

*Running head: Climate-induced faunal change*

# Projected climate-induced faunal change in the western hemisphere

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## 1 *Abstract*

2 Climate change is predicted to be one of the greatest drivers of ecological change in the  
3 coming century. Increases in temperature over the last century have clearly been linked to  
4 shifts in species distributions. Given the magnitude of projected future climatic changes, we  
5 can expect even larger range shifts in the coming century. These changes will, in turn, alter  
6 ecological communities and the functioning of ecosystems. Despite the seriousness of  
7 predicted climate change, the uncertainty in climate-change projections makes it difficult for  
8 conservation managers and planners to proactively respond to climate stresses. To address  
9 one aspect of this uncertainty, we identified predictions of faunal change for which a high  
10 level of consensus was exhibited by different climate models. Specifically, we assessed the  
11 potential effects of 30 coupled atmosphere-ocean general circulation model (AOGCM)  
12 future-climate simulations on the geographic ranges of 2,954 species of birds, mammals, and  
13 amphibians in the western hemisphere. Eighty percent of the climate projections based on a  
14 relatively low greenhouse-gas emissions scenario result in the local loss of at least 10% of the  
15 vertebrate fauna over much of North and South America. The largest changes in fauna are  
16 predicted for the tundra, Central America, and the Andes Mountains where, assuming no  
17 dispersal constraints, specific areas are likely to experience over 90% turnover, so that faunal  
18 distributions in the future will bear little resemblance to those of today.

19

20 *Key words: climate change, range shifts, future projections, climate envelope models, species*  
21 *distributions, birds, mammals, amphibians*

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23

## INTRODUCTION

24

25

Recent climatic changes have already caused shifts in species distributions (Parmesan  
2006). In general, species have been found to be moving their ranges poleward in latitude

26 and upward in elevation at rates that are consistent with recent temperature increases.  
27 Because future changes in climate are projected to be even greater than those of the last  
28 century (Alley et al. 2007), they will likely produce even larger range shifts (Thomas et al.  
29 2004, Thuiller et al. 2005). In many instances, the impacts of these range shifts will go far  
30 beyond the mere addition or subtraction of a species to or from a system. Some range shifts  
31 will have cascading effects on community structure and the functioning of ecosystems  
32 (Lovejoy and Hannah 2005).

33 A number of studies have projected range shifts for plants and animals in response to  
34 potential climatic changes. Projections have been made for plants and animals in Europe  
35 (Bakkenes et al. 2002, Berry et al. 2002, Thuiller et al. 2005, Araújo et al. 2006), Africa  
36 (Midgley et al. 2002, Midgley et al. 2003, Thuiller et al. 2006), and Australia (Williams et al.  
37 2003, Meynecke 2004). In the western hemisphere, projections have been made for animals  
38 in Mexico (Peterson et al. 2002), plants in Brazil (Siqueira and Peterson 2003), and plants in  
39 the United States (Iverson and Prasad 2001, Shafer et al. 2001). In general, these studies  
40 conclude that many species are likely to experience relatively large changes in their  
41 distributions over the next century.

42 Most studies that project climate-induced shifts in species ranges at continental scales  
43 use bioclimatic models. The bioclimatic modelling approach involves building a statistical or  
44 machine-learning based model that relates the current distribution of a species to current  
45 climate and then uses this relationship to project a potential future range based on future  
46 climate projections (Pearson and Dawson 2003). The approach has the advantage of  
47 requiring relatively little data on the specific biology of a given species and thus models can  
48 be built for large numbers of species and used over large geographic areas. Tests of  
49 bioclimatic models using historic data indicate that these models can accurately capture shifts  
50 in species distributions (Araújo et al. 2005).

51 Bioclimatic models provide a useful first approximation of how the biota of a region  
52 may respond to climate change. However, they have their limitations (Pearson and Dawson  
53 2003). The approach does not directly model biotic interactions, dispersal, or evolution. It  
54 also assumes that the climate variables used in the models are adequate surrogates for the  
55 factors that determine a species' range, which may not be the case for some species.  
56 Furthermore, the predictions of the models are difficult to validate. Ideally, bioclimatic  
57 models should be tested with completely independent datasets (Araújo et al. 2005). In the  
58 absence of these data, estimates of model accuracy from semi-independent model-validation  
59 approaches can approximate validation estimates from more independent data sources,  
60 particularly for models that more accurately predict semi-independent data sets (Araújo et al.  
61 2005).

62 Despite these limitations, bioclimatic models can play a significant role in developing  
63 our understanding of the potential future effects of climate change. Bioclimatic models  
64 should be seen as providing base-line estimates of the magnitude and the distribution of  
65 climate-induced changes in biota and not as accurate predictors of the future distributions of  
66 individual species (Pearson and Dawson 2004). Although more complex process-based  
67 models have been built to project climate-induced shifts in vegetation types or biomes, these  
68 models also have limitations and relatively large associated uncertainties (Cramer et al. 2001,  
69 Bachelet et al. 2003). The lack of accurate data on the biology of all but the most well-  
70 studied species makes building accurate process-based models for more than a few vertebrate  
71 species unrealistic. Even with accurate biological data, there is no guarantee that these  
72 process-based models would provide more accurate future projections (Robertson et al.  
73 2003).

74 Range-shift predictions have typically been based on no more than seven climate-  
75 change projections (Thuiller et al. 2005). There are, however, many credible projections of



101 overestimates of species richness (Hurlbert and White 2005, Hurlbert and Jetz 2007).

102 Although the scale dependence of range maps affects patterns of species richness, it should  
103 have minimal effects on our estimates of relative faunal change.

104 We used a 50-km grid to capture the continental-scale climate patterns that influence  
105 species distributions. Coarser grids may fail to capture climatic conditions associated with  
106 strong elevation gradients in areas of topographic complexity, such as occur across mountain  
107 ranges. Furthermore, coarser grids can also result in spurious extrapolations of finer-scale  
108 species distribution patterns to larger areas (Rahbek and Graves 2001, Rahbek 2005). The  
109 50-km grid was chosen to strike a balance between the inaccuracies associated with applying  
110 a fine-resolution grid to relatively coarse resolution digital-range maps and the inaccuracies  
111 incurred by mapping climate at too coarse a resolution. To assess the effect of a grid's spatial  
112 resolution on the patterns of faunal change, we projected changes in species ranges at two  
113 additional, coarser grid-cell resolutions (100-km by 100-km and 200-km by 200-km).

114 Modern climate data were created using cloud-cover data from the 30-min CRU CL  
115 1.0 (New et al. 1999) data set (1961-1990 30-year mean), temperature, precipitation, and  
116 sunshine data from the 10-min CRU CL 2.0 (New et al. 2002) data set (1961-1990 30-year  
117 mean), and monthly temperature, precipitation, and cloud-cover data from the 30-min CRU  
118 TS 2.1 (Mitchell and Jones 2005) data set (1901-2002). We used a locally-weighted lapse-  
119 rate-adjusted interpolation method to interpolate the CRU CL 1.0 and 2.0 datasets to the 50-  
120 km grid of the western hemisphere. We calculated anomalies for each month in the CRU TS  
121 2.1 dataset against a 1961-1990 30-year mean climatology created from the CRU TS 2.1  
122 1961 to 1990 monthly data. Temperature anomalies were calculated as differences (each  
123 monthly value minus the 1961-1990 30-year mean value for the same month) and  
124 precipitation and sunshine anomalies were calculated as ratios (each monthly value divided  
125 by the 1961-1990 30-year mean value for the same month). These anomalies were

126 interpolated to the 50-km grid using a geographic-distance-weighted bilinear interpolation  
127 method. The temperature, precipitation, and sunshine anomalies were applied to the  
128 interpolated CRU CL 2.0 data on the 50-km grid to create a 1901-2002 monthly dataset of  
129 temperature, precipitation, and sunshine. We calculated a 1961-1990 30-year mean  
130 climatology from these data to use as our modern climate dataset.

131 We used 30 climate simulations to project potential future ranges of species for the  
132 time period of 2071-2100. The 30 climate simulations consisted of projections from 10  
133 coupled atmosphere-ocean general circulation models (AOGCMs; Appendix A) run under  
134 three different greenhouse-gas emissions scenarios (B1, A1B, and A2). These scenarios  
135 represent the lower, mid, and mid-high range of the IPCC Special Report on Emissions  
136 Scenarios (SRES) (Nakicenovic et al. 2000). We chose these 30 climate simulations because  
137 they cover a broad range of future greenhouse-gas emissions scenarios and they were all  
138 produced as part of the World Climate Research Programme's (WCRP's) Coupled Model  
139 Intercomparison Project phase 3 (CMIP3), allowing us to compare results of our analyses  
140 among AOGCMs and across the three scenarios. The future projections, along with their  
141 corresponding twentieth-century simulations, were obtained from the WCRP CMIP3 multi-  
142 model archive ([http://www-pcmdi.llnl.gov/ipcc/about\\_ipcc.php](http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php)).

143 A 1961-1990 30-year mean climatology was calculated from the monthly data in each  
144 future simulation's corresponding twentieth century simulation. For each future climate  
145 simulation, monthly anomalies were calculated between each month of the future simulation  
146 and the matching month in the simulated 1961-1990 30-year mean dataset. Annual  
147 temperature anomalies were calculated as differences (future minus present) and precipitation  
148 and cloud-cover anomalies were calculated as ratios (future divided by present). These  
149 anomalies were interpolated to the western hemisphere 50-km grid using geographic-  
150 distance-weighted bilinear interpolation. The anomalies were then applied to the 1961-1990

151 30-year mean CRU CL 2.0 temperature and precipitation data and the CRU CL 1.0 cloud-  
152 cover data to create monthly future climate data for the period 2001-2100. For both the CRU  
153 TS 2.1 and simulated future datasets, percent cloud cover data were converted to percent  
154 sunshine using local regression relationships between percent cloud cover and percent  
155 sunshine in the CRU CL 1.0 and 2.0 datasets.

156 We calculated 37 bioclimatic variables (Appendix B) from both the modern and  
157 future climate data using an approach modified from Cramer and Prentice (1988). These  
158 bioclimatic variables represent the biological mechanisms that influence the distributions of a  
159 wide range of vertebrate species. We used mean monthly temperature (°C) and sunshine (%),  
160 total monthly precipitation (mm), and soil texture data (Global Soil Data Task 2000) to  
161 calculate the bioclimatic variables. Modern bioclimatic variables were created using the  
162 1961-1990 30-year mean climate data and future bioclimatic variables were created using the  
163 monthly data for 2071-2100 from each of the 30 AOGCM simulations. These monthly  
164 bioclimatic data were then averaged for the period 2071-2100 to create 30-year mean datasets  
165 for each future simulation. For four of the 30 AOGCM simulations, data were not available  
166 for the year 2100 and thus, 29-year means (2071-2099) were calculated for these simulations.

167

#### 168 *Modeling approach*

169 The modeling approach involved three steps. First, we used bioclimatic models to  
170 relate the observed current range of each species to current climate. Next, we used the 30  
171 different future climate projections to generate 30 potential future ranges for the 2,954  
172 species for which we were able to build the most accurate bioclimatic models (Appendix C).  
173 Finally, we summarized the projected range shifts across all species and climate-change  
174 projections.

175 All models were built with random forest classifiers (Breiman 2001, Cutler et al.  
176 2007). Random forest classifiers are a model-averaging or ensemble-based approach in  
177 which multiple classification or regression tree models are built using random subsets of the  
178 data and predictor variables. The model predictions are then combined to produce one  
179 prediction for each observation. For each species in the study, 100 classification tree models  
180 were built. For our western hemisphere data set, the random forest approach produced more  
181 accurate predictions of species' current ranges than each of five other commonly used  
182 approaches (Lawler et al. 2006).

183 Our approach involved fitting individual models to species' current distributions by  
184 treating areas within the extent of the range maps as presences and the areas outside of the  
185 current range as absences. As with other correlative bioclimatic models, this approach  
186 involves modeling the realized niche (*sensu* Hutchinson 1957) of a species (Guisan and  
187 Thuiller 2005). Thus, the models are based not only on the climatic constraints on species'  
188 distributions, but also on any biotic interactions, human land-use effects, historic extirpations,  
189 or other constraints on species' fundamental niches that are evident at a coarse spatial  
190 resolution. The climatic variables in the models act as proxies, albeit imperfect ones, for  
191 many of these other non-climatic factors. The degree to which the models are able to  
192 accurately project species distributions in an altered, future climate depends in part on  
193 whether those proxies or relationships are similar in the future. For some species, with  
194 ranges that are strongly determined by climatic constraints or habitat relationships that are  
195 clearly dictated by climate, the models will more accurately project range shifts. This is  
196 likely to be the case for many species when models are applied at a coarse spatial resolution.  
197 In fact, many of the documented shifts in species distributions have been in directions and at  
198 rates that correspond directly with climatic changes (Parmesan and Yohe 2003). For species  
199 with ranges that tend to be determined largely by interspecific interactions or, more

200 importantly, interspecific interactions that will change with climate change, correlative  
201 bioclimatic models will be less accurate at projecting potential range shifts.

202         We built the models using 80% of each of the presence and absence observations for  
203 each species. We then used the remaining 20% of the data to test the models. In our  
204 calculations of potential faunal change, we used only those models that correctly predicted at  
205 least 80% of the presences and at least 90% of the absences in the test-data sets. This model-  
206 selection process produced models that accurately predicted the current distributions for  
207 1,818 bird, 723 mammal, and 413 amphibian species (Appendix C).

208         To summarize the projected range shifts across all species and climate-change  
209 scenarios, we used each of the 30 climate-change projections to estimate potential faunal  
210 changes for each of the 15,323 50-km grid cells in the western hemisphere. As climate  
211 changes, species will differ in their ability to track the change and to move into newly created  
212 suitable habitat. We calculated potential faunal change on a cell-by-cell basis assuming no  
213 dispersal to new areas with suitable climatic conditions and conversely, assuming unlimited  
214 dispersal into new suitable areas. The actual responses of species will likely fall between  
215 these two extremes. For the assumption of no dispersal, we calculated “species loss” for a  
216 cell as the percentage of all modeled species currently occurring in the cell whose predicted  
217 future range did not include the cell. Under the assumption of unlimited dispersal, we  
218 calculated “species gains” as the number of species potentially moving into a cell as a result  
219 of a projected range expansion expressed as a percentage of the current number of species in  
220 the cell. We also calculated “species turnover,” a composite measure of both potential  
221 species losses and gains. Turnover was calculated as the sum of all species in a cell whose  
222 predicted future range did not include the cell plus all species not in the cell whose future  
223 range did include the cell, expressed as a percentage of the number of species currently  
224 occurring in the cell.

225 We used a probabilistic ensemble-modeling approach to summarize the 10 predictions  
226 of faunal change for each greenhouse-gas emissions scenario by taking the 20<sup>th</sup> percentiles of  
227 the distributions of loss, gain, and turnover values for each grid cell. These values were used  
228 to identify areas in which 80% (8 out of 10) of the climate projections for each greenhouse-  
229 gas emissions scenario predicted large changes in the vertebrate fauna. We further  
230 summarized our results for 23 of 24 major ecoregions in the western hemisphere (Appendix  
231 D). Due to the difficulties inherent in modeling range shifts for island species, we did not  
232 summarize predictions for the West Indies ecoregion.

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## RESULTS

235 Eighty percent (8 out of 10) of the climate-change projections resulted in an average  
236 loss of 11% of species per grid cell across North and South America under the lower B1  
237 greenhouse-gas emissions scenario and at least 17% loss under the mid-high A2 scenario  
238 (Fig. 1a and 1c). Several areas in the western hemisphere were consistently projected to  
239 experience large losses of the current fauna. Eighty percent of the analyzed climate-change  
240 projections predicted at least 20% species loss under the lower B1 emissions scenario, and at  
241 least 50% loss under the mid-high A2 scenario as a result of range contractions in parts of  
242 Mexico, Central America, and the Andes Mountains (Fig. 1a and 1c).

243 Assuming no limitations to dispersal, several areas were projected to gain new species  
244 as a result of range expansions (Fig. 1d-f). Proportionally, the largest potential gains were  
245 projected for the high northern latitudes and for the central and northern Andes Mountains.  
246 For example, 80% of the climate projections resulted in average gains of at least 30% per grid  
247 cell in the Tundra ecoregion under the lower B1 greenhouse-gas emissions scenario and at  
248 least 57% gains under the mid-high A2 scenario (Appendix E). In the Northern Andes  
249 ecoregion, average gains were at least 21% under the lower B1 scenario and at least 27%

250 under the mid-high A2 scenario. The maximum gains in both of these regions were predicted  
251 to be well over 100% under both scenarios.

252 Combining both potential range contractions and range expansions resulted in  
253 relatively large estimates of species turnover (Fig. 1g-i). On average, 80% of the climate  
254 projections resulted in at least 25% turnover across all of North and South America under the  
255 lower B1 scenario and at least 38% turnover under the mid-high A2 scenario. Again, the  
256 largest changes were projected for the Arctic tundra, Mexico, Central America, and the  
257 Andes. On average, in the Northern Andes ecoregion, turnover was projected to be at least  
258 41% under the lower B1 emissions scenario and at least 49% under the mid-high A2 scenario  
259 (Appendix E). At least one grid cell in each of the 23 major ecoregions in North and South  
260 America was predicted to experience at least 60% turnover under the lower B1 emissions  
261 scenario and cells in 11 of the 23 ecoregions were predicted to experience at least 100%  
262 turnover under the mid-high A2 scenario, which means the vertebrate communities in these  
263 areas would bear almost no resemblance to today's fauna. Species turnover estimates derived  
264 from range shifts projected on both 100-km by 100-km and 200-km by 200-km grids showed  
265 very similar patterns to those based on the 50-km by 50-km grid (Fig. 2)

266 Both the magnitude and the pattern of predicted changes differed across taxonomic  
267 groups (Fig. 3). In general, our results indicate that we should expect greater changes in  
268 local amphibian fauna than in either mammal or bird fauna. Although all three taxonomic  
269 groups were predicted to experience large changes at high northern latitudes, and in the  
270 Andes, Mexico, and Central America, amphibians were uniquely predicted to also undergo a  
271 high degree of turnover in the central and eastern United States.

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## 275 DISCUSSION

276 Many of the areas predicted to experience large changes in fauna are in mountainous  
277 regions where environmental conditions vary significantly over relatively short distances and  
278 where the edges of many species' ranges occur. Other areas of high turnover were predicted  
279 at ecoregional boundaries such as the southern and western boundaries of the Cerrado of  
280 Brazil's central high plains. Several of the areas of high turnover also coincide with  
281 identified conservation priority areas. For example, the World Wildlife Fund lists the  
282 Atlantic Rainforest of South America as one of 200 global conservation priority areas based  
283 on its unique and threatened biota (Olson and Dinerstein 1998). Our analyses indicate that  
284 the Bahia interior and coastal forests of this region are likely to experience large changes in  
285 fauna. The potential for large species losses does not mean that these regions should be  
286 neglected by conservation efforts, but rather that climate change may significantly limit  
287 efforts directed at retaining specific species in these regions.

288 It is important to note that our estimates of faunal change are all reported as  
289 percentages of the number of species currently at a site. Due to latitudinal trends in species  
290 richness, the largest changes in the absolute number of species were predicted for the tropics.  
291 Given the potential for overestimating species richness from inaccuracies in the underlying  
292 species' range maps, we chose not to report raw species numbers. Nonetheless, even a  
293 modest percentage of turnover in the tropics will translate into a large number of species  
294 potentially moving in or out of an area.

295 In addition to regional differences, there are likely to be taxonomic differences in  
296 responses to climate change (Parmesan 2006). Previous studies have predicted that  
297 amphibians will be more susceptible to climate change than birds or mammals because of  
298 their dependence on microhabitats and hydrological regimes, limited dispersal abilities  
299 (Blaustein et al. 1994), and susceptibility to diseases that may be influenced by climate

300 change (Pounds et al. 2006). Our models predict substantially larger changes in amphibian  
301 fauna than in bird or mammal fauna based solely on potential future range contractions and  
302 expansions. In combination, this multitude of projected impacts will likely exacerbate the  
303 current declines being observed across many amphibian populations (Stuart et al. 2004).

304         Our analyses provide a conservative estimate of the future climate-driven changes in  
305 biodiversity across North and South America. Because the approach we used does not  
306 consider interspecific interactions, it is likely that shifts in the ranges of other species and  
307 particularly in the distributions of pathogens (Pounds et al. 2006) will further alter ecological  
308 communities, although in some cases, interspecific interactions may buffer the effects of  
309 climate change (Wilmers and Getz 2005). Our models also do not account for climate-driven  
310 changes in disturbance regimes such as fire or hydrology that may further alter habitat. Nor  
311 do our models account for land-use change, which will potentially have even greater impacts  
312 than climate change on habitat availability for many species in the coming century (Jetz et al.  
313 2007).

314         Much of the land in several of the areas highlighted by our analyses has already been  
315 converted to agriculture or other human land uses. The Atlantic Forest of Brazil and the  
316 Amazon Basin are just two examples of areas that have undergone, and are projected to  
317 undergo, substantial land conversion in the future (Skole and Tucker 1993, Ranta et al. 1998,  
318 Nepstad et al. 1999). Although the range maps used in our analyses have been updated and  
319 revised by experts, rapid land conversion in these regions may have recently eliminated some  
320 species from particular grid cells. Thus, there may be some overestimate of faunal change  
321 due to climate change in these areas of rapid land conversion. For those species that have not  
322 been recently extirpated, however, the effects of climate change in these areas will likely be  
323 even more profound. For many species, these changes will result in the loss of potential  
324 future habitat hence limiting potential future distributions. In addition, for many species,

325 fragmented habitats and human land-uses will hinder movement further reducing the ability  
326 of species to shift their distributions in response to climate change.

327         Our projections may also be conservative if future greenhouse-gas emissions surpass  
328 the levels specified in the three emissions scenarios used in our analyses. We used the three  
329 emissions scenarios on which the IPCC focused their attention for the CMIP3. It is possible,  
330 of course, that human activities will result in higher greenhouse-gas concentrations than those  
331 resulting from these three scenarios. If that were to be the case, we would expect even larger  
332 changes in the distribution of fauna.

333         Most notably, however, our projections are likely to be conservative because we  
334 included in our analyses only those species for which we were able to build models that  
335 accurately predicted current ranges. This restriction generally biased us towards excluding  
336 species with small and fragmented ranges. These species are likely to be more susceptible to  
337 climate-induced range loss and range contraction due to their restrictive habitat requirements.  
338 Many of the species with the smallest ranges occur in Central America, the Andes, and in the  
339 Atlantic rainforests where our projections also predict major changes in fauna. Other areas  
340 such as Mediterranean California, the Mexican Tropical Dry Forests, and the southern  
341 Appalachian Mountains of North America were not highlighted by our analyses as areas of  
342 projected high faunal change, but may, nonetheless, experience significant changes due to the  
343 larger numbers small-range endemic species they harbor.

344         As discussed above, bioclimatic models have their limitations. Previous studies have  
345 demonstrated that the uncertainties in future range projections attributable to the bioclimatic-  
346 modeling process can be even greater than the uncertainties inherent in future climate-change  
347 projections (Thuiller 2004). There are several ways to reduce this uncertainty. We chose to  
348 use a consensus-based modeling approach that reduced the model errors that are largely  
349 responsible for differences in bioclimatic-model predictions. Alternatively, others have

350 suggested model ensembles that combine a wider array of modeling approaches (Thuiller et  
351 al. 2005) or combining correlative and mechanistic modeling approaches to produce more  
352 realistic models (Botkin et al. 2007). Mechanistic approaches hold great promise for more  
353 accurately projecting species future distributions. However, directly modeling the effects of  
354 climate change on competitive interactions, predator-prey relationships, and other factors that  
355 define species distributions will require much more experimental research in these areas.

356       There are also a number of limitations associated with the climate simulations that we  
357 have used to project future range changes. Future climate simulations include uncertainties  
358 that range from differences in how individual AOGCMs are parameterized to stochastic  
359 processes in the climate system that are difficult for models to predict (Giorgi 2005).  
360 Similarly, the greenhouse-gas emissions scenarios also contain many assumptions about the  
361 forces driving emissions, including future population growth rates, economic trends, future  
362 technological advancements, and societal responses to climate change (IPCC 2007). In our  
363 analyses we used simulations from multiple AOGCMs to include a range of simulated future  
364 climate changes and then assessed areas where multiple simulations produced similar  
365 projected species range changes. Agreement among AOGCM simulations may be interpreted  
366 as a simple measure of model reliability (Giorgi 2005), but it does not necessarily imply  
367 increased simulation accuracy.

368       Our analyses map a geography of projected severe faunal change. Despite the  
369 differences among climate projections, our results indicate that even the lower greenhouse-  
370 gas emissions scenarios will likely lead to substantial changes in biodiversity. We conclude  
371 that as a result of climate change, many areas in the western hemisphere will likely  
372 experience a significant reorganization of their vertebrate fauna over the coming century.  
373 While much discussion of climate impacts has focused on absolute extinction (which is  
374 difficult to predict), faunal change alone is a matter of great concern. Change of the

375 magnitude we predict for many regions in the western hemisphere, even when it includes the  
376 addition of new species to a region, is likely to profoundly alter local ecology and ecosystem  
377 functioning. The consequences of such highly altered ecosystems represent one of the great  
378 uncertainties climate science needs to begin to address.

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#### FIGURE LEGENDS

547

548 Figure 1. Consistent predictions of climate-induced species range losses (a-c), expansions (d-  
549 f), and species turnover (g-i) for lower B1 (a, d, g), mid A1B (b, e, h), and mid-high A2 (c, f,  
550 i) greenhouse-gas emissions scenarios. Each map was created using predictions of faunal  
551 change based on 10 different climate-change projections. Species-loss values assume no  
552 dispersal of individuals to newly created suitable climatic environments whereas both  
553 expansion and turnover values assume that species will be able to move into expanding  
554 ranges. Eighty percent of the climate projections (8 of the 10) resulted in losses, gains, and  
555 turnover values greater than the values represented in the maps.

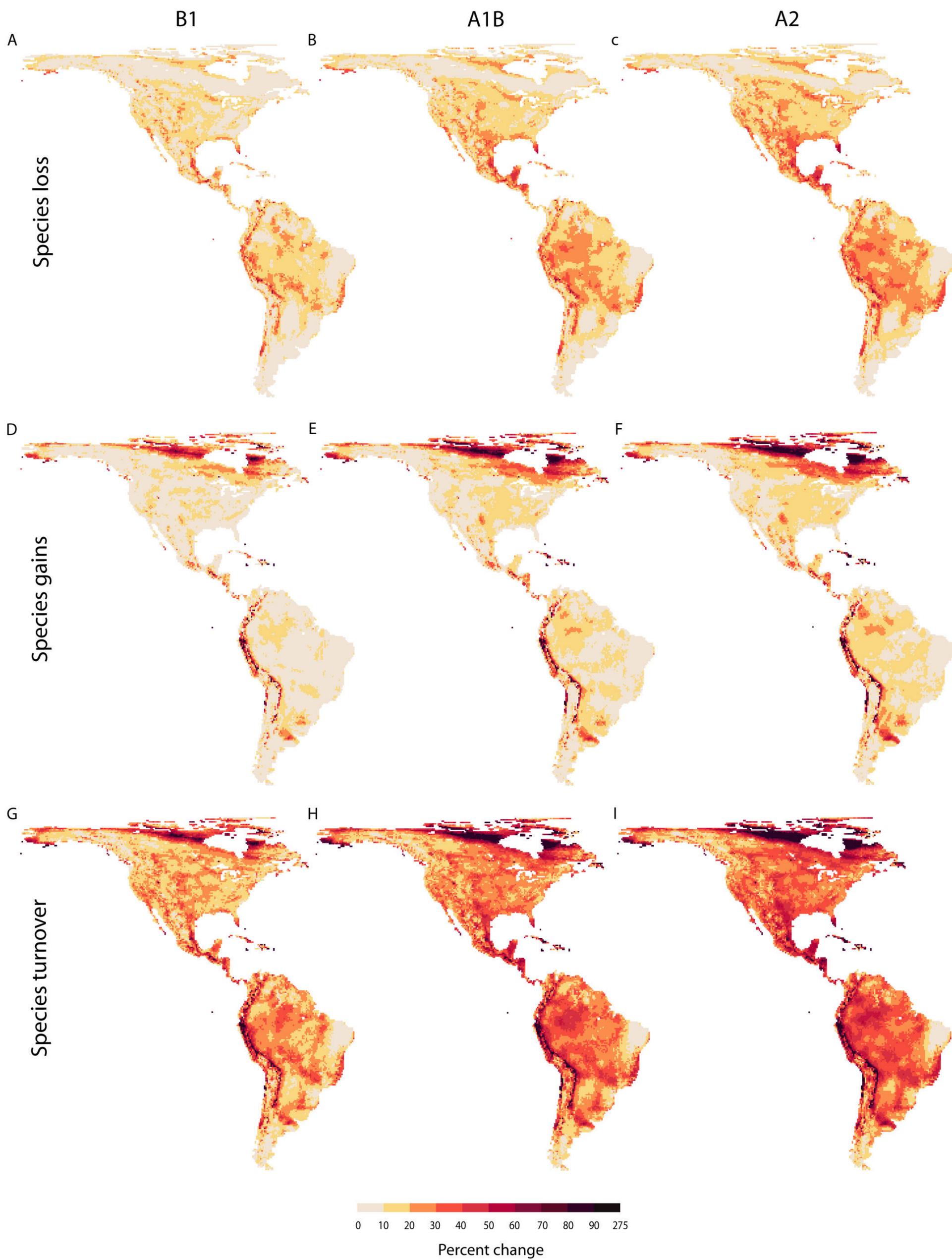
556

557 Figure 2. Consistent predictions of changes in species composition for the mid A1B  
558 greenhouse-gas emissions scenarios projected for a 100-km by 100-km grid (a) and for a 200-  
559 km by 200-km grid (b). Eighty percent (8 of 10) of the future climate projections made for  
560 the A1B emissions scenario resulted in greater changes than the values represented in the  
561 maps. These maps are directly comparable to Figure 1h that depicts similar projections made  
562 for a 50-km by 50-km grid.

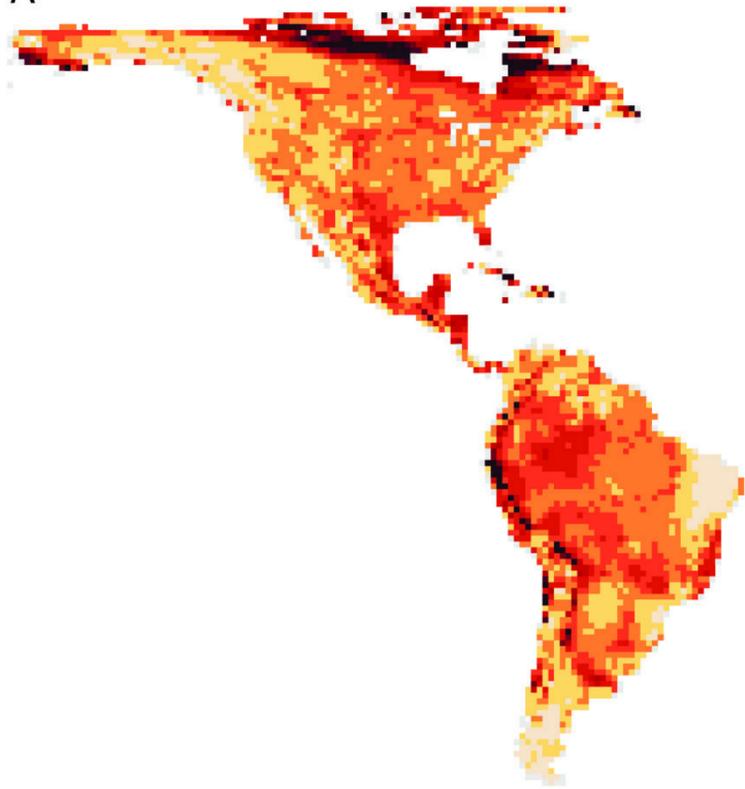
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564 Figure 3. Consistent predictions of climate-induced species turnover for three major  
565 vertebrate taxa. Predictions were made using 10 different climate projections for the A1B  
566 mid-range greenhouse-gas emission scenario. Eighty percent (8 of 10) of the climate-change

567 projections resulted in greater species turnover than the values in these maps. For the light  
568 grey areas (a), small sample sizes precluded reliable estimates of species-turnover.



A



B

