set	Selected variables
Phelsuma inexpectata	Base	Bio1, Bio15, Bio18
	Restricted background	Bio1, Bio15, Bio18
	Worldclim baseline	Bio1, Bio3, Bio14, Bio16
Mantella aurantiaca	Base	Bio1, Bio3, Bio4, Bio5
	Restricted background	Bio1, Bio18, Bio19
	Worldclim baseline	Bio10, Bio11, Bio14, Bio16

222

223 *Future climate suitability*

224 All scenarios indicated an important decrease in climate suitability in the entirety of the current range of both

225 species by 2070 (Fig. 2–7). On average across scenarios and GCMs, suitability scores decreased by 59% for

226 *P. inexpectata* (Fig. 8) and 73% for *M. aurantiaca* at the presence points (Fig. 9). For *M. aurantiaca*, only

227 one scenario out of 30 showed high suitability values within the current range (i.e. the MIROC5 GCB,

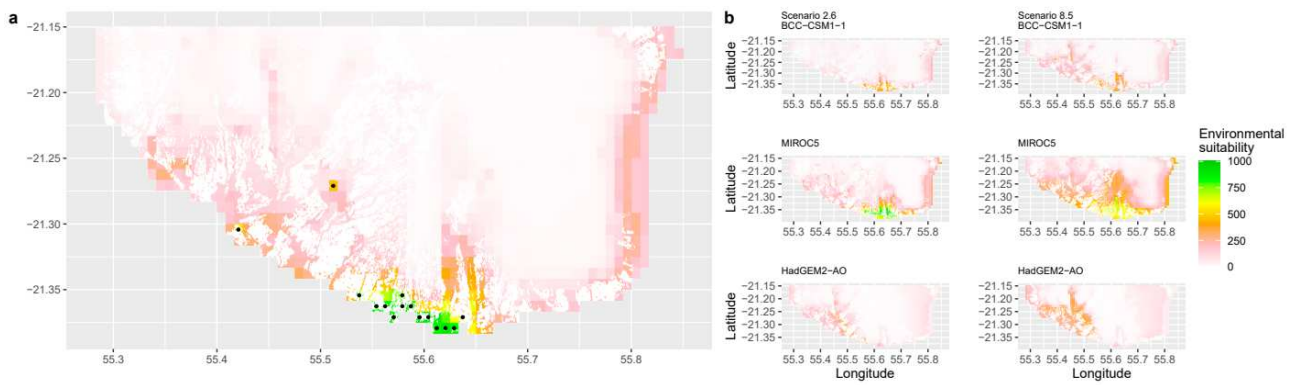228 RCP85, Chelsa baseline, restricted background).

229 In Reunion Island, predictions were the most variable between GCMs, but most ensemble models predicted a

230 low climate suitability across the island. The highest suitability was found for the MIROC5 GCM,

231 distributed along a band at higher altitudes (Fig. 2b). However, the MESS analyses indicated novel

conditions in the most suitable areas, suggesting model extrapolations in these areas for this GCM (Fig. S13).

According to the response curves (Fig. S14) and the predicted decrease in summer precipitations (Fig. S3c-d),

climate suitability may have been overestimated.

In Madagascar, predictions varied the most with the background extent. Apart from the restricted background

sets, none of the ensemble models identified any suitable area in the future. Nevertheless, we consistently

identified a thin forest band in central Madagascar, south the current distribution, as the most suitable area

across GCMs and scenarios (Fig. 3b). Models identified clear climatic windows, with no issue related to
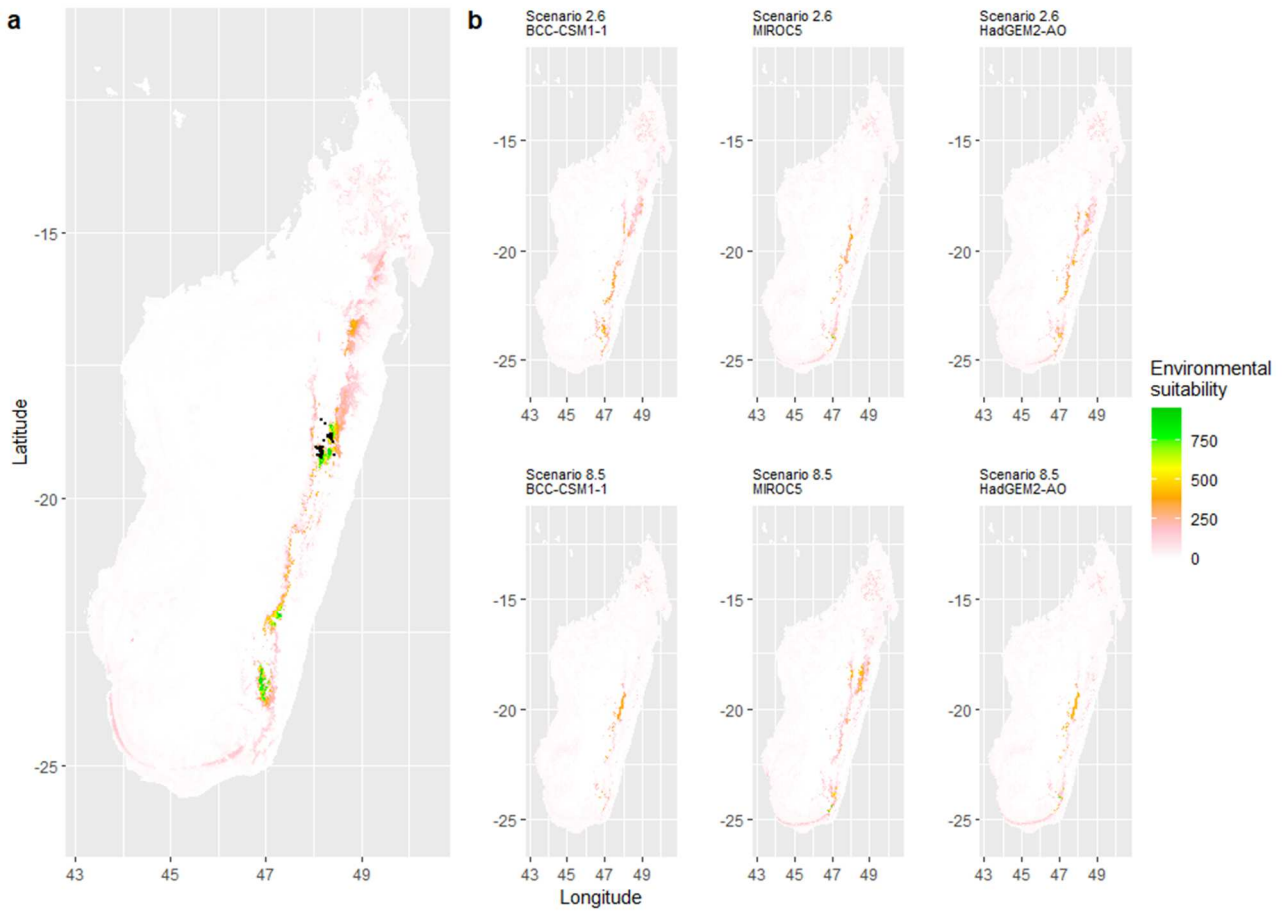
model extrapolation (Fig. S15, S16).

Fig. 2 Current (a) and projected future (b) environmental suitability for *Phelsuma inexpectata* using Chelsa

as baseline climate data, no prevalence setting and the whole island as a background. Predictions were

filtered the remove agricultural areas. X and Y axes represent the coordinates (WGS84). Black points

represent the occurrence data. Future projections (2070) were estimated from three Global Circulation

models (GCM) and two RCP scenarios. Left panels represent the most optimistic scenario (RCP26) and right

panels represent the most pessimistic scenario (RCP85). Models produced similar results when setting

prevalence to 0.5 (Equal total weights).

Fig. 3 Current (a) and projected future (b) environmental suitability for *Phelsuma inexpectata* using Chelsa as baseline climate data, no prevalence setting and restricted background. Predictions were filtered the remove agricultural areas. X and Y axes represent the coordinates (WGS84). Black points represent the occurrence data. Future projections (2070) were estimated from three Global Circulation models (GCM) and two RCP scenarios. Left panels represent the most optimistic scenario (RCP26) and right panels represent the most pessimistic scenario (RCP85). Models produced similar results when setting prevalence to 0.5 (Equal total weights).
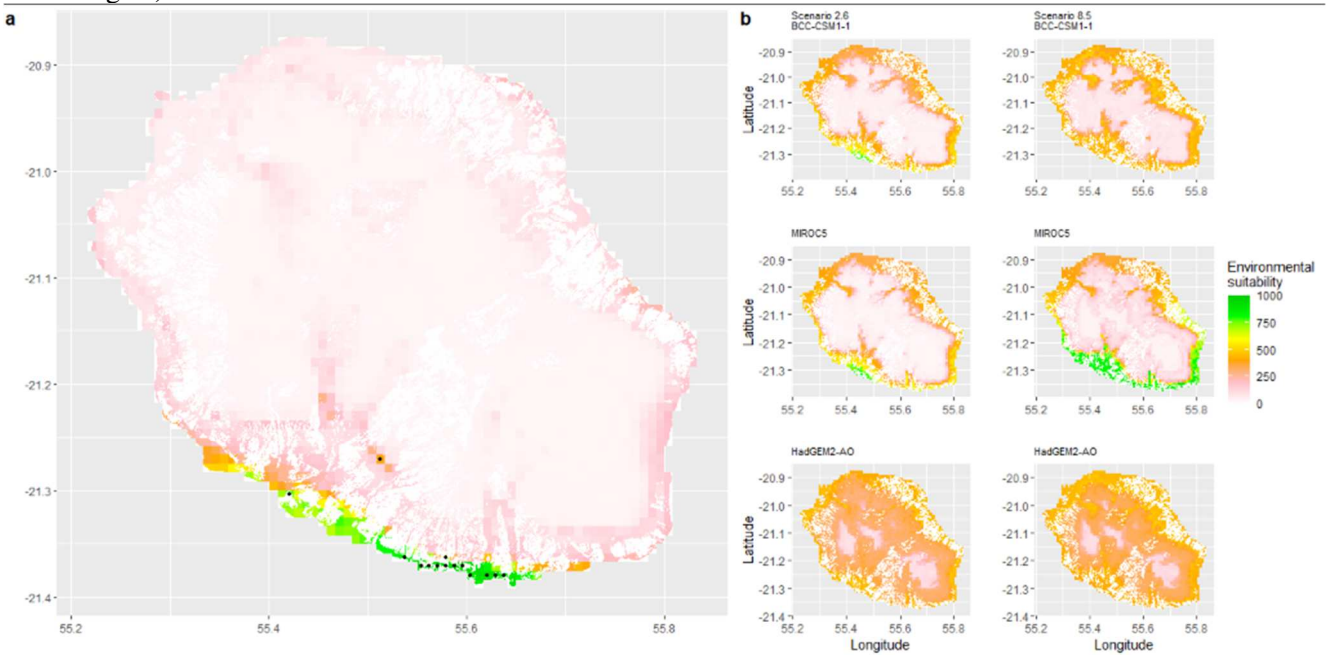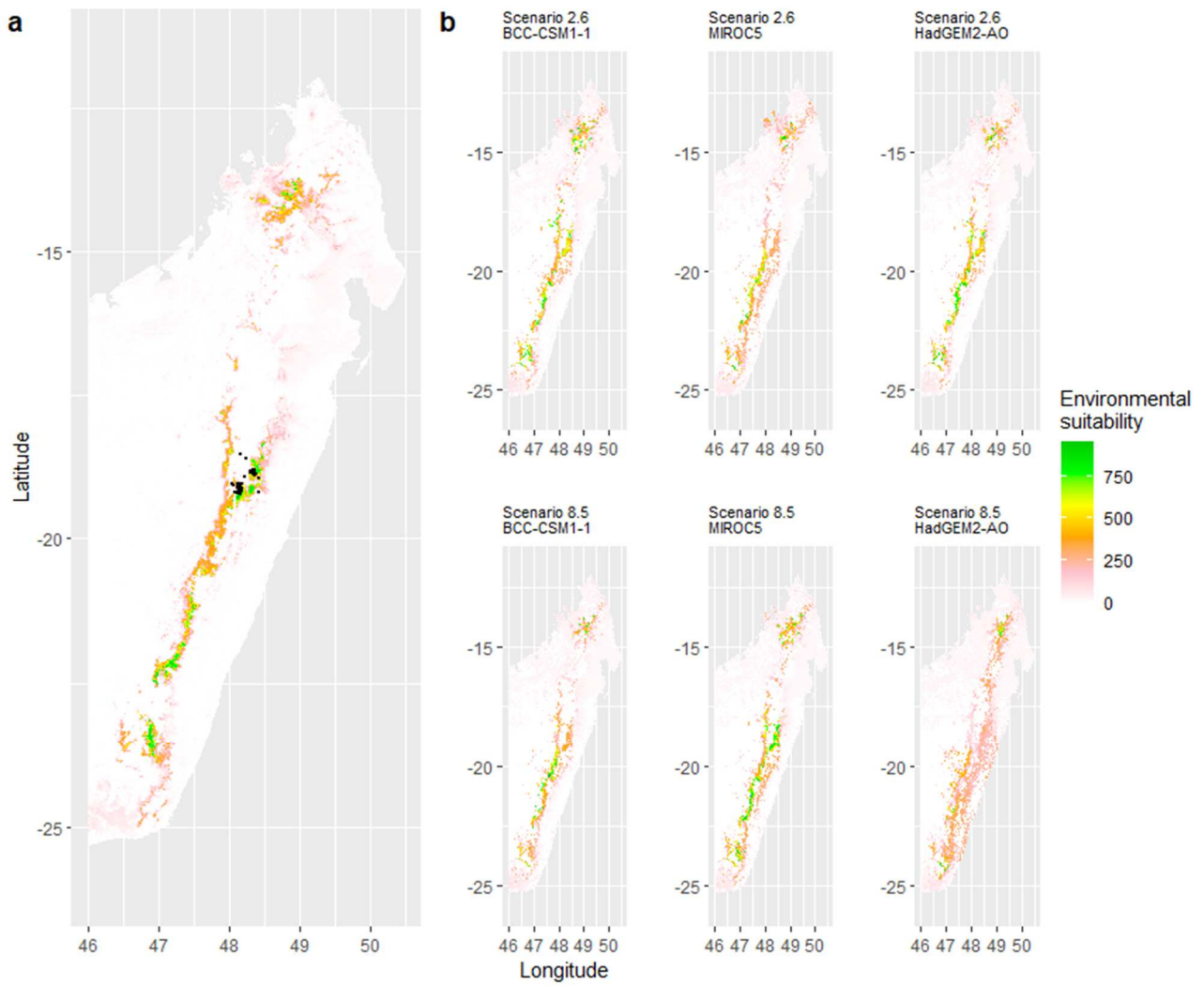

Fig. 4 Current (a) and projected future (b) environmental suitability for *Phelsuma inexpectata* using Worldclim as baseline climate data. Predictions were filtered the remove agricultural areas. X and Y axes represent the coordinates (WGS84). Black points represent the occurrence data. Future projections (2070) were estimated from three Global Circulation models (GCM) and two RCP scenarios. Left panels represent the most optimistic scenario (RCP26) and right panels represent the most pessimistic scenario (RCP85).

Fig. 5 Current (a) and projected future (b) environmental suitability for *Mantella aurantiaca* using the Chelsa baseline climate, no prevalence setting and the whole island as a background. Predictions were filtered to include only forested areas. X and Y axes represent the coordinates (WGS84). Black points represent the occurrence data. Future projections (2070) were estimated from three Global Circulation models (GCM) and two RCP scenarios. Top panels represent the most optimistic scenario (RCP26) and bottom panels represent the most pessimistic scenario (RCP85). Models produced similar results when setting prevalence to 0.5 (Equal total weights).
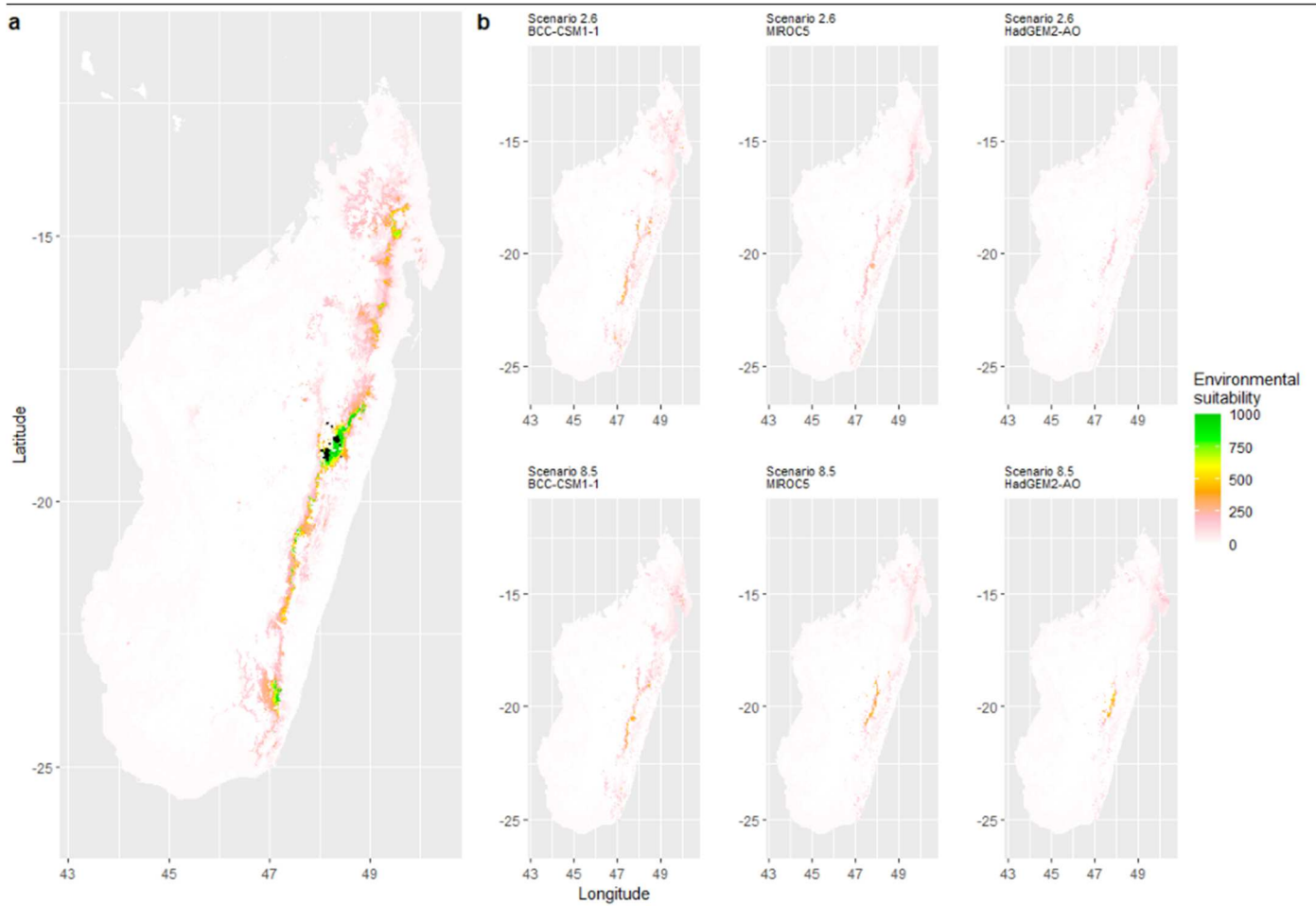
Fig. 6 Current (a) and projected future (b) environmental suitability for *Mantella aurantiaca* using the Chelsa baseline climate, no prevalence setting and a restricted background. The background was filtered to include only the western rainforest corridor. X and Y axes represent the coordinates (WGS84). Black points represent the occurrence data. Future projections (2070) were estimated from three Global Circulation models (GCM) and two RCP scenarios. Top panels represent the most optimistic scenario (RCP26) and bottom panels represent the most pessimistic scenario (RCP85). Models produced similar results when setting prevalence to 0.5 (Equal total weights).

274

275

Fig. 7 Current (a) and projected future (b) environmental suitability for *Mantella aurantiaca* using the

Worldclim baseline climate. Predictions were filtered to include only forested areas. X and Y axes represent

the coordinates (WGS84). Black points represent the occurrence data. Future projections (2070) were

estimated from three Global Circulation models (GCM) and two RCP scenarios. Top panels represent the

most optimistic scenario (RCP26) and bottom panels represent the most pessimistic scenario (RCP85).
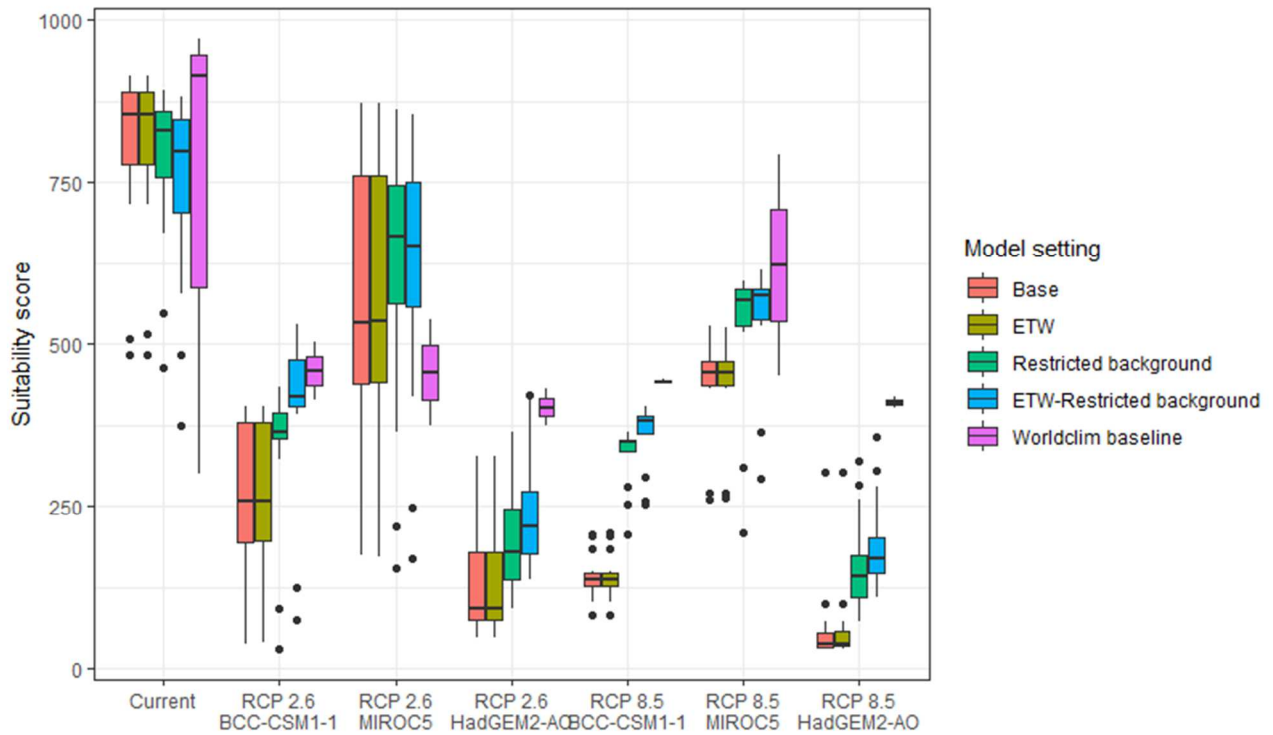
Fig. 8 Variation in climate suitability scores at the occurrence points of *Phelsuma inexpectata* under current

283 climate and 2070 climate. We show the variability in model predictions related to the climate scenario (RCP

284 2.6 versus RCP 8.5), the Global circulation model (3 GCMs), the background extent (wide versus restricted),

285 prevalence setting (no setting versus Equal Total Weights, ETW) and baseline climate (Chelsa versus

286 Worldclim). Each boxplot is composed of the first decile, the lower hinge, the median, the upper hinge and

287 the nineth decile.

288

289
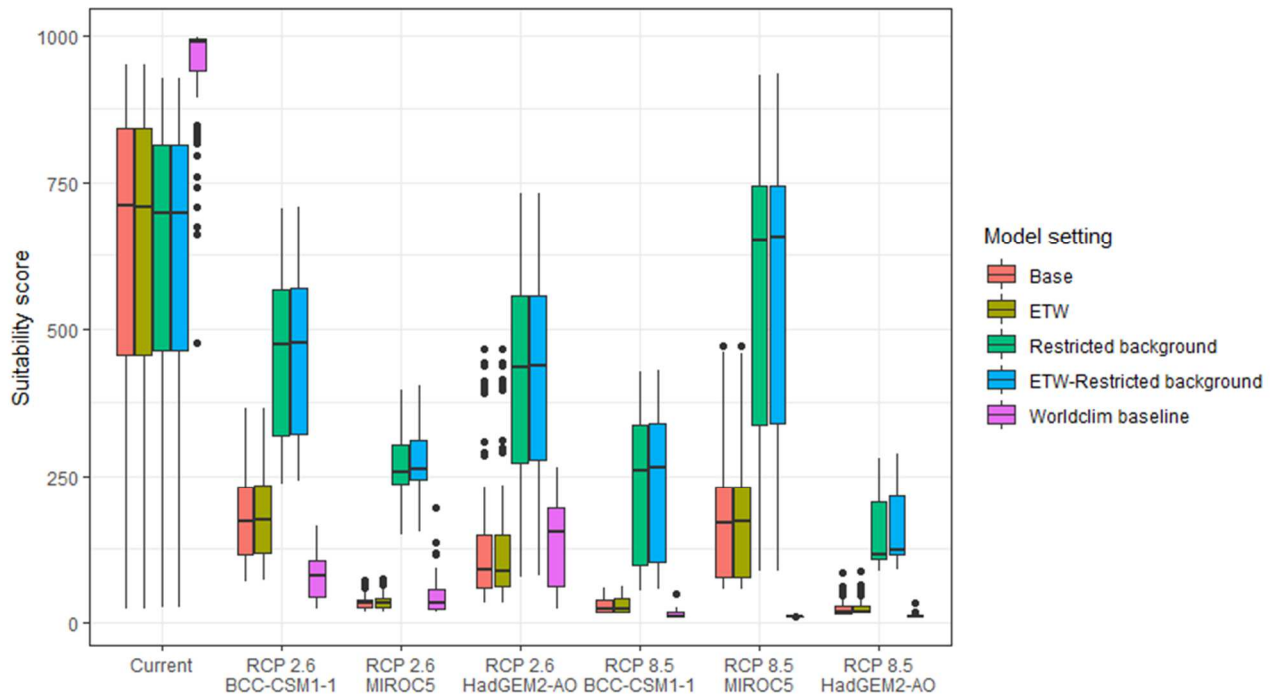
Fig. 9 Variation in climate suitability scores at the occurrence points of *Mantella aurantiaca* under current

climate and 2070 climate. We show the variability in model predictions related to the climate scenario (RCP

2.6 versus RCP 8.5), the Global circulation model (3 GCMs), the background extent (wide versus restricted),

prevalence setting (no setting versus Equal Total Weights, ETW) and baseline climate (Chelsa versus

Worldclim). Each boxplot is composed of the first decile, the lower hinge, the median, the upper hinge and

the nineth decile.

296

Discussion

Dramatic and widespread decline in climate suitability

We predict a strong decline of climate suitability in the whole current distribution area of both species by

2070. The subsequent high extinction risk in these species is not surprising, since small occupied areas are

known to be good predictors of vulnerability to climate change (Pearson *et al.*, 2014), but forecasting models

302   were lacking and we contribute to fill this gap. We also predict that few or no zone will be suitable in the

303   future across the entirety of their respective regions if those species are not given the opportunity to adapt.

304   Depending on the Global Circulation model and the scenario, future projections still identified areas with

305   suboptimal climatic conditions. In Reunion Island, the higher suitability found at ca. 20km west from the

306   current distribution was presumably driven by an increase in precipitation. *Phelsuma inexpectata* is mostly

307   present where precipitation is the lowest (< 500mm during the wet season, Fig., S10). The identified area

308   coincides with the region with the driest conditions in Reunion Island in the future, according to these GCMs

309   (Fig. S1). In all model sets, the MIROC5 GCM showed a higher—but suboptimal—climate suitability

310   around the southern coast of the island, with the highest suitability along a band following the upper lands.

311   This prediction is likely driven by the increase in overall temperature, along with reduced precipitation. The

312   species lives under the hottest and driest conditions of the island, which fits the thermal requirements of the

313   species for reproduction in captivity (28°C; McKeown, 1993). However, we believe this GCM is

314   questionable because (1) the reduction in precipitation does not reflect the possible global increase in cyclone

315   risk, and (2) the MESS analysis and response curves suggest an overestimation of the suitability scores. Note

316   that this scenario (i.e. RCP 8.5)—which was the least pessimistic for *P. inexpectata*—is of interest to explore

317   the widest range of possibilities in the future, but is considered unlikely (Hausfather & Peters, 2020).

318   In Madagascar, the current distribution is mainly explained by both winter (i.e. the dry season) and summer

319   (i.e., the wet season) conditions with a short interval of suitability (Fig. S15). An important decline in climate

320   suitability may therefore be driven by small changes in either winter or summer conditions. During winter,

321   individuals migrate up the hills to shelter under dead woods and leaves and presumably enter a state of torpor

322   or hibernation (Randrianavelona *et al.*, 2010; Edmonds *et al.*, 2020). The narrow climatic window may

323   represent optimal conditions that minimise the risk of desiccation during this period of low activity. The

324   species is also dependent on summer conditions, with a narrow window of suitable temperature and

325   precipitations. This is highly consistent with a field study which recorded a surface temperature of 20-23°C

326   at the occupied sites (Edwards et al., 2019) and an experimental design which found a decrease in activity

327   when temperature deviates from 21.5°C (Edwards, 2019) with warm and rainy conditions (Fig. S12).

328 Summer corresponds to the period of reproduction, where females lay eggs under dead leaves on slopes,

329 which are likely washed down into temporary pond during heavy rain episodes. This may explain the

330 dependence with summer high precipitation and temperatures. This combination of climatic conditions is

331 unlikely to be met in the future, except for the MIROC5 GCM under the RCP85 scenario (but this scenario is

332 unlikely, Hausfather & Peters, 2020). However, we consistently identified potential suboptimal areas in the

333 central-south of the eastern forest corridor and in one small area in the north east (corresponding to the top of

334 mountains). For both species *P. inexpectata* and *M. aurantiaca*, the high level of habitat fragmentation

335 associated to agricultural areas may limit potential distribution shifts, which calls the need for human

336 intervention.

337

338 *Sources of uncertainty*

339 The largest source of uncertainty was related to the GCM for *P. inexpectata*, and to the background extend

340 for *M. aurantiaca*. We followed a protocol that attempted to mitigate most sources of uncertainty,

341 corresponding to the acceptable standards defined in Araújo *et al.* (2019). The long term, extensive and

342 repeated efforts dedicated to species sampling enabled to define the current distributions of both species with

343 high accuracy. Uncertainty map showed a high level of agreement between model replicates (i.e. modelling

344 techniques, cross-validation runs and pseudo-absence runs; Fig. S17, S18).

345 In absence of information regarding the dispersal capacity of both species, we used two background

346 corresponding to past dispersal hypotheses. The background covering the whole respective islands seems the

347 most appropriate when assuming that only the sea could represent a dispersal barrier and that species could

348 have dispersed throughout the whole island with regard to past climate and forest cover (Crottini et al. 2019),

349 as assumed in Fieldsend et al. (2021). This might be the case for both species, especially *P. inexpectata* since

350 the island is smaller and mostly occupied by a closely related species (*P. borbonica*; Dubos et al. 2021a). The

351 restricted background corresponds to a hypothesis where *M. aurantiaca* dispersal is limited by current forest

352 cover, and where *P. inexpectata* is limited to the driest part of Reunion Island. This procedure enabled to

353 encompass the widest range of possibilities with respect to two extreme hypotheses.

354 We included the 19 bioclimatic variables for the selection process, which is not recommended in most cases.

355 However, we reduced the number of variables by removing the intercorrelated ones, and then selected the

356 most biologically meaningful variables. We used the finest resolution available for climate data (i.e. 30 arc

357 sec) which seems sufficient to discriminate suitable to unsuitable areas at the scale of Reunion Island and

358 Madagascar. The inclusion of high-resolution land use variables enabled to improve the realism of both

359 distributions and provides specific guidelines for conservation applications. In addition, we found a causal

360 interpretation for the selected variables, which supports the biological significance of our models (Fourcade

361 et al. 2018; Dubos et al. 2021b). An important limitation is that we did not use scenarios of future land use.

362 This may lead to an overestimation of the available habitat in Madagascar, since the country is under

363 important rates of deforestation (Veilledent et al., 2018). In Reunion Island, most of the natural habitats is

364 incorporated in private properties or public gardens and in steep zones with limited access for agricultural

365 practices. We believe that the apparent stability in agricultural areas would maintain the applicability of our

366 results in the future. The inclusion of a range of different greenhouse-gas emission scenarios and GCMs

367 showed an important uncertainty in the future suitability for *P. inexpectata*. However, this uncertainty is

368 mostly related to one GCM (i.e. MIROC5), which we assume to be doubtful. The remaining ones

369 consistently identified the most suitable area by 2070. Uncertainty related to model design was mitigated by

370 the limitation of model complexity (with the ESM approach and the post-filtering technique), the removal of

371 collinearity and the testing of a range of input parameters (number of pseudo-absences sets and coss-

372 validation subsets). Model performance was assessed with random partitions for *M. aurantiaca*, while spatial

373 partitions are recommended. However, we argued that this methods is not appropriate for highly localised

374 species due to strong imbalance between spatial blocks. We used multiple evaluation metrics, including

375 discrimination (AUC and TSS) and reliability (i.e. calibration; Boyce index) metrics, all showing a high

376 performance overall. We did not account for species dispersal ability, because the purpose was not to predict

377 potential shifts, but to assess how suitable will be the climate in the future in order to identify candidate sites

378 for restoration and translocation. Both species have low dispersal ability and their habitat is highly

379 fragmented. Therefore, the potential for distributional shifts may be strongly limited and future projections

380 must not be interpreted as the future distributions of our study species. An important limitation may be the

381 absence of empirical knowledge on species thermal tolerances or other features of their climatic niche,

382 adaptability and plasticity, which prevents us from determining whether our future projections

383 underestimated the environmental suitability. Similarly, the extent of the species' fundamental niche is

384 unknown, and differs from the realised niche as a result of competition, habitat loss and environmental

385 history, which may particularly important in endemic narrow-ranging species.

386

387 *A glimmer of hope*

388 Despite the predicted low suitability in climate conditions, it is possible that species persist under changing

389 conditions through adaptation or plasticity (Chevin *et al.*, 2010; Hoffmann & Sgró, 2011). This hypothesis is

390 supported by the persistence of two introduced populations of *P. inexpectata* away from their current range in

391 suboptimal environments (Fig. 2). Their persistence may result either from physiological or behavioural

392 adaptation while benefiting from a combination of urban island effect and access to microclimate refuges in

393 anthropogenic structures, as it is the case for *Phelsuma grandis* in Florida (Fieldsend *et al.*, under review). It

394 is also frequent that the current distribution of a given species represents only a fragment of its climatic niche

395 (e.g., Guisan *et al.*, 2014). For instance, experimental design on *M. aurantiaca* showed no expression of a

396 thermal stress during periods of extreme heat (Edmonds *et al.*, 2015). Therefore, predictions of climate

397 suitability may underestimate the bounds of our model species niches. Further studies are needed to better

398 characterise their climatic niche, and explore potential adaptive and plastic responses to changing conditions

399 in these species and, more generally, in other threatened narrow-ranging species. Meanwhile, we encourage

400 practitioners to implement conservation measures to grant those species a chance to adapt and persist.

401 Nevertheless, the rate of climate change is generally faster than that of animal adaptive responses (Radchuk

402 *et al.*, 2019), which stresses the need for urgent actions. In the tropics, extinction risks may be greatly

403   reduced with the development of land conservation programs provided climate change is mitigated by inter-

404   governmental actions (Hannah et al., 2020).

405

406   *Conservation application*

407   In Reunion Island, we identified two potential areas suitable for habitat restoration of *Phelsuma inexpectata*

408   around the south-western coast and along a mid-altitude band. Despite climate conditions are predicted to be

409   suboptimal, we believe these might represent the best options to ensure the long-term persistence of the

410   species. Habitat restoration should be focussed on natural habitats invaded by non-native plants and in

411   urbanised areas. Habitat restoration will consist in promoting the spread of native species (*Pandanus utilis*,

412   *Latania lontaroides*, *Scaevola taccada* and *Psiadia retusa*) for which the species depends on (Bour, 1995).

413   Finally, natural colonisation of newly suitable environments will be likely impossible for the species due to

414   its poor dispersal ability and the high level of habitat fragmentation. We therefore encourage the design of

415   translocation programs in management schemes.

416   In Madagascar, the area with the highest future climate suitability is located at the south of the current

417   distribution, along the eastern rainforest corridor between the current distribution area and the north-west of

418   the Vatovavy-Fitovinany region. The forest cover within the distribution range of *M. aurantiaca* has

419   experienced a continued decline, regardless of the conservation status of the inhabited area (Piludu *et al.*,

420   2015; Vieilledent *et al.*, 2018). We recommend to reinforce the level of protection and to improve

421   governance and management of the Mangabe (Moramanga region) and the Marolambo (Vatovavy-

422   Fitovinany region) reserves. This can be achieved by promoting the development of alternative economic

423   solutions through the development of valuable and sustainable activities that mitigate the rate of conversion

424   of natural areas, the long-term management of soil fertility, and by considering the development of

425   ecotourism. This species was included into a program that enabled to develop amphibian husbandry

426   capacities in Madagascar, and that succeeded to establish captive bred colonies for this species

427   (Rakotonanahary et al. 2017). Efforts of captive husbandry should be maintained (and possibly expanded to

428 other species) and we encourage the design of translocation programs accounting for both local habitat

429 characteristics and future climate suitability. Further study of biotic interaction between *M. aurantiaca* and

430 other amphibians is needed to assess the consequences of its introduction.

431

432 *Are all endangered narrow-ranging species doomed to extinction?*

433 Narrow-ranging species usually live under very specific environmental conditions and are the most

434 vulnerable to climate change (Botts *et al.*, 2013). Not only they are more prone to face distribution shifts and

435 range contractions, but they might also disappear due to the strong alteration of their climatic envelope

436 throughout their entire region. This may be the case for most narrow-ranging species with a specialised niche

437 in regions with heterogeneous climates and high levels of endemism such as Madagascar but also Central

438 America, South East Asia, tropical islands and more generally in tropical rainforests and mountains (Kier *et*

439 *al.*, 2009). In such regions, small shifts in climatic conditions may induce important changes in local

440 environmental suitability for endemic—often specialised—species (e.g., Raxworthy *et al.*, 2008). The risk is

441 greater in tropical regions where species live closer to the upper bound of their thermal tolerance (Tewksbury

442 *et al.*, 2008; Şekercioĝlu *et al.*, 2012; Dubos *et al.*, 2019). Species that are already under threats are at the

443 greatest risk because of a large array of synergistic effects (Şekercioĝlu *et al.*, 2012). This might be the case

444 for our two model species, which are threatened by habitat destruction and invasive species (Dubos, 2013;

445 Piludu *et al.*, 2015). Among the few Critically Endangered species for which the impact of climate has been

446 investigated, most predict severe reductions in the climate suitability (e.g., Alamgir *et al.*, 2015; Zhang *et al.*,

447 2020), with the suitable range of the giant salamander *Andrias davidianus* predicted to decrease by more than

448 two thirds by 2050 (Zhang *et al.*, 2020). This species has faced a number of threats and climate change may

449 be leading to imminent extinction despite a larger distribution range. Despite recent efforts developed for the

450 monitoring of rare species in the tropics (e.g., Dubos et al., 2020), there is still an important lack of species

451 occurrence data in these regions (Feeley & Silman, 2011). With the newly available high-resolution climate

452 and land use data, the spectre of eligible species for SDMs has enlarged. We urge filling this data void by

453 starting to assess the effect of climate change for narrow-ranging species at broader taxonomic scales,

454 promote field investigations, assess species thermal requirements, and develop proactive conservation

455 actions.

456

457 **Acknowledgements**

460

461 **Conflict of Interest Statement**

462 The authors declare no conflict of interests.

463

464 **Data availability statement**

465 The dataset and the scripts used in this analysis are available as R objects in the supporting information.

466

467 **References**

468 Acevedo, P., Jiménez-Valverde, A., Lobo, J.M., Real, R., 2012. Delimiting the geographical background in

469   species distribution modelling. J. Biogeogr. 39, 1383–1390. https://doi.org/10.1111/j.1365-

470   2699.2012.02713.x

471 Alamgir M, Mukul SA, Turton SM, 2015. Modelling spatial distribution of critically endangered Asian

472   elephant and Hoolock gibbon in Bangladesh forest ecosystems under a changing climate. Applied

473   Geography, 60, 10–19.

474 Araújo MB, Anderson RP, Barbosa AM et al., 2019. Standards for distribution models in biodiversity

475   assessments. Science Advances, 5, 1–12.

476   Bellard C, Bertelsmeier C, Leadley P, Thuiller W, Courchamp F., 2012. Impacts of climate change on the

477   future of biodiversity. Ecology Letters, 15, 365–377.

478   Bellis J, Bourke D, Maschinski J, Heineman K, Dalrymple S., 2020. Climate suitability as a predictor of

479   conservation translocation failure. Conservation Biology, 1–9.

480   Bora P, Dolch R, Jenkins R et al.., 2008. Geographical distribution of three species of Malagasy poison frogs

481   of high conservation priority: Mantella aurantiaca , M . crocea and M . milotympanum. Herpetology

482   Notes, 1, 39–48.

483   Botts EA, Erasmus BFN, Alexander GJ., 2013. Small range size and narrow niche breadth predict range

484   contractions in South African frogs. Global Ecology and Biogeography, 22, 567–576.

485   Bour R, Probst J, Ribes S., 1995. Phelsuma inexpectata Mertens, 1966, le lézard vert de Manapany-les-Bains

486   (La Réunion): données chorologiques et écologiques (Reptilia, Gekkonidae). Dumerilia, 2, 99–124.

487   Butt, N., Chauvenet, A. L., Adams, V. M., Beger, M., Gallagher, R. V., Shanahan, D. F., ... & Possingham, H.

488   P., 2020. Importance of species translocations under rapid climate change. Conservation Biology.

489   https://doi.org/10.1111/cobi.13643

490   Chevin LM, Lande R, Mace GM., 2010. Adaptation, plasticity, and extinction in a changing environment:

491   Towards a predictive theory. PLoS Biology, 8.

492   Crottini, A., Orozco-Terwengel, P., Rabemananjara, F.C.E., Susanne Hauswaldt, J., Vences, M., 2019.

493   Mitochondrial introgression, color pattern variation, and severe demographic bottlenecks in three

494   species of malagasy poison frogs, genus mantella. Genes (Basel). 10.

495   https://doi.org/10.3390/genes10040317

496   Deso G., 2001. Note sur le transport insolite de Geckos verts, le cas du Phelsuma inexpectata. Bulletin

497   Phaethon, 13, 56.

498 Draper D, Marques I, Iriondo JM., 2019. Species distribution models with field validation, a key approach

499   for successful selection of receptor sites in conservation translocations. Global Ecology and

500   Conservation, 19.

501 Dubos, N., 2010. Analyse des habitats et déclin du Gecko vert de Manapany, Phelsuma inexpectata Mertens,

502   1966 sur l'île de La Réunion: implications pour sa conservation. Muséum national d'Histoire Naturelle.

503 Dubos, N., 2013. New locality record for Phelsuma grandis (Sauria: Gekkonidae) in Reunion, in sympatry

504   with the Critically Endangered Phelsuma inexpectata. Herpetology Notes, 6, 309–311.

505 Dubos, N., Dehorter, O., Yves, P., & Viol, I. Le., 2019. Thermal constraints on body size depend on the

506   population's position within the species' thermal range in temperate songbirds. Global Ecology and

507   Biogeography, 28(2), 96–106. https://doi.org/10.1111/geb.12805

508 Dubos, N., Morel, L., Crottini, A., Freeman, K., Honoré, J., Lava, H., Noël, J., Porton, I., Rendryrendry, G.,

509   Rosa, G., & Andreone, F., 2020. High interannual variability of a climate-driven amphibian community

510   in a seasonal rainforest. Biodiversity and Conservation, 29, 893–912. https://doi.org/10.1007/s10531-

511   019-01916-3

512 Dubos, N., Augros, S., Deso, G., Probst, J., Notter, J., Markus, A., Associations, M., 2021. Here be dragons :

513   important spatial uncertainty driven by climate data in forecasted distribution of an endangered insular

514   reptile. BioRxiv. https://doi.org/10.1101/2021.06.14.448338.

515 Dubos N, Preau C, Lenormand M et al., 2021. Assessing the effect of sample bias correction in species

516   distribution models when independent data is unavailable. ArXiv:2103.07107.

517 Dupuy S, Gaetano R (2019. Reunion island - 2017, Land cover map (Pleiades).

518 Edmonds D, Rakotoarisoa JC, Rasoanantenaina S et al., 2015. Captive husbandry, reproduction, and

519   fecundity of the golden mantella (Mantella aurantiaca) at the Mitsinjo breeding facility in Madagascar.

520   Salamandra, 51, 315–325.

521   Edmonds D, Adamovicz L, Rakotoarisoa JC, Soamiarimampionona J, Harris R., 2020. Seasonal Activity

522   Patterns of Golden Mantellas (Mantella aurantiaca). Journal of Herpetology, 54, 325–330.

523   Edwards, W. M., 2019. Conservation of the golden mantella in Madagascar : Integrating in situ and ex situ

524   research. Kent University.

525   Edwards, W. M., Griffiths, R. A., Bungard, M. J., Rakotondrasoa, E. F., Razafimanahaka, J. H.,

526   Razafindraibe, P., Andriantsimanarilafy, R. R., & Randrianantoandro, J. C., 2019. Microhabitat

527   preference of the critically endangered golden mantella frog in Madagascar. Herpetological Journal,

528   29(4), 207–213. https://doi.org/10.33256/hj29.4.207213

529   Feeley KJ, Silman MR., 2011. The data void in modeling current and future distributions of tropical species.

530   Global Change Biology, 17, 626–630.

531   Fick SE, Hijmans RJ., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas.

532   International Journal of Climatology, 37, 4302–4315.

533   Fieldsend T, Dubos N, Krysko K, Raxworthy CJ, Malone S., 2021. In situ adaptation and ecological release

534   facilitate the occupied niche expansion of a non-native reptile. Ecology and Evolution, 11, 9410–9422.

535   Fourcade, Y., Engler, J.O., Rödder, D., Secondi, J., 2014. Mapping species distributions with MAXENT

536   using a geographically biased sample of presence data: A performance assessment of methods for

537   correcting sampling bias. PLoS One 9, 1–13. https://doi.org/10.1371/journal.pone.0097122

538   Gábor L, Moudrý V, Barták V, Lecours V., 2019. How do species and data characteristics affect species

539   distribution models and when to use environmental filtering? International Journal of Geographical

540   Information Science, 00, 1–18.

541   Galante PJ, Alade B, Muscarella R, Jansa SA, Goodman SM, Anderson RP., 2018. The challenge of

542   modeling niches and distributions for data-poor species: a comprehensive approach to model

543   complexity. Ecography, 41, 726–736.

544   Gillard M, Thiébaut G, Deleu C, Leroy B., 2017. Present and future distribution of three aquatic plants taxa

545   across the world: decrease in native and increase in invasive ranges. Biological Invasions, 19, 2159–

546   2170.

547   Guisan A, Petitpierre B, Broennimann O, Daehler C, Kueffer C., 2014. Unifying niche shift studies: Insights

548   from biological invasions. Trends in Ecology and Evolution, 29, 260–269.

549   Hausfather, Z., & Peters, G. P., 2020. Emissions–the 'business as usual'story is misleading. Nature 577, 618–

550   620.

551   Hoffmann AA, Sgró CM., 2011. Climate change and evolutionary adaptation. Nature, 470, 479–485.

552   IUCN, MNHN, 2010. La Liste rouge des espèces menacées en France. Premiers résultats pour la faune de La

553   Réunion. 26pp pp.

554   IUCN SSC Amphibian Specialist Group, 2020. Mantella aurantiaca. IUCN Red List Threat. Species.

555   https://doi.org/https://dx.doi.org/10.2305/IUCN.UK.2020-3.RLTS.T12776A508612.en

556   Karger DN, Conrad O, Böhner J et al., 2017. Climatologies at high resolution for the earth's land surface

557   areas. Scientific Data, 4, 1–20.

558   Kier G, Kreft H, Tien ML et al., 2009. A global assessment of endemism and species richness across island

559   and mainland regions. Proceedings of the National Academy of Sciences of the United States of

560   America, 106, 9322–9327.

561   Lannuzel G, Balmot J, Dubos N, Thibault M, Fogliani B., 2021. High-resolution topographic variables

562   accurately predict the distribution of rare plant species for conservation area selection in a narrow-

563   endemism hotspot in New Caledonia. Biodiversity and Conservation, 30, 963–990

564   Leroy B, Bellard C, Dubos N et al., 2014. Forecasted climate and land use changes, and protected areas: the

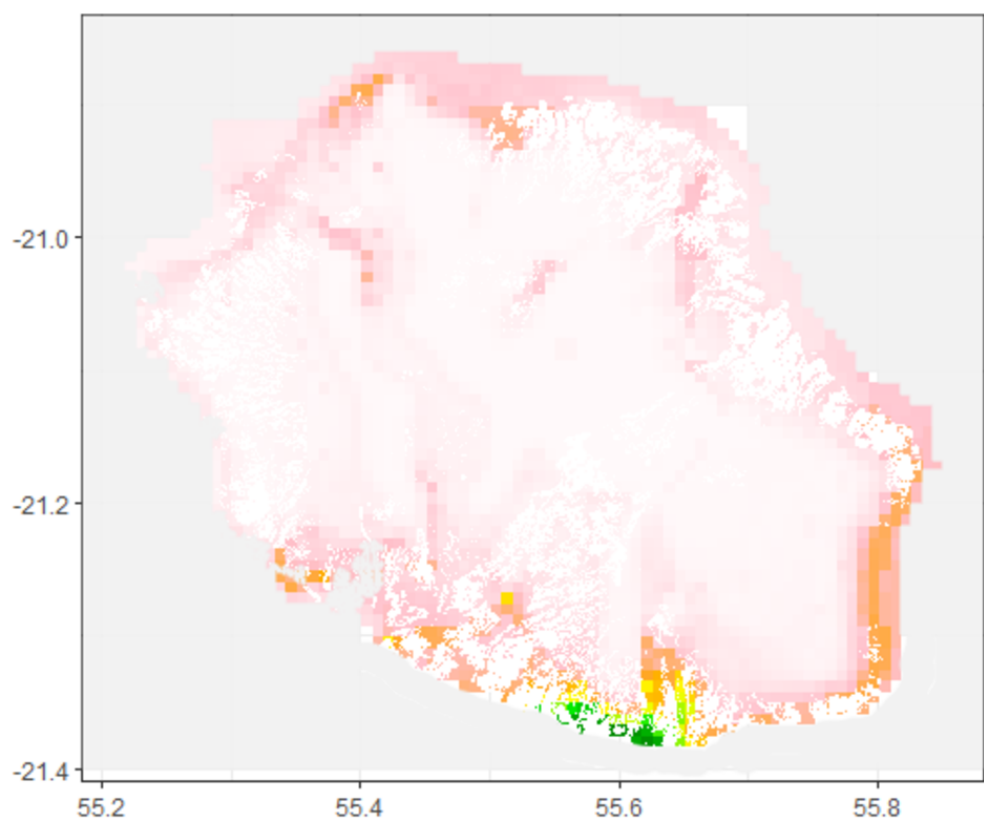565   contrasting case of spiders (ed Bradley B). Diversity and Distributions, 20, 686–697.

566   Liu, C., Newell, G., White, M., 2019. The effect of sample size on the accuracy of species distribution

567   models: considering both presences and pseudo-absences or background sites. Ecography (Cop.). 42,

568   535–548. https://doi.org/10.1111/ecog.03188

569   Mckeown S. (1993. The general care and maintenance of day geckos. In: Advanced Vivarium Systems.

570   Pearson RG, Raxworthy CJ, Nakamura M, Townsend Peterson A., 2007. Predicting species distributions

571   from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. Journal of

572   Biogeography, 34, 102–117.

573   Pearson RG, Stanton JC, Shoemaker KT et al., 2014. Life history and spatial traits predict extinction risk due

574   to climate change. Nature Climate Change, 4, 217–221.

575   Phillips SJ, Dudík M, Elith J, Graham CH, Lehmann A, Leathwick J, Ferrier S., 2009. Sample selection bias

576   and presence-only distribution models: Implications for background and pseudo-absence data.

577   Ecological Applications, 19, 181–197.

578   Piludu N, Dubos N, Razafimanahaka JH, Razafindraibe P, Christian J, Jenkins RKB., 2015. Distribution ,

579   threats and conservation of a Critically Endangered amphibian (Mantella aurantiaca) in eastern

580   Madagascar. Herpetology Notes, 8, 119–123.

581   Platts PJ, Garcia RA, Hof C, Foden W, Hansen LA, Rahbek C, Burgess ND., 2014. Conservation

582   implications of omitting narrow-ranging taxa from species distribution models, now and in the future.

583   Diversity and Distributions, 20, 1307–1320.

584   Porcel, X., Deso, G., Probst, J., & Dubos, N., 2021. Sympatrie entre le Gecko vert de Manapany Phelsuma

585   inexpectata endémique de la Réunion et le Gecko vert poussière d'or P. laticauda introduits au Domaine

586   du café grillé : peuvent-ils cohabiter ? Bulletin Phaethon, 53, 36–38.

587   Probst J-M, Turpin A., 1997. Disparition d'une population de Gecko de Manapany dans le secteur littoral de

588   Saint-Joseph. Bulletin Phaethon, 6, 104.

589   Radchuk V, Reed T, Teplitsky C et al., 2019. Adaptive responses of animals to climate change are most likely

590   insufficient. Nature Communications, 10, 1–14.

591   Randrianavelona R, Rakotonoely H, Ratsimbazafy J, Jenkins RKB, 2010. Conservation assessment of the

592   critically endangered frog Mantella aurantiaca in Madagascar. African Journal of Herpetology, 59, 65–

593   78.

594   Rakotonanahary, T. F., Dawson, J., Andreone, F., Rakotoarisoa, J. C., Edmonds, D., 2017. Amphibian

595   Captive Breeding Programs for Madagascar: Where We Are Now and the Road Ahead. FrogLog, 118,

596   37–39.

597   Raxworthy CJ, Pearson RG, Rabibisoa N et al., 2008. Extinction vulnerability of tropical montane endemism

598   from warming and upslope displacement: a preliminary appraisal for the highest massif in Madagascar.

599   Global Change Biology, 14, 1703–1720.

600   Şekercioĝlu çaĝan H, Primack RB, Wormworth J., 2012. The effects of climate change on tropical birds.

601   Biological Conservation, 148, 1–18.

602   Tewksbury JJ, Huey RB, Deutsch CA., 2008. Putting the Heat on Tropical Animals The Scale of Prediction.

603   Science (New York, N.Y.), 320, 1296–1297.

604   Thomas CD., 2011. Translocation of species, climate change, and the end of trying to recreate past ecological

605   communities. Trends in Ecology and Evolution, 26, 216–221.

606   Vences, M. and Raxworthy, C.J., 2008. Mantella aurantiaca. 2008: e.T12776A3381123.

607   http://dx.doi.org/10.2305/IUCN.UK.2008.RLTS.T12776A3381123.en.

608   Vieilledent G, Grinand C, Rakotomalala FA, Ranaivosoa R, Rakotoarijaona JR, Allnutt TF, Achard F, 2018.

609   Combining global tree cover loss data with historical national forest cover maps to look at six decades

610   of deforestation and forest fragmentation in Madagascar. Biological Conservation, 222, 189–197.

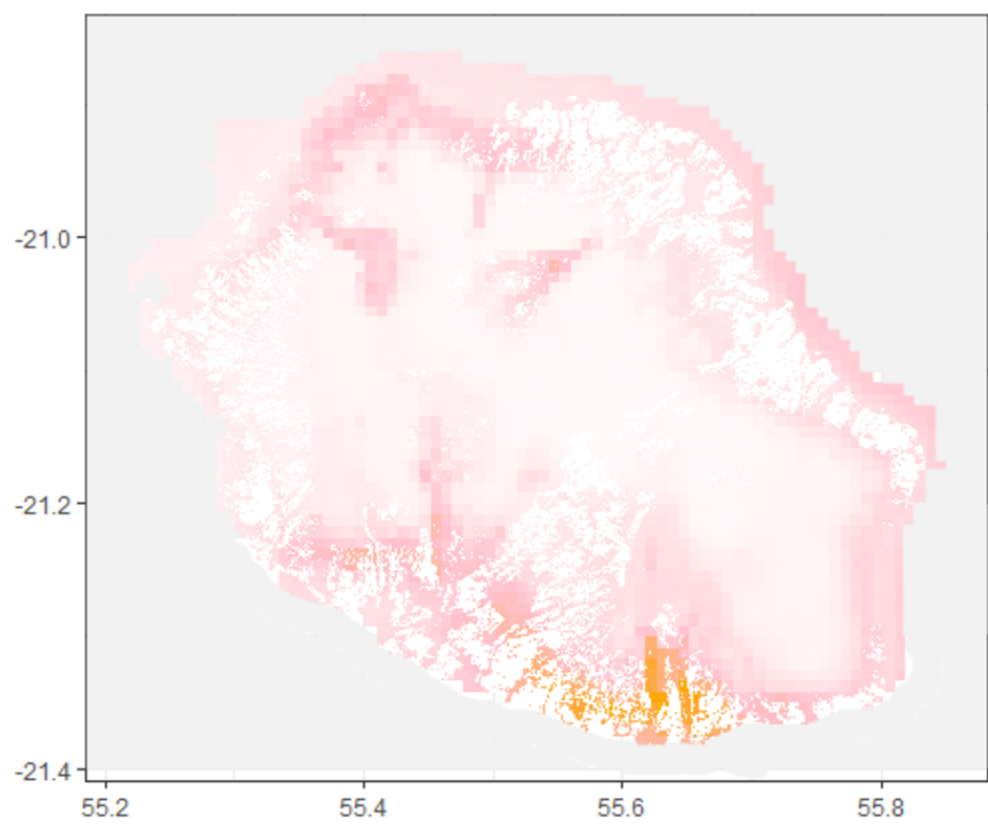611   Vinson J.M., 1975. Notes on the reptiles of Round Island. Mauritian Institute Bulletin, 8, 49–67.

612 Vollering, J., Halvorsen, R., Auestad, I. & Rydgren, K., 2019. Bunching up the background betters bias in

613   species distribution models. Ecography, 42, 1717–1727.

614 Westwood R, Westwood AR, Hooshmandi M, Pearson K, LaFrance K, Murray C., 2020. A field-validated

615   species distribution model to support management of the critically endangered Poweshiek skipperling

616   (Oarisma poweshiek) butterfly in Canada. Conservation Science and Practice, 2, 1–15.

617 Zhang Z, Mammola S, Liang Z et al., 2020. Future climate change will severely reduce habitat suitability of

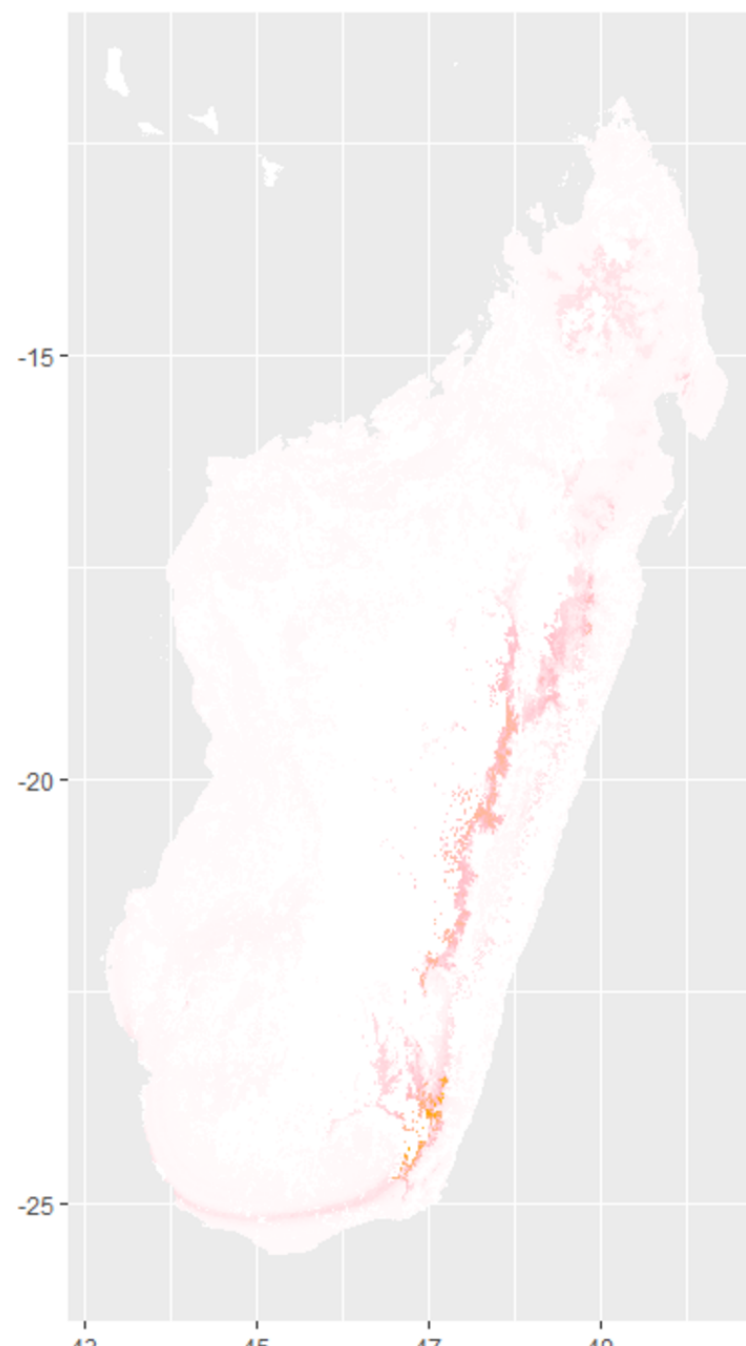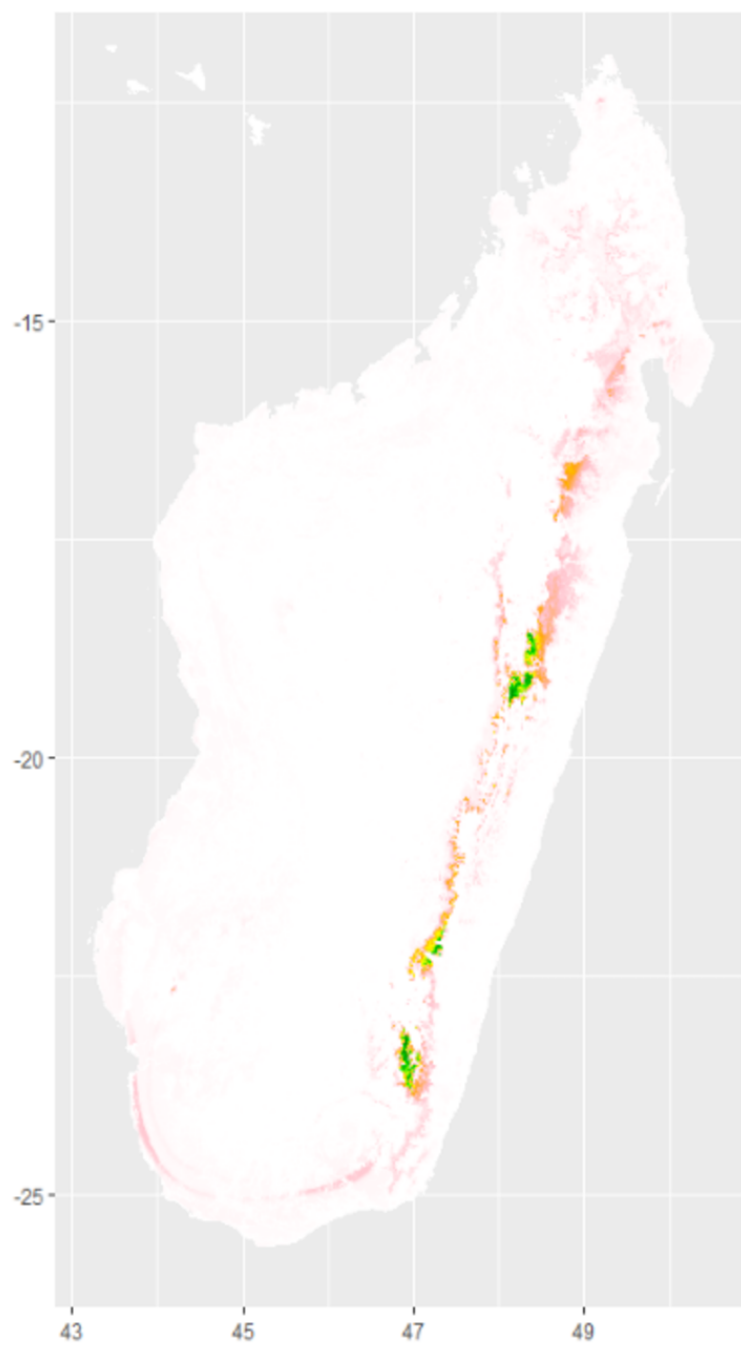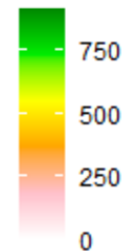618   the Critically Endangered Chinese giant salamander. Freshwater Biology, 65, 971–980.

Current

2070

Suitability