



Projecting Global Mangrove Species and Community Distributions under Climate Change

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1 Projecting global mangrove species and community distributions under climate change

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13 **Abstract**

14 Given the multitude of ecosystem services provided by mangroves, it is important to
15 understand their potential responses to global climate change. Extensive reviews of the literature
16 and manipulative experiments suggest that mangroves will be impacted by climate change, but
17 few studies have tested these predictions over large scales using statistical models. We provide
18 the first example of applying species and community distribution models (SDMs and CDMs,
19 respectively) to coastal mangroves worldwide. Species distributions were modeled as ensemble
20 forecasts using BIOMOD. Distributions of mangrove communities with high species richness
21 were modeled in three ways: as the sum of the separate SDM outputs, as binary hotspots (with
22 >3 species) using a generalized linear model, and continuously using a general boosted model.
23 Individual SDMs were projected for 12 species with sufficient data and CDMs were projected
24 for 30 species into 2080 using global climate model outputs and a range of sea-level rise
25 projections. Species projected to shift their ranges polewards by at least 2 degrees of latitude
26 consistently experience a decrease in the amount of suitable coastal area available to them.
27 Central America and the Caribbean are forecast to lose more mangrove species than other parts
28 of the world. We found that the extent and grain size, at which continuous CDM outputs are
29 examined, independent of the grain size at which the models operate, can dramatically influence
30 the number of pseudo-absences needed for optimal parameterization. The SDMs and CDMs
31 presented here provide a first approximation of how mangroves will respond to climate change
32 given simple correlative relationships between occurrence records and environmental data.
33 Additional, precise georeferenced data on mangrove localities and concerted efforts to collect
34 data on ecological processes across large-scale climatic gradients will enable future research to
35 improve upon these correlative models.

36 Key words: climate envelope; community; global; mangal; sea-level rise; species richness.

37 **Introduction**

38 Sea-level rise and altered weather patterns resulting from global climate change have
39 impacted and will continue to impact coastal systems, altering the ecological and economic
40 services that they offer (Nicholls et al. 2007). In coastal tropical and sub-tropical areas
41 throughout the world, salt-tolerant mangrove trees are of vital ecological and societal importance
42 (reviewed by Walters et al. 2008). For instance, mangroves have the ability to sequester five
43 times the amount of carbon than upland tropical forests (Siikimäki et al. 2012). Mangroves also
44 provide critical habitat for organisms occupying the land-sea interface (Ellison 2008). Seafood
45 production in many developing and developed countries throughout the world relies directly or
46 indirectly on mangroves (Rönnbäck 1999, Ellison 2008). Mangroves may also provide a buffer
47 that protects coastal and nearby inland human settlements from erosion and tropical storm
48 damage (Das and Vincent 2009).

49 To better understand the uncertainty in projecting the global economic potential for
50 decreasing carbon dioxide emissions from mangrove loss and because many other ecosystem
51 services provided by mangroves also are affected by the diversity and distribution of mangroves,
52 it is important to understand how large-scale patterns in their distributions are likely to respond
53 to global climatic change (Ellison 1993, Ellison 2002). Extensive reviews of the literature
54 summarize relationships between mangroves and environmental drivers in contemporary and
55 historic times to speculate on how global climate change might affect mangroves worldwide
56 (Ellison 1994, Snedaker 1995, Alongi 2008, Gilman et al. 2008). Manipulative laboratory
57 experiments have explored fine-scale responses of mangroves to drivers associated with global
58 climate change (e.g., elevated sea level and CO₂ concentrations) (Farnsworth et al. 1996, Ellison
59 and Farnsworth 1997, Ye et al. 2003). These reviews and experiments suggest that individual

60 mangrove species' distributions may contract and local species richness and productivity may
61 decrease in regions where climate-change scenarios forecast that precipitation and run-off will
62 decrease while salinity soil sulfides increase (Snedaker 1995, Ellison 1994). In contrast, where
63 precipitation and run-off increase, upland nutrients will be deposited, salinity will be reduced,
64 and acid-sulfide soils will be moderated, leading to increased productivity, opportunities for
65 range expansion of individual mangrove species, and potential for increases in local species
66 richness. Latitudinal range limits of mangroves are forecast to increase as air temperatures warm;
67 current mangrove distributions are limited by the 16°C isotherm of the coldest month (Ellison
68 1994, Gilman et al. 2008).

69 Manipulative experiments and literature-based predictions of range and compositional
70 shifts suggest hypotheses of how mangroves will respond to climate change that can be
71 addressed using large-scale (macroecological) statistical models that directly relate future
72 climate-change to mangrove distributions (Ellison 2002). Although they have not been widely
73 applied to mangroves (cf., Gilman et al. 2007 for an example of a regional study), species and
74 community distribution models (SDMs and CDMs, respectively) are a common tool used by
75 macroecologists to assess potential threats of climate change to biodiversity (e.g., Fitzpatrick et
76 al. 2011). These models use simple correlative relationships between species occurrences or
77 indices of community composition and current environmental data to extrapolate species (or
78 community) distributions across space and/or time (Guisan and Thuiller 2005, Peterson et al.
79 2011). While such SDMs and CDMs do not incorporate many ecologically relevant factors (e.g.,
80 biotic interactions, evolutionary change), they do provide a first approximation for thinking
81 about the large-scale impacts of climate change on organisms (Pearson and Dawson 2003).

82 Previous mangrove modeling research has focused on topics such as mangrove
83 demography (Clarke 1995), distributions (Cohen et al. 2005), stand dynamics (Chen and Twilley
84 1998, Twilley et al. 1999, Berger and Hildenbrandt 2000; individual-based models reviewed by
85 Berger et al. 2008), ecosystem function and services (Heald 1971, Grasso 1998), and foodwebs
86 (Odum and Heald 1975) at geographic extents much smaller than the range of a species. Here we
87 use SDMs and CDMs to explore how mangrove biodiversity may respond to global climatic
88 change at large spatial extents encompassing the entirety of species' ranges. SDMs generate
89 detailed information on potential ranges of individual species, but are meaningful only when data
90 are extensive (Fitzpatrick et al. 2011). In contrast, CDMs provide additional insights into rare
91 species because they are capable of including infrequently sampled species. Of the SDMs we
92 ask: 1) will each species' coastal range expand, contract, or remain the same; and 2) if the
93 species' range does change, does it shift poleward or towards the equator? We use CDMs to ask:
94 1) will there be poleward shifts in areas with multiple mangrove species; and 2) given reasonable
95 scenarios of climatic change, where do we forecast gains and losses in mangrove species
96 richness?

97 **Methods**

98 *Mangrove occurrence data*

99 We focus our analyses on 30 species in the eight major mangrove genera (sensu
100 Tomlinson 1986) that contribute most to the community structure in mangrove forests and
101 provide the majority of ecosystem services (Rönnbäck 1999, Khatiresan and Bingham 2001,
102 Ellison 2008). Mangrove occurrence (presence-only) data (Table 1) were obtained from the
103 Global Biodiversity and Information Facility Database (GBIF: <http://www.gbif.org>; Appendix 1),
104 and included data from museum specimens, peer-reviewed papers, and the Mangrove Database

105 of the Flanders Marine Institute (<http://www.vliz.be/vmcddata/mangroves>). Occurrence records
106 were checked against species distribution maps (Spalding et al. 2010); outliers (including living
107 specimens in botanic gardens) were removed before analysis (cf., Yesson et al. 2007).

108 We limited our modeling to coastal regions because mangroves are primarily coastal
109 (Tomlinson 1986). We generated global coastal GIS layers by applying the “contour list” tool in
110 ArcMAP 9.3 to a global topography and bathymetry digital elevation model
111 (<http://www.ngdc.noaa.gov>). We generated coastlines at 0, 1, 3, and 6m contours, which
112 correspond respectively to the current coastline and three projected increases in global sea-level.
113 A 1-m rise corresponds to the upper limits of forecasted sea-level rise not accounting for rapid
114 dynamical changes in ice-mass loss (IPCC 2007). Given the uncertainty in the magnitude of ice-
115 mass loss in areas such as Greenland over the next 100 years, however, we also modeled 3 and 6
116 m rises in sea-level (Bromwich and Nicolas 2010).

117 The coastal GIS layers were converted to 2.5-minute resolution (4,318 m grid cells) in a
118 Goode homologous projection for all subsequent modeling. A 2.5 minute resolution balances a
119 sufficiently fine scale for non-climatic predictors (e.g., horizontal tide, river discharge) with
120 computational resources. All GBIF data within 40 km of the coastline were assigned to the
121 nearest grid cell of the current coast; these occurrence records yielded 7,085 unique records
122 distributed across 1,847 grid cells that were used in the models, which treated each coastal grid
123 cell as an observation unit. All data used in this study are available online through the Harvard
124 Forest Data Archives (<http://harvardforest.fas.harvard.edu/data-archives>).

125 *Environmental predictors*

126 We compiled a data set of 21 climatic, hydrological, and geomorphological variables
127 associated with mangrove distribution patterns (Duke et al. 1998, Gilman et al. 2007, Alongi

128 2008). Bioclimatic variables were obtained from the WorldClim database
129 (<http://www.worldclim.org>). These nineteen variables include summary statistics for temperature
130 and rainfall (e.g., mean, range) at different temporal resolutions (e.g., annually, quarter annually)
131 and represent average climatic conditions from 1950-2000 interpolated from weather station
132 data. We refer to these data as “current” climate data (Hijmans et al. 2005). Estimates of
133 horizontal tide and river discharge were based on catchment size. Horizontal tide was estimated
134 by dividing the vertical tidal amplitude by slope, where vertical tides were obtained by summing
135 the primary tidal amplitude constituents, M2 and K1 (Lyard et al. 2006), obtained from the
136 NASA Planetary Geodynamics Lab, and slope was obtained from the global bathymetry and
137 topography digital elevation model. River discharge was obtained using the “Flow
138 Accumulation” tool in ArcMAP 9.3 applied to a global topography layer; flow accumulation was
139 weighted by mean annual rainfall for the current and future scenarios.

140 For each of the 21 predictors, we used WorldClim data to generate a corresponding set of
141 future environmental values based on the 2080 projections of the National Center for
142 Atmospheric Research's (NCAR) CCSM3 general circulation model (GCM) under the
143 Intergovernmental Panel on Climate Change IV's SRES A1b scenario. We chose this rapid
144 growth, carbon intensive scenario because observed data on global fossil fuel emissions
145 increased from 2000-2008 by 29%, suggesting that despite efforts to stabilize CO₂ emissions to
146 curtail global climatic change our planet is experiencing the more extreme of the SRES scenarios
147 (Le Quéré et al. 2009). This GCM forecasts a +2 °C change in annual temperature within the
148 current latitudinal limits of mangroves (32 °N and 40 °S; Spalding et al. 2010). Precipitation
149 projections are more variable; some mangrove areas are forecast to have 50% less annual
150 precipitation (most of Central America and the Caribbean), whereas other areas are forecast to

151 have 50% more (most of Southeast Asia). Although we recognize that there also is variation
152 among GCMs (IPCC 2007), it was beyond the scope of this study to run different GCMs on the
153 SRES A1b scenario.

154 As we did for the mangrove occurrence data, we assigned to each coastal grid cell the
155 nearest value (within a 40-km radius) of each of the current and future environmental variables.
156 To account for possible spatial error in the river discharge layer to coastal cells, this layer was
157 first resampled at a 14 km grid size, taking the maximum value within that larger region before
158 assigning values to the coastal cells.

159 *Species distribution modeling*

160 We used BIOMOD (Thuiller et al. 2009) to generate SDMs for the 12 mangrove species
161 that occurred in at least 50 modeled grid cells (Table 1). Note that while there were 15 species in
162 the GBIF data with >50 occurrences, there were only 12 species with >50 occupied 2.5 minute
163 resolution grid cells. Outputs of SDMs and CDMs are sensitive to the type of statistical model fit
164 to the occurrence data, so it is preferable to fit many statistical models to the data and combine
165 them into an “ensemble forecast” (Araujo and New 2007). BIOMOD generates ensemble
166 forecasts of species distributions based on contributions from multiple statistical models and
167 initial conditions. We fit and compared all nine of the statistical models available in BIOMOD
168 R2.14: generalized linear models, generalized boosting models, classification and regression
169 trees, generalized additive models, artificial neural networks, surface range envelopes, flexible
170 discriminant analyses, multiple adaptive regression splines, and random forests (detailed in
171 Thuiller et al. 2009, R Development Core Team 2011).

172 BIOMOD models require both presence and absence data. Creating pseudo-absences
173 (i.e., background absences) is common when fitting SDMs because presence only data often are

174 obtained from herbaria records or online databases, so pseudo-absences are generated to better
175 characterize the set of environmental conditions a specie's experiences within its current range
176 (Thuiller et al. 2009). The results of SDMs can be sensitive to the selection of pseudo-absences,
177 the ratio of presences to pseudo-absences, and the geographic extent of pseudo-absences (Lobo
178 et al. 2010, Barbet-Massin et al. 2012). We therefore used several approaches to generating
179 pseudo-absences to accompany our presence-only data on mangroves. One approach we used for
180 selecting pseudo-absences was to use all locations within 40 kilometers of the coastline in the
181 entire mangrove occurrence data set as absences, including locations where the focal species had
182 been found. Phillips et al. (2009) showed that including localities with known occurrences as
183 pseudo-absences helps to minimize spatial bias in survey effort (i.e., bias due to some areas
184 being easier to access and sample for presences than other areas). Random selection of pseudo-
185 absences is a common method (Stockwell and Peters 1999, Fitzpatrick et al. 2011), and the
186 selection of a large number of pseudo-absences at random has been shown to have better
187 predictive performance than more sophisticated methods based on fitting a preliminary model to
188 identify areas of low habitat suitability (Wisz and Guisan 2009). We generated a random
189 selection of 500, 1000, and 10,000 locations within 40 kilometers of the coastline between
190 latitudes 47°S and 47°N, with an equal weight of presence to background data. The geographic
191 extent of the pseudo-absence locations was limited to a lower latitude area of the world because
192 previous studies found that artificial absences that were too far from the presence locations in
193 environmental space were not helpful in differentiating suitable from non-suitable conditions
194 (Lobo et al. 2010, Barbet-Massin et al. 2012).

195 To avoid model over-fitting and to identify the most important current climate
196 environmental variables associated with mangrove distributions, we used generalized boosted

197 models (GBMs) for each species within BIOMOD. GBMs allow for correlated predictors and
198 average across all regression trees created by the boosting algorithm to give robust estimates of
199 the relative importance of each environmental predictor in the model (Friedman 2001, Elith et al.
200 2008). To reduce uncertainties due to the method used to generate pseudo-absences and due to
201 the stochastic nature of the GBM algorithm, ten GBMs were fit for each of the four pseudo-
202 absence data sets (a total of 40 GBMs). The average relative importance of each predictor over
203 these 40 GBMs was then used to identify the five most important predictor variables for each
204 species to be used in the final SDMs (following Friedman 2001) (Tables 2 and 3). For weights in
205 these and the final models, we used the total number of occurrence records for each species per
206 grid cell.

207 These top five most important variables for each species were then used to fit the
208 statistical models in BIOMOD for each combination of presence / pseudo-absence data. Data
209 combinations were split randomly ten times into calibration (70%) and evaluation (30%)
210 components, and the models were run on each of the ten calibrations and evaluation data sets. We
211 assessed the predictive performance of each of the SDMs with the True Skill Statistic (TSS) as it
212 is independent of prevalence (i.e., the proportion of locations with presences) and it accounts for
213 omission and commission errors (i.e., false negatives and false positives, respectively) (Allouche
214 et al. 2006). TSS ranges from -1 to $+1$; a value of $+1$ indicates perfect agreement between model
215 predictions and the validation data, whereas values < 0 indicate model predictions no better than
216 random. We present here the ensemble forecast for the current climatic conditions and future
217 scenarios from models fit using presence / 500 random pseudo-absence data, because this
218 combination yielded the highest TSS value. The contribution of each statistical model to the

219 ensemble was based on a weighted average in which the relative weight of the model's TSS score
220 was calculated using BIOMOD's default decay value of 1.6 (Thuiller et al. 2009).

221 Binary (presence/absence) outputs were generated from the continuous outputs of
222 BIOMOD by selecting the threshold that maximized the TSS score. From these data, we
223 calculated the percent of the total number of coastal cells occupied by each species under each
224 scenario. We also calculated the minimum, maximum, mean, and standard deviation of the
225 absolute value of latitude of predicted occurrences for each species. Because the models do not
226 account for dispersal limitation, we cropped model outputs to meaningful regions for each
227 species before summarizing. We used the GBIF data and distribution maps (Spalding et al. 2010)
228 to determine the oceans in which the species occur, and then set projected probabilities to zero at
229 longitudes beyond these regions (Table 4). After selecting crop lines for each species, we
230 examined global projected distributions to ensure that the crop lines did not intersect areas
231 predicted to have continuous occurrences. Thus, summary statistics of model outputs should not
232 be very sensitive to the location of crop lines.

233 *Community distribution models and species richness*

234 Mangroves tend to occur in association with multiple mangrove species, each of which
235 may occur at specific tidal elevations (Macnae 1968). At the coarse scale of this study, we are
236 interested primarily in identifying areas where multi-species mangrove assemblages are likely to
237 occur, rather than distinguishing between different types of mangrove communities. We modeled
238 local species richness ("alpha diversity") because we had inadequate data to model species
239 turnover ("beta diversity").

240 We modeled mangrove species richness using three different approaches: a composite
241 model, a continuous-response model, and a binary-response model. For the composite model, we

242 combined the independent projections of the 12 individual SDMs by summing the predicted
243 occurrences within each coastal cell. For the continuous and binary models, we calculated the
244 current species richness within each coastal cell based upon all 30 major mangrove species in our
245 GBIF data set (Table 1).

246 In the binary model, we sought to identify those cells where multi-species mangrove
247 communities are most likely to exist. To do this, we assigned each cell with three or more species
248 out of the 30 total species in our GBIF data a value of one and each cell with less than three
249 species was assigned a value of zero. In this analysis, we modeled presence of cells with high
250 species richness relative to the other cells in our data set. This process yielded 355 presences of
251 high richness cells. We used three species as the threshold because this was the highest value that
252 would yield enough presences of these high richness cells for sufficient predictor-to-response
253 ratios in the models. The presence of three species may not indicate a true hotspot of mangrove
254 diversity in the field. However, this threshold is appropriate within the context of the GBIF data
255 set, and allows us to confidently weed out cells where only one or two mangrove species exist.
256 We considered using different thresholds for defining high richness in the eastern and western
257 hemispheres, because one might expect greater overall richness in the eastern hemisphere.
258 However, we only see more high-richness cells in the east when the threshold is set at four or
259 five species per cell (Fig. 1), at which levels there are insufficient sample sizes. We further felt
260 that it was more appropriate to treat all of the data uniformly in the model, rather than imposing
261 further rules that may introduce more potential for bias.

262 We ran the binary richness data through the same BIOMOD modeling process that we did
263 for each of the individual species. For weights in the binary model, we used the actual number of
264 species observed in each cell (Fig. 1).

265 For the continuous CDMs, we did not have access to a comprehensive software package
266 for ensemble distribution model selection and prediction based on non-binary data (e.g.,
267 BIOMOD does not model abundance). Instead, we fit the full GBM and GLM models using all
268 21 environmental variables as predictors and the number of mangrove species reported within
269 each grid cell as the response. We compared models with the full suite of predictor variables to
270 those fit using subsets of variables: the five variables with the greatest influence; or by iteratively
271 discarding the least influential variable between pairs of variables with greater than 0.7
272 correlations and rerunning the model until there were no more correlated environmental variables
273 (Dormann et al. 2012). We used AIC stepwise selection to discard variables that were not
274 significant at the 0.05 level. As we did with the SDMs, the mangrove presence data were
275 combined with pseudo-absences generated by selecting 0, 500, 1000, or 10000 random cells
276 from within 40 kilometers of the entire coastline.

277 To determine which type of model yielded the best predictive performance, we divided
278 the world into eastern and western regions defined by a longitudinal division through central
279 Africa at 22.46° where there are no recorded mangrove occurrences. We then trained each model
280 on the separate halves of the world and evaluated their predictive performance on the observed
281 data in the other half of the world. To assess predictive performance, we used the likelihood of
282 univariate GLMs comparing observed species richness in the holdout data sets to predicted
283 species richness. Because our ultimate aim was to examine large-scale patterns in mangrove
284 species diversity, we also tested predictive performance of the full GBM and full GLM models at
285 a coarser resolution. In the coarse-resolution tests, we aggregated the predicted and observed
286 data in the holdout regions to a 500-km grid cell size before comparing predicted and observed
287 species densities. For the final selected model, we fit the subset of predictor variables to the

288 entire world, and then projected forward using the environmental variables in the 2080 3m sea
289 level rise scenario because the results of the SDMs we ran previously were not sensitive to the
290 different sea-level rise scenarios.

291 For the composite, binary, and continuous CDMs, we generated 500-km grid cell maps of
292 forecasted change in species richness between current conditions and future scenarios. We also
293 calculated means of latitude in each cell weighted by the fitted species richness in current and
294 future scenarios for the three models. The GBM model with the full suite of variables had the
295 best predictive performance in most scenarios (Table 5), and so we used this model for our future
296 projections. As with the SDMs, model evaluation with holdout data suggested that models
297 trained with the least pseudo-absences had the best predictive performance when tested against
298 the data with the original ~4 km (i.e., 2.5 minute) grid size. However, coarse scale maps
299 produced by these models exhibited many nonsensical predictions for current mangrove
300 occurrences, including high species richness in high latitude regions. When examining
301 predictions that had first been re-scaled to a 500 km grid size, inclusion of pseudo-absences
302 improved model likelihoods, and produced maps of current fitted distributions that better
303 matched our expectations. Because our study is focused on global changes in mangrove
304 distributions, we opted for including 2000 pseudo-absences in the final model. This yielded an
305 approximate presence to absence ratio of 1:1, similar to that used in the individual SDMs with
306 500 pseudo-absences. Code for all SDMs and CDMS performed using R statistical software
307 version 4.0 are included in Supplementary Material.

308 *Evaluation of SDM and CDM outputs*

309 We evaluated model outputs by generating summary maps at a coarser resolution in order
310 to generalize patterns across regions. We generated these maps with 500 km grid cells and 1000

311 km grid cells. Within each of the larger cells, we summed the predicted species richness in all of
312 the 4 km grid cells. The result is a mangrove species density value for each of the measured cells.
313 This density is different from the mean species richness, because it incorporates both species
314 richness and the number of occupied cells. A 500-km cell centered on Panama has much more
315 coastline than a 500-km cell centered on the coast of Peru. Thus, even if every 4 km coastal cell
316 had the same number of species, the species density measured in the 500 km grid cells would be
317 higher in Panama than Peru.

318 *Coastline versus Latitude*

319 Our study analyzes latitudinal shifts in coastal species. To frame our results, we also
320 needed to understand how the world's coastlines are distributed with respect to latitude. To this
321 end, we summed the total number of ~4 km grid cells within each 2-degree latitudinal bin. We
322 also performed a separate analysis using ArcMap in which we compared the total length of our
323 coastline vector data within 15° of the equator, and between 15° and 30° from the equator. The
324 vector data was generated at a 1.7 km resolution.

325 **Results**

326 *Species distribution models*

327 The current distribution of each of the most common 12 mangrove species was best
328 predicted by a different set of five environmental variables (Tables 2 and 3); precipitation in the
329 warmest and coldest quarters appeared in the list of top five predictors for more than half of the
330 mangrove species. In the variable selection process, river discharge and horizontal tide were
331 identified as important environmental predictors only for *Rhizophora apiculata*, *R. racemosa*,
332 and *R. stylosa* (Tables 2 and 3). The predictive performance of the models was high: TSS values
333 for the twelve species averaged 0.97 (range 0.950 – 0.988), but in a few instances the SDMs

334 predicted current mangrove distributions outside of their current known latitudinal range (Fig. 2).
335 Rather than focusing only on minimum and maximum latitudes, we therefore also examined the
336 mean and standard deviations of the absolute values of latitude.

337 All 12 common mangrove species were forecast to change their absolute mean latitude
338 and total suitable coastal area relative to current climatic conditions (Fig. 2). Half of the modeled
339 species were projected to have a poleward shift of two degrees of latitude or more in the absolute
340 mean latitudes of their distributions under the future climate scenario (Fig. 2). These six species
341 also were forecast to suffer losses in the total area of suitable coastal habitat available within
342 their expanded ranges (Fig. 2). This loss of the amount of suitable coastal habitat available for
343 species with poleward range shifts could be due to the lower amount of total coastline in higher
344 tropical latitudes compared to equatorial areas (Fig. 3). All of the species that did not experience
345 a poleward shift in the absolute mean values of their distributions gained total suitable coastal
346 habitat under the future scenario regardless of the amount of sea-level rise.

347 The four species with current ranges limited to the Americas, western and central Africa,
348 and the western Pacific islands – *Avicennia germinans*, *Laguncularia racemosa*, *Rhizophora*
349 *mangle*, *Rhizophora racemosa* – were all forecast to experience overall losses in total suitable
350 coastal habitat and poleward shifts under the future climate scenario compared to current
351 climatic conditions (Figs. 2, and 4-27). The NCAR-CCSM3 GCM forecasts that the annual
352 precipitation in these regions will decrease by at least 50% and that annual temperature will
353 increase by at least 2°C. Our forecasts of mangrove loss in these areas supports previous
354 hypotheses that individual mangrove species' distributions will contract and richness will decline
355 as rainfall and runoff decrease while salinity and extent of acid-sulfide soils increase (Snedaker
356 1995, Ellison 1994).

357 The remaining eight species, with current ranges limited to eastern Africa, Asia, and
358 Australia, had more variable forecasts. *Lumnitzera littorea* and *Rhizophora mucronata* were
359 projected to shift polewards and lose suitable coastal habitat, while *Avicennia marina*, *Ceriops*
360 *tagal*, *Lumnitzera racemosa*, and *Rhizophora apiculata* were forecasted to gain potential coastal
361 area with absolute mean latitudinal gains of less than two degrees. *Sonneratia alba* and
362 *Rhizophora stylosa* were projected to gain coastal habitat and experience decreases in absolute
363 mean latitude (i.e., equatorial range contractions). With forecasted gains in suitable coastal area
364 of 260% to 290% of its current projected distribution, *R. stylosa* was forecast to gain a
365 remarkable 110 to 185% additional habitat relative to its current distribution.

366 *Community distribution models and species richness*

367 The means of the absolute value of latitude weighted by fitted current species density
368 were 14.5°, 14.3° and 17.0° for the composite model, the binary model, and the continuous
369 model, respectively. The projected mean latitudes for the 3m sea-level rise were 14.6°, 14.2°, and
370 15.7° for the same three models. The projected maps of change in species density differed
371 between the three model types, although there were a few areas of overlap (Fig. 28). All three
372 models predicted gains in mangrove species density across much of southeastern Asia, southern
373 Brazil, northern Chile, eastern Australia, southeastern Africa, parts of northern Africa, and parts
374 of northwestern Mexico. All three models also predicted losses of mangrove species density in
375 the Caribbean Islands, parts of Central America and parts of northern Australia (Fig. 28).

376 *Coastline versus latitude*

377 In summing the ~4 km coastal cells vs. latitude, we found that the total length of coastline
378 between the equator and $\pm 15^\circ$ was 42% greater than the length of coastline between 15° and
379 30°N or S (i.e., 182,000 km versus 129,000 km, respectively; Fig. 3). The vector analysis

380 similarly showed 43% more coastline within 15° of the equator than between 15° and 30° from
381 the equator.

382 **Discussion**

383 Species and community distribution models are widely used techniques for evaluating the
384 potential impacts of climatic change on biodiversity (Fitzpatrick et al. 2011). These models use
385 simple correlative relationships to project potential distributions for future climate scenarios in
386 order to inform management and climate-change policy (Hannah et al. 2007). Although
387 distribution models usually perform well in characterizing and predicting current distributions
388 (Franklin and Miller 2009), a number of issues have been raised in regards to the lack of
389 important ecological processes and the methodological issues of such models (e.g., Pearson and
390 Dawson 2003, Record et al. 2013). Previous mangrove species distribution modeling research
391 has been performed at geographic extents much smaller than the ranges of the species modeled
392 (Cohen et al. 2005, Gilman et al. 2007). The work presented here is the first application of
393 species and community distribution modeling to provide a first approximation of how future
394 climate-change scenarios will influence global distributions of mangrove species and
395 assemblages at geographic extents encompassing the entirety of species' ranges. Understanding
396 the response of mangrove distributions to climate change is timely because mangroves are
397 substantial potential carbon sinks (Siikamäki et al. 2012). Our results provide insights into the
398 effort to understand how coastal organisms, such as mangroves, will be impacted by climate
399 change at the global level. Our study also highlights some of the methodological limitations and
400 untested ecological assumptions of distribution models.

401 First, we found that species projected to shift their ranges polewards by at least 2 degrees
402 of latitude consistently experience a decrease in the amount of suitable coastal area available to

403 them. Previous studies have suggested that mangroves will occupy higher latitudes in a warmer
404 climate because current mangrove distributions are limited to the 16°C isotherm for annual
405 temperature of the coldest month (Ellison 1994, Alongi 2008, Gilman et al. 2008), but the link
406 between mangrove distributional shifts and coastal area losses at higher latitudes has not been
407 previously explored.

408 Second, Central America and the Caribbean are forecast to suffer a greater loss of
409 mangrove species density than other parts of the world. Three of the four species exhibiting
410 declines in Central America and the Caribbean are the best represented species in the GBIF
411 dataset, suggesting that our forecasts for these species are more robust than those for species with
412 sparser occurrence records, such as many species in the Indo-West Pacific (Table 1). Continued
413 contributions of quality georeferenced occurrence records by researchers is imperative to
414 improving our understanding of whether the variation we see in species forecasted distributions
415 in locations such as the Indo-West Pacific are realistic or reflect only artifacts of sampling and
416 reporting.

417 Third, our study also highlights the importance of considering spatial scale (both grain
418 size and extent) in SDMs. Past studies have demonstrated that mangroves are sensitive to factors
419 including sea-level rise, tidal zones, and river discharge (Ellison and Farnsworth 1997, Ye et al.
420 2003, reviewed by Duke et al. 1998, Gilman et al. 2007, Alongi 2008). However, these forces are
421 primarily important in influencing the distribution of individual mangrove species at relatively
422 small scales. At larger scales, these relationships break down in the field (Bunt 1996, Ellison et
423 al. 2000), and this breakdown is reflected in the coarser-scale (500-km grid cell) analysis of our
424 community distribution models.

425 For researchers hoping to advance techniques for distribution models based on
426 continuous data, our model selection process offers a further lesson in considering spatial scale.
427 We found that the extent and grain size at which continuous model outputs are examined,
428 independent of the grain size at which the models operate, can dramatically influence the number
429 of pseudo-absences needed for optimal parameterization. That small scales are best modeled
430 without pseudo-absences, but large-scale models are benefited by pseudo-absence is somewhat
431 intuitive. Without pseudo-absences, the models evaluate finer scale differences within sites
432 occupied by mangroves, whereas with many pseudo-absences, the models can better evaluate the
433 coarser scale differences between areas with and without mangroves. This issue should only
434 apply to continuous data where all presences are not identical, unlike in binary data.

435 The SDMs and CDMs presented here provide a first approximation of how mangroves
436 will respond to climate change given simple correlative relationships between occurrence records
437 and environmental data (Peterson et al. 2011). In reality, additional factors, such as coastal
438 development, forestry, and biotic processes (e.g., propagule dispersal, recruitment limitation,
439 interspecific competition, and plant-animal interactions) will also play important roles in
440 structuring future mangrove distributions (e.g., Rabinowitz 1978, Clarke and Kerrigan 2002,
441 Farnsworth and Ellison 1997b, Ellison 2008). Our modeling forecasts are thus optimistic because
442 they assume that species will occur wherever the environmental conditions are suitable for them
443 and these other processes will remain constant (cf., Farnsworth and Ellison 1997a). Future
444 studies in which researchers across the world collaborate to provide consistent data on such
445 biotic and social drivers of mangrove distributions across a range of spatial and temporal scales
446 (Farnsworth 1998) would help to make it possible to better understand and model the future fate
447 of mangroves in a global context.

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608 **Table 1.** List of the 30 mangrove species for which there were data in the Global Biodiversity
 609 Information Facility (GBIF) database.

Species	Abbreviated name	# GBIF records	# modeled grid cells
<i>Avicennia alba</i> Blume	AVAL	15	11
<i>A. bicolor</i> Standley	AVBI	156	43
<i>A. eucalyptifolia</i> (Zipp. ex Miq.) Moldenke	AVEU	20	12
<i>A. germinans</i> (L.) Stearn†	AVGE	1569	569
<i>A. integra</i> Duke	AVIN	5	3
<i>A. lanata</i> Ridley	AVLA	1	1
<i>A. marina</i> (Forssk.) Vierh. †	AVMA	1244	394
<i>A. schaueriana</i> Stapf. & Leechman ex Moldenke	AVSC	4	3
<i>Ceriops australis</i>	CEAU	72	45
<i>C. decandra</i> (Griff.) Ding Hou	CEDE	23	19
<i>C. tagal</i> (Perr) c.B. Robinson†	CETA	196	142
<i>Kandelia candel</i> (L.) Druce	KACA	72	23
<i>K. obovata</i> Sheue, Liu & Yong	KAOB	30	7
<i>Laguncularia racemosa</i> (L.) Gaertn. F. †	LARA	1385	556

<i>Lumnitzera littorea</i> (Jack) Voigt†	LULI	72	56
<i>L. racemosa</i> Willd. †	LURA	184	137
<i>Nypa fruticans</i> (Thunb.) Wurmmb.	NYFR	37	24
<i>Rhizophora apiculata</i> Bl. †	RHAP	85	59
<i>R. harrisonii</i> Leechman	RHHA	29	13
<i>R. mangle</i> Guppy†	RHMA	1166	528
<i>R. mucronata</i> Lamk. †	RHMU	126	75
<i>R. racemosa</i> Meyer†	RHRA	227	89
<i>R. stylosa</i> Griff. †	RHST	167	118
<i>R. x. harrisonii</i> Leechman	RHHAx	33	13
<i>R. x. lamarckii</i> Montr.	RHLAx	7	7
<i>Sonneratia alba</i> J. Smith†	SOAL	127	89
<i>S. apetala</i> Buch. -Ham.	SOAP	2	1
<i>S. caseolaris</i> (L.) Engler	SOCA	36	31
<i>S. ovate</i> Backer	SOOV	6	2
<i>S. x. gulngai</i> N.C. Duke	SOGUx	2	1

611 *Note:* Abbreviated names follow a 4-5 letter naming convention (first two letters of the
612 generic and specific epithets followed by a lowercase 'x' for hybrids). Modeled grid cells
613 were 2.5 minutes in size. Tables 2 and 3 and Figure 2 refer to the abbreviated names.

614 † Footnote: indicates that the species had >50 occupied 2.5 minute resolution grid cells
615 and were modeled by the individual species distribution models.

616

617 **Table 2.** The five most important environmental predictors identified by general boosted models
618 and the exclusion of correlated variables for *Avicennia germinans*, *A. marina*, *Ceriops tagal*,
619 *Laguncularia racemosa*, *Lumnitzera littorea*, and *L. racemosa*. These species' names are
620 indicated by abbreviations from Table 1. All of these species individual distributions were
621 modeled.

Bioclimatic variable	AVGE	AVMA	CETA	LARA	LULI	LURA
Annual mean temp.	1
Mean diurnal range	2	3	4	...
Isothermality	...	3	5	2
Temp. seasonality
Max. temp. of warmest month	...	5	...	1
Min. temp. of coldest month
Temp. annual range
Mean temp. of wettest quarter	...	4	1	2
Mean temp. of driest quarter	...	1	3	2	...	4
Mean temp. of warmest quarter
Mean temp. of coldest quarter	3	...
Annual precip.
Precip. of wettest month
Precip. of driest month
Precip. seasonality	4	3
Precip. of wettest quarter	5	...

Precip. of driest quarter
Precip. of warmest quarter	5	2	4	...	1	1
Precip. of coldest quarter	3	...	2	4	...	5
Flow accumulation
Horizontal tide

622 *Note:* Other abbreviations are as follows: temperature (temp.), precipitation (precip.),
623 maximum (max.), and minimum (min.). Mean diurnal range is the mean of
624 monthly(maximum temperature - minimum temperature). Isothermality is (mean diurnal
625 range/temperature annual range) multiplied by 100. Temperature seasonality is the
626 standard deviation of temperature values multiplied by 100. Temperature annual range is
627 the maximum temperature of the warmest month minus the minimum temperature of the
628 coldest month. Precipitation seasonality is the coefficient of variation of precipitation
629 values. Not all of the 19 bioclimatic predictors listed here were in the top predictor lists
630 for the mangrove species. Ellipses indicate when a variable was not one of the five most
631 important environmental predictors for one of the mangrove species modeled by an
632 individual species distribution model.
633

634 **Table 3.** The five most important environmental predictors identified by general boosted models
635 and the exclusion of correlated variables for *Rhizophora apiculata*, *R. mangle*, *R. mucronata*, *R.*
636 *racemosa*, *R. stylosa*, and *Sonneratia alba*. These species' names are indicated by abbreviations
637 from Table 1. All of these species individual distributions were modeled.

Bioclimatic variable	RHAP	RHMA	RHMU	RHRA	RHST	SOAL
Annual mean temp.
Mean diurnal range	...	4	...	4
Isothermality	...	1	5	...
Temp. seasonality	5	...	5	2	...	2
Max. temp. of warmest month	...	2
Min. temp. of coldest month
Temp. annual range
Mean temp. of wettest quarter	4	...	3	5	1	1
Mean temp. of driest quarter	...	5
Mean temp. of warmest quarter
Mean temp. of coldest quarter
Annual precip.
Precip. of wettest month	1
Precip. of driest month	1
Precip. seasonality	4
Precip. of wettest quarter	4	...
Precip. of driest quarter	4

Precip. of warmest quarter	3	...	1	...	3	5
Precip. of coldest quarter	...	3	2	3
Flow accumulation	2
Horizontal tide	3	2	...

638

639 **Table 4.** Minimum and maximum longitudinal values of extents used to crop outputs of
 640 individual species projections.

Species	Longitude minimum (m)	Longitude maximum (m)
<i>Avicennia germinans</i>	-2.1×10^7	1.8×10^6
<i>Avicennia marina</i>	-1.8×10^6	2.0×10^7
<i>Ceriops tagal</i>	-1.8×10^6	2.0×10^7
<i>Laguncularia racemosa</i>	-2.1×10^7	1.8×10^6
<i>Lumnitzera littorea</i>	7.0×10^6	2.0×10^7
<i>Lumnitzera racemosa</i>	1.8×10^6	2.0×10^7
<i>Rhizophora apiculata</i>	7.0×10^6	2.0×10^7
<i>Rhizophora mangle</i>	-2.1×10^7	1.8×10^6
<i>Rhizophora mucronata</i>	1.8×10^6	2.0×10^7
<i>Rhizophora racemosa</i>	-1.5×10^7	2.0×10^7
<i>Rhizophora stylosa</i>	1.0×10^7	2.0×10^7
<i>Sonneratia alba</i>	1.8×10^6	2.0×10^7

641

642 *Note:* Map projection is Interrupted Goode Homolosine, land-centered.

643

644 **Table 5.** Negative log-likelihoods of continuous community distribution models used to predict
 645 mangrove species densities.

Model	Resolution (km)	Training data	Validation data	Number of absences	Mean	Standard deviation
GBM full	4	East	West	0	-7156	37.0
GBM full	4	West	East	0	-6629	16.0
GBM full	4	East	West	500	-7301	29.0
GBM full	4	West	East	500	-6631	14.0
GBM full	4	East	West	1000	-7380	32.0
GBM full	4	West	East	1000	-6632	13.0
GBM full	4	East	West	2000	-7526	12.0
GBM full	4	West	East	2000	-6655	9.8
GBM full	4	East	West	10000	-7603	2.5
GBM full	4	West	East	10000	-6674	0.6
GBM top 5 variables	4	East	West	0	-7245	49.0
GBM top 5 variables	4	West	East	0	-6670	10.0
GBM top 5 variables	4	East	West	500	-7396	33.0
GBM top 5 variables	4	West	East	500	-6669	4.1
GBM top 5 variables	4	East	West	1000	-7487	32.0
GBM top 5 variables	4	West	East	1000	-6668	8.2
GBM top 5 variables	4	East	West	2000	-7586	13.0
GBM top 5 variables	4	West	East	2000	-6680	7.2

GBM top 5 variables	4	East	West	10000	-7614	2.4
GBM top 5 variables	4	West	East	10000	-6708	0.8
GBM uncorrelated variables	4	East	West	0	-7245	49.0
GBM uncorrelated variables	4	West	East	0	-6670	10.0
GBM uncorrelated variables	4	East	West	500	-7396	33.0
GBM uncorrelated variables	4	West	East	500	-6669	4.1
GBM uncorrelated variables	4	East	West	1000	-7487	32.0
GBM uncorrelated variables	4	West	East	1000	-6668	8.2
GBM uncorrelated variables	4	East	West	2000	-7586	13.0
GBM uncorrelated variables	4	West	East	2000	-6680	7.2
GBM uncorrelated variables	4	East	West	10000	-7614	2.4
GBM uncorrelated variables	4	West	East	10000	-6708	0.8
GLM full	4	East	West	0	-7582	280.0

GLM full	4	West	East	0	-6673	19.0
GLM full	4	East	West	500	-7629	190.0
GLM full	4	West	East	500	-6687	17.0
GLM full	4	East	West	1000	-7554	180.0
GLM full	4	West	East	1000	-6693	9.0
GLM full	4	East	West	2000	-7803	57.0
GLM full	4	West	East	2000	-6711	3.2
GLM full	4	East	West	10000	-7831	1.0×10^{-12}
GLM full	4	West	East	10000	-6721	4.5×10^{-13}
GLM AIC stepwise	4	East	West	0	-7363	57.0
GLM AIC stepwise	4	West	East	0	-6688	31.0
GLM AIC stepwise	4	East	West	500	-7524	68.0
GLM AIC stepwise	4	West	East	500	-6697	28.0
GLM AIC stepwise	4	East	West	1000	-7610	49.0
GLM AIC stepwise	4	West	East	1000	-6705	13.0
GLM AIC stepwise	4	East	West	2000	-7782	20.0
GLM AIC stepwise	4	West	East	2000	-6728	16.0
GLM AIC stepwise	4	East	West	10000	-7844	1.4×10^{-12}
GLM AIC stepwise	4	West	East	10000	-6721	5.6×10^{-13}
GLM significant variables	4	East	West	0	-7276	190.0
GLM significant variables	4	West	East	0	-6664	44.0

GLM significant variables	4	East	West	500	-7414	88.0
GLM significant variables	4	West	East	500	-6694	39.0
GLM significant variables	4	East	West	1000	-7618	75.0
GLM significant variables	4	West	East	1000	-6703	19.0
GLM significant variables	4	East	West	2000	-7803	12.0
GLM significant variables	4	West	East	2000	-6738	6.2
GLM significant variables	4	East	West	10000	-7850	1.3×10^{-12}
GLM significant variables	4	West	East	10000	-6752	3.2×10^{-13}
GLM uncorrelated variables	4	East	West	0	-7724	190.0
GLM uncorrelated variables	4	West	East	0	-6725	29.0
GLM uncorrelated variables	4	East	West	500	-7338	56.0
GLM uncorrelated variables	4	West	East	500	-6725	31.0

variables						
GLM uncorrelated variables	4	East	West	1000	-7366	16.0
GLM uncorrelated variables	4	West	East	1000	-6667	48.0
GLM uncorrelated variables	4	East	West	2000	-7492	110.0
GLM uncorrelated variables	4	West	East	2000	-6700	11.0
GLM uncorrelated variables	4	East	West	10000	-7819	3.2×10^{-13}
GLM uncorrelated variables	4	West	East	10000	-6716	0.0
GBM full	500	East	West	0	-2641	2.4
GBM full	500	West	East	0	-2297	0.3
GBM full	500	East	West	500	-2429	22.0
GBM full	500	West	East	500	-2248	4.8
GBM full	500	East	West	1000	-2467	34.0
GBM full	500	West	East	1000	-2244	5.4
GBM full	500	East	West	2000	-2517	31.0
GBM full	500	West	East	2000	-2237	4.6
GBM full	500	East	West	10000	-2640	21.0
GBM full	500	West	East	10000	-2217	4.5

GLM full	500	East	West	0	-2401	0.0
GLM full	500	West	East	0	-2285	0.0
GLM full	500	East	West	500	-2997	650.0
GLM full	500	West	East	500	-2270	7.3
GLM full	500	East	West	1000	-2722	450.0
GLM full	500	West	East	1000	-2275	5.7
GLM full	500	East	West	2000	-2977	410.0
GLM full	500	West	East	2000	-2281	6.2
GLM full	500	East	West	10000	-3192	190.0
GLM full	500	West	East	10000	-2310	5.9

646

647

Note: Models were fit using only data from the eastern or western world regions, and

648

then tested against data in the other regions. Values represent negative log-likelihoods of

649

generalized linear models comparing observed species densities to predicted densities in

650

the holdout regions.

651 **Figure 1.** Number of 4,318 km coastal grid cells containing at least zero to eight mangrove
652 species in the Global Biodiversity Information Facility database. One grid cell in the eastern
653 region had 11 species in it. All other grid cells had fewer than eight species.

654 **Figure 2.** Predicted latitudinal distributions of 12 mangrove species under each sea-level rise
655 scenario. Thin vertical bars represent minimum and maximum latitudes, thick vertical bars
656 represent standard deviations, and horizontal bars represent means. Labels above each maximum
657 represent the current ('c') fitted distributions as well as the projections for sea level rise of 0m, 1
658 m, 3 m, or 6 m. The colors of the projected vertical bars represent the percent change in the total
659 number of predicted occupied cells relative to the current fitted values (see color legend).
660 Species names are as in Table 1. Species are ordered from left to right in decreasing order of the
661 number of GBIF occurrence records.

662 **Figure 3.** Length of coastline plotted against absolute value of latitude. Coastline is calculated as
663 the sum of coastal grid cells in our data set multiplied by the cell width (4,318 m).

664 **Figure 4.** Change in predicted occupancy for *Avicennia germinans* under the National Center for
665 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
666 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
667 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
668 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
669 occurrence records.

670 **Figure 5.** Change in predicted occupancy for *Laguncularia racemosa* under the National Center
671 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
672 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
673 each 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain

674 the focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
675 occurrence records.

676 **Figure 6.** Change in predicted occupancy for *Rhizophora mangle* under the National Center for
677 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
678 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
679 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
680 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
681 occurrence records.

682 **Figure 7.** Change in predicted occupancy for *Avicennia marina* under the National Center for
683 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
684 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
685 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
686 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
687 occurrence records.

688 **Figure 8.** Change in predicted occupancy for *Ceriops tagal* under the National Center for
689 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
690 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
691 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
692 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
693 occurrence records.

694 **Figure 9.** Change in predicted occupancy for *Lumnitzera racemosa* under the National Center
695 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
696 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within

697 each 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain
698 the focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
699 occurrence records.

700 **Figure 10.** Change in predicted occupancy for *Rhizophora stylosa* under the National Center for
701 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
702 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
703 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
704 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
705 occurrence records.

706 **Figure 11.** Change in predicted occupancy for *Rhizophora racemosa* under the National Center
707 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
708 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
709 each 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain
710 the focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
711 occurrence records.

712 **Figure 12.** Change in predicted occupancy for *Sonneratia alba* under the National Center for
713 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
714 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
715 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
716 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
717 occurrence records.

718 **Figure 13.** Change in predicted occupancy for *Rhizophora mucronata* under the National Center
719 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for

720 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
721 each 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain
722 the focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
723 occurrence records.

724 **Figure 14.** Change in predicted occupancy for *Rhizophora apiculata* under the National Center
725 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
726 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
727 each 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain
728 the focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
729 occurrence records.

730 **Figure 15.** Change in predicted occupancy for *Lumnitzera littorea* under the National Center for
731 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
732 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
733 1,000 km cell represents the change in the number of 2.5-minute cells predicted to contain the
734 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
735 occurrence records.

736 **Figure 16.** Change in predicted occupancy for *Avicennia germinans* under the National Center
737 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
738 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
739 each 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
740 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
741 occurrence records.

742 **Figure 17.** Change in predicted occupancy for *Laguncularia racemosa* under the National Center
743 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
744 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
745 each 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
746 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
747 occurrence records.

748 **Figure 18.** Change in predicted occupancy for *Rhizophora mangle* under the National Center for
749 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
750 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
751 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
752 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
753 occurrence records.

754 **Figure 19.** Change in predicted occupancy for *Avicennia marina* under the National Center for
755 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
756 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
757 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
758 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
759 occurrence records.

760 **Figure 20.** Change in predicted occupancy for *Ceriops tagal* under the National Center for
761 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
762 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
763 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the

764 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
765 occurrence records.

766 **Figure 21.** Change in predicted occupancy for *Lumnitzera racemosa* under the National Center
767 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
768 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
769 each 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
770 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
771 occurrence records.

772 **Figure 22.** Change in predicted occupancy for *Rhizophora stylosa* under the National Center for
773 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
774 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
775 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
776 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
777 occurrence records.

778 **Figure 23.** Change in predicted occupancy for *Rhizophora racemosa* under the National Center
779 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
780 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
781 each 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
782 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
783 occurrence records.

784 **Figure 24.** Change in predicted occupancy for *Sonneratia alba* under the National Center for
785 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
786 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each

787 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
788 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
789 occurrence records.

790 **Figure 25.** Change in predicted occupancy for *Rhizophora mucronata* under the National Center
791 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
792 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
793 each 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
794 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
795 occurrence records.

796 **Figure 26.** Change in predicted occupancy for *Rhizophora apiculata* under the National Center
797 for Atmospheric Research's CCSM3 general circulation model climate scenario projected for
798 2080 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within
799 each 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
800 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
801 occurrence records.

802 **Figure 27.** Change in predicted occupancy for *Lumnitzera littorea* under the National Center for
803 Atmospheric Research's CCSM3 general circulation model climate scenario projected for 2080
804 and 3m of sea-level rise relative to current fitted predicted occupancy. Color shading within each
805 200 km cell represents the change in the number of 2.5-minute cells predicted to contain the
806 focal species. Species in figures 4-15 are ordered in decreasing order of the number of GBIF
807 occurrence records.

808 **Figure 28.** Change in predicted mangrove species richness in 2080 with a 3m rise in sea level.
809 Color shading within each 500-km grid cell represents sum over 2.5-minute grid cells of: (a)

810 species richness as observed in the GBIF data; (b) change in the number predicted occupancies
811 for 12 independently modeled species; (c) predicted distribution of mangrove "hot spots" based
812 on a binary model of cells where more than 3 species co-occur; and (d) predicted species
813 richness based on a continuous model of species richness within each cell. The color scale for the
814 three projected maps has been standardized to represent change in future fitted predictions
815 relative to the mean over all cells in the current fitted predictions.

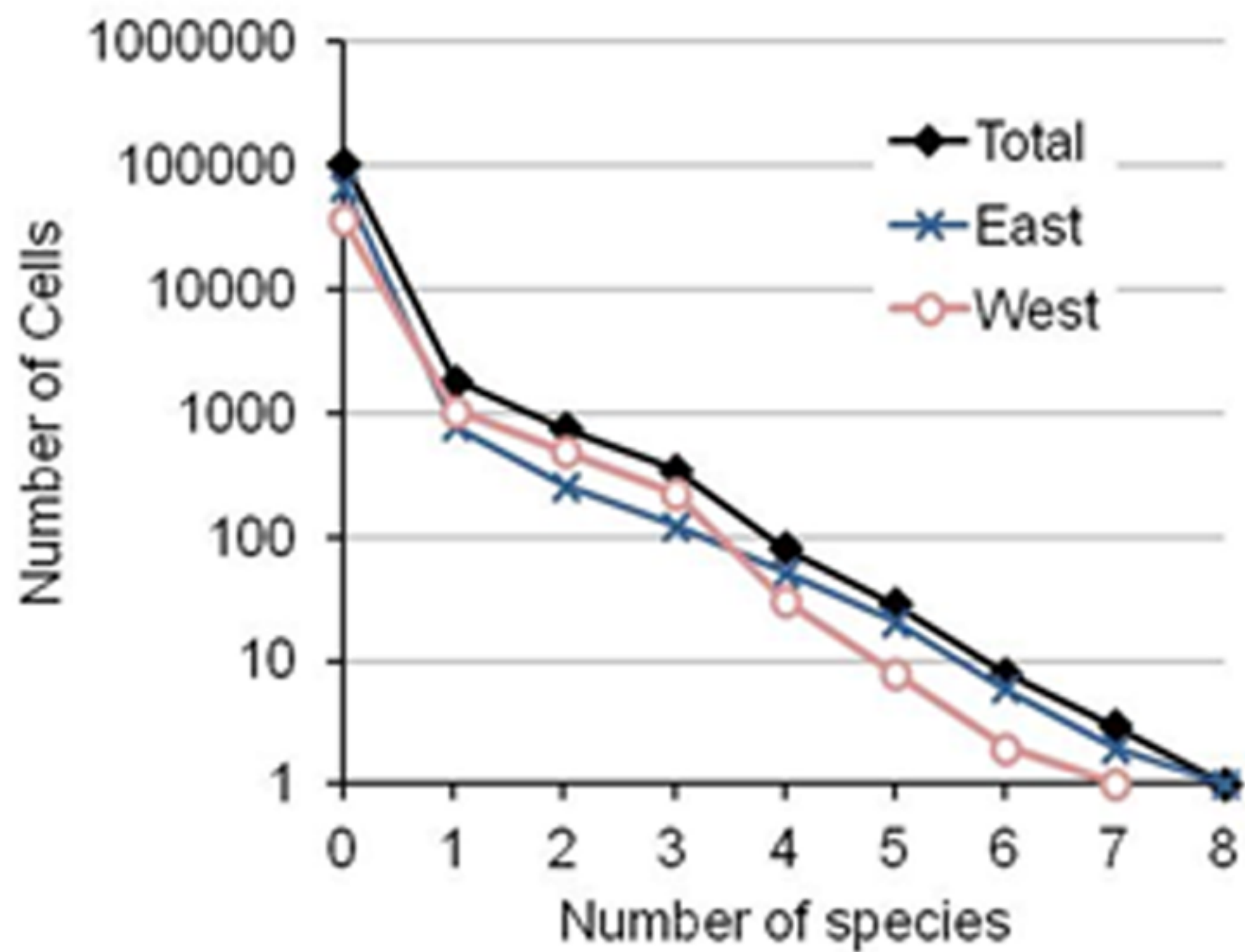
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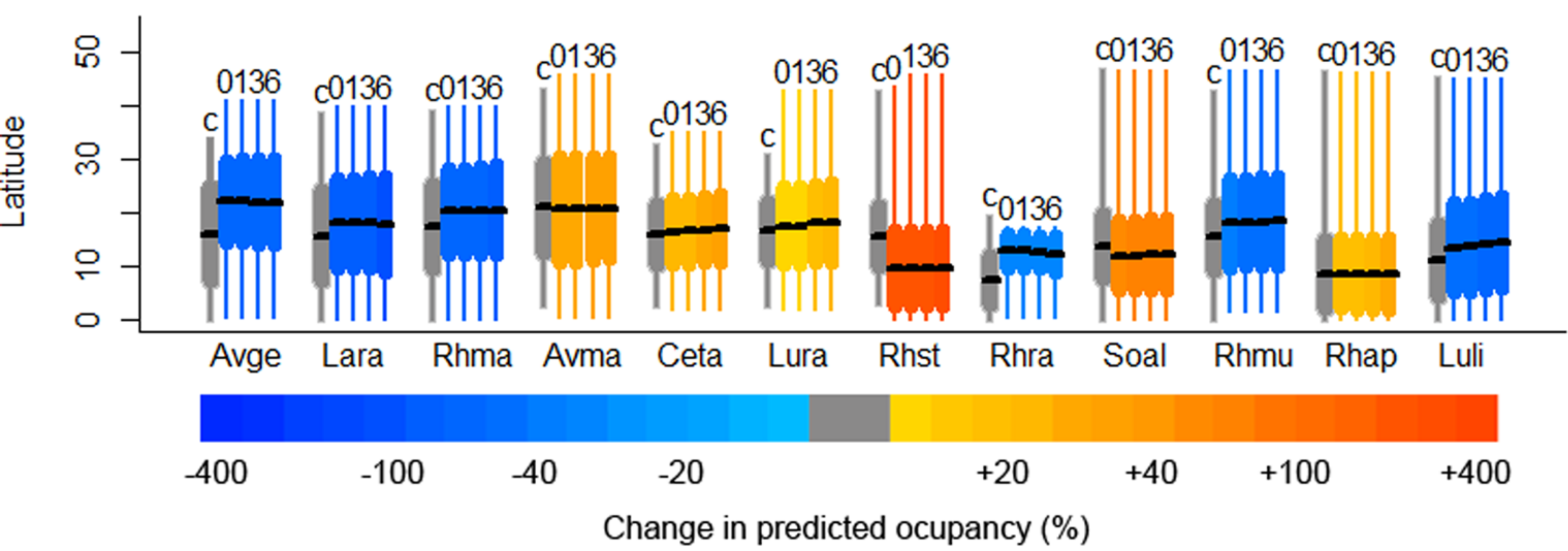
817 **Appendix:** A list of the Global Biodiversity Information Facility data contributors.
818 Biodiversity occurrence data published by: Australian National Herbarium, Berkeley Natural
819 History Museums, Bernice Pauahi Bishop Museum of Natural History, Biologiezentrum Linz
820 Oberoesterreich, Botanic Garden and Botanical Museum Berlin-Dahlem, Botanical Museum
821 Copenhagen, Botanical Research Institute of Texas, Cameroon National Herbarium, Colecciones
822 Instituto Alexander von Humboldt, Comision Nacional para el Conocimiento y Uso de la
823 Biodiversidad de Mexico, Conservation International Rapid Assessment Program Biodiversity
824 Survey Database, Consortium of California Herbaria, Ecole de Faune de Garoua, Fairchild
825 Tropical Botanic Garden, Finnish Museum of Natural History, Flora del Municipio de la Huerta
826 Jalisco, Harvard University Herbaria, Herbario del Jardin Botanic Marimurtra, Herbarium
827 Hamburgense, Herbarium of the Institute of Traditional Medicine Tanzania, Herbarium of the
828 New York Botanical Garden, Herbarium of Plantae TAIIF (Tawian e-Learning and Digital
829 Archives Program TELDAP), Herbarium of the University of Aarhus, Herbarium of the
830 University Libre de Bruxelles, Herbarium Universitat Ulm, Herbarium of the University of
831 Zurich, Herbarium Senckenbergianum, Herbario del CIBNOR, Herbario del Instituto de
832 Ecologia Mexico, Herbario los Tuxtlas, Herbario de la Universidad de Granada, Herbario de la
833 Universidad de Salamanca, Herbario SANT Universidad de Santiago de Compostela, Herbier
834 des Conservatoires et Jardins Botaniques de Nancy, Herbier de la Guyane, Herbier du Bacnin,
835 Indian Ocean Node of OBIS, Institut Botanic de Barcelona, Institute of Ecology and
836 Evolutionary Biology National Taiwan University, Instituto de Botanica Daewinion, Instituto de
837 Ciencias Naturales, Instituto de Investigacion Cientifica Tropical, Instituto Nacional de
838 Biodiversidad (INBio) Costa Rica, Kew Royal Botanic Gardens, Taiwan Forestry Research
839 Institute, Louisiana State University Herbarium, Missouri Botanical Garden, Museo Nacional de

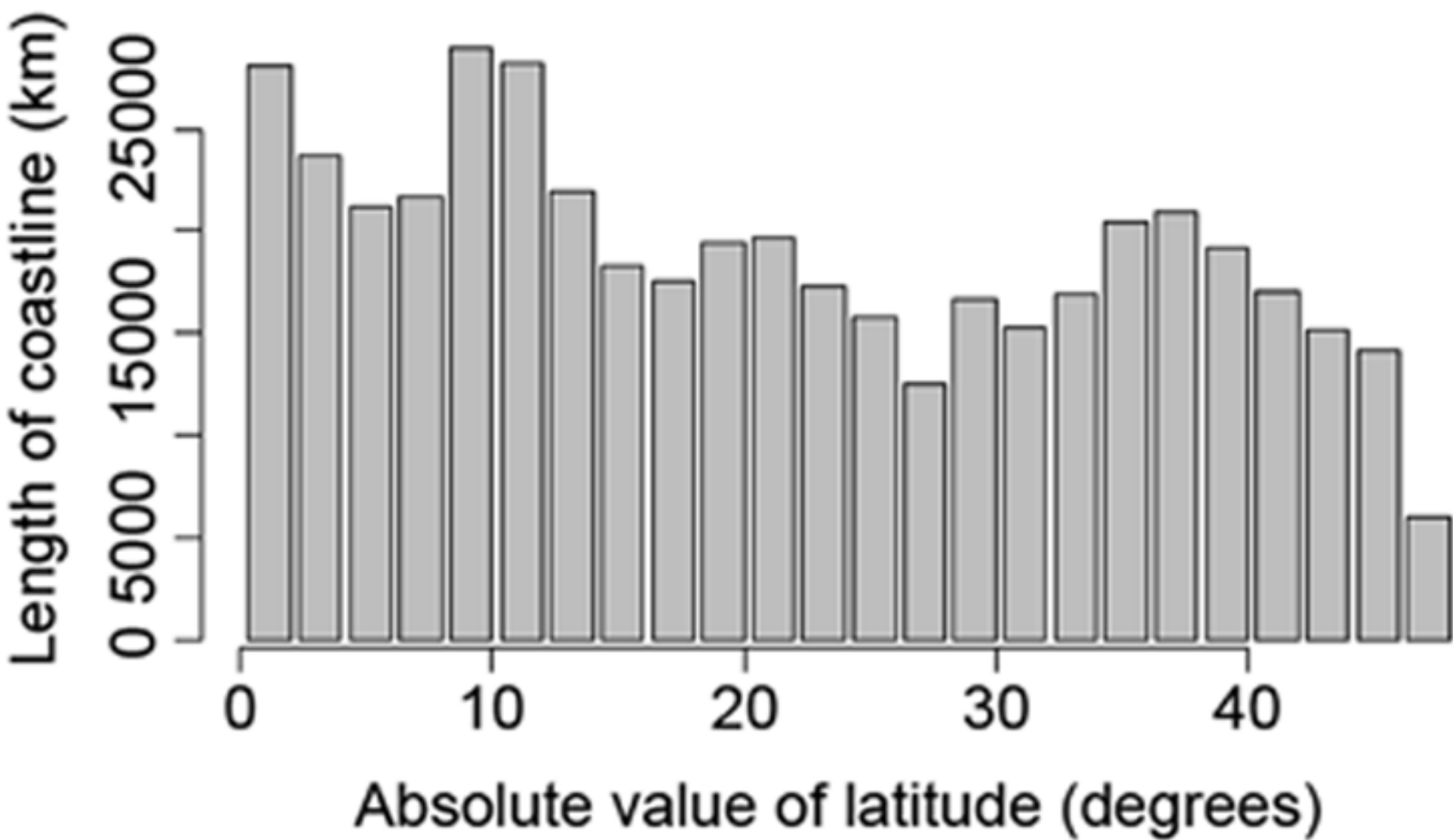
840 Costa Rica, Museum National d'Histoire Naturelle, National Herbarium of the Netherlands,
841 National Herbarium of New South Wales, National Museum of Nature and Science Japan,
842 Natural History Museum Vienna, New South Wales Department of Environment Climate
843 Change and Water, New Zealand National Plant Herbarium, Ocean Biogeographic Information
844 System Bioresources Library (OBIS Australia), Phanerogamic Botanical Collections of Sweden,
845 Real Jardin Botanico de Madrid, Royal Botanic Garden Herbarium Edinburgh, Royal Museum of
846 Central Africa, South African National Biodiversity Institute, South Australia Department of
847 Environment and Natural Resources, Southern Cape Herbarium, Taiwan National Museum of
848 Natural Science, Tama Forest Science Garden Forestry and Forest Products Research Institute,
849 Tela-Botanica, TELDAP Endemic Species Research Institute, The European Genetic Resources
850 Catalogue, UNIBIO IBUNAM Coleccion de Plantas Acuaticas, United States National Museum
851 of Natural History Botany Collections, Univerisidad de Costa Rica, University of Alabama
852 Biodiversity and Systematics Herbarium, University of Alberta Museums Vascular Plant
853 Herbarium, University of Arizona Herbarium, University of California Davis Herbarium,
854 University of California Santa Barbara Marine Science Institute, University of Connecticut
855 Herbarium, University of Gottingen Herbarium, University of Kansas Biodiversity Research
856 Center, University of Loma Herbarium, University of Montreal Marie-Victorin Herbarium,
857 University of Oregon Museum of Natural and Cultural History, University of Strasbourg
858 Herbarium, University of Tennessee Knoxville, University of Vienna Institute for Botany
859 Herbarium, University of Washington Burke Museum, USDA PLANTS Database, Western
860 Australian Herbarium, Wildlife Institute of India, Yale University Peabody Museum (Accessed
861 through GBIF Data Portal, <http://www.data.gbif.org>, 2012-03-15).
862

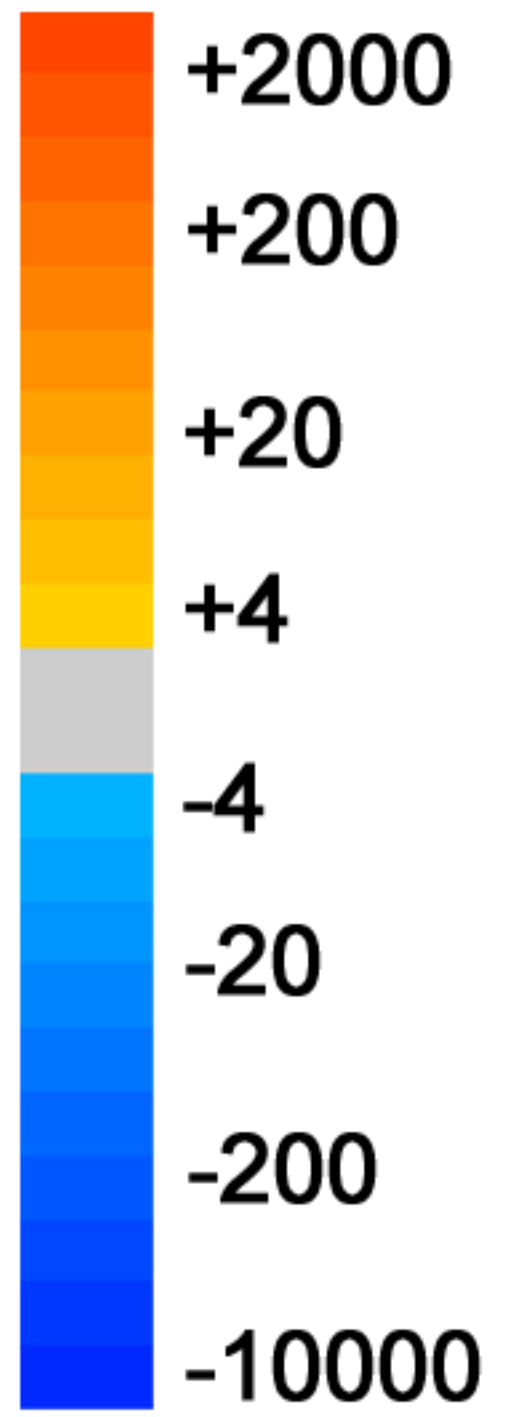
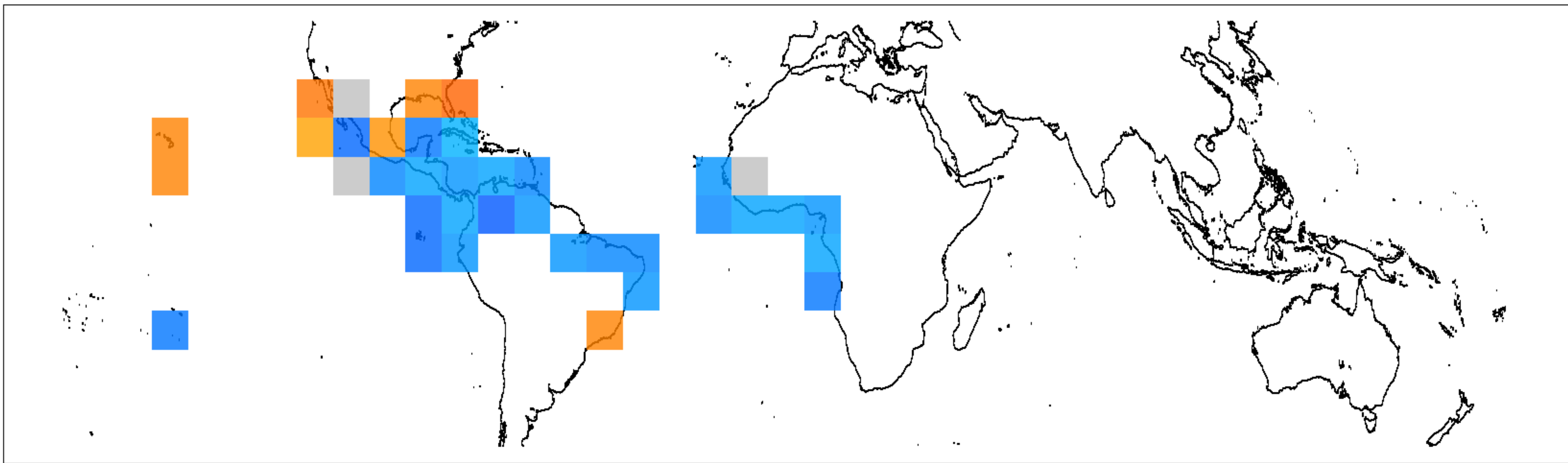
863 **Supplement**

864 R code for single species and community distribution models.

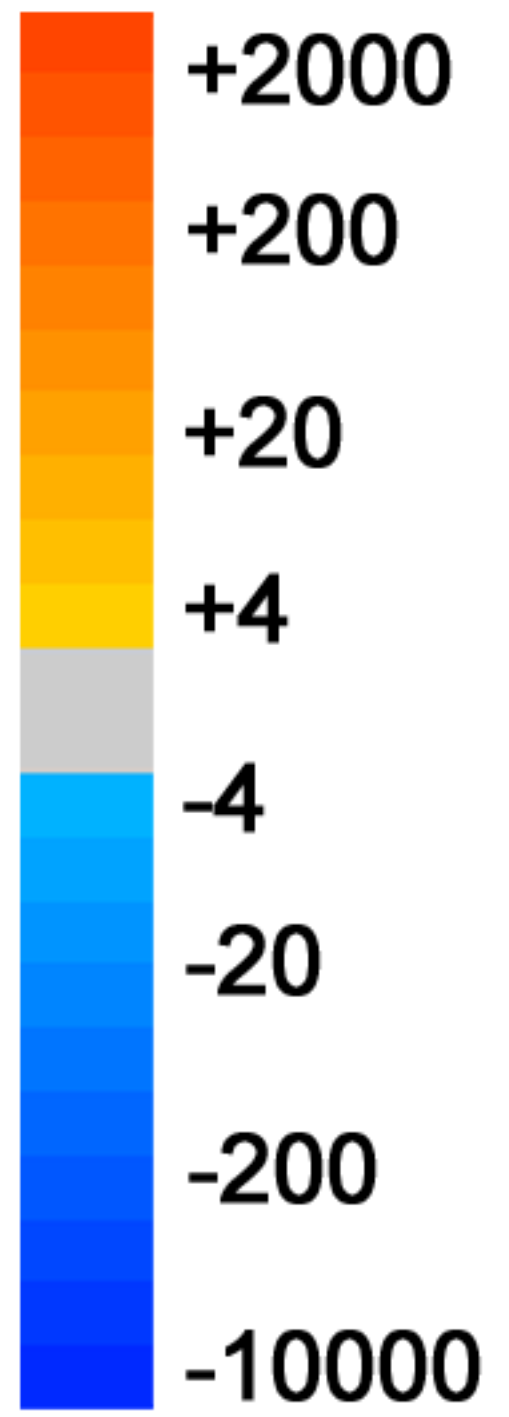
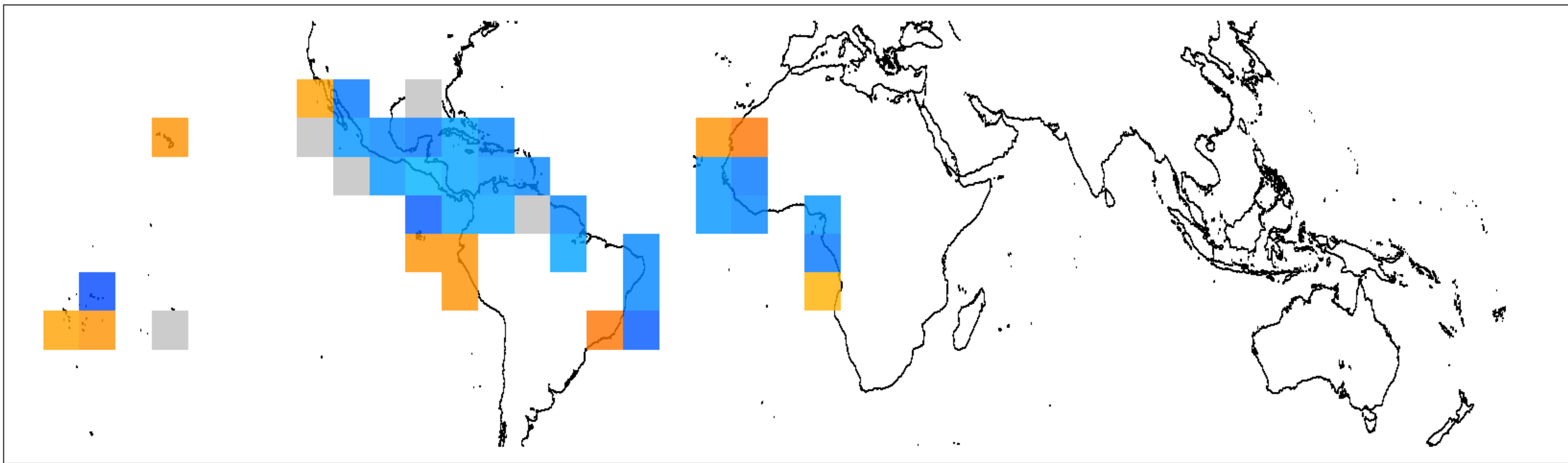




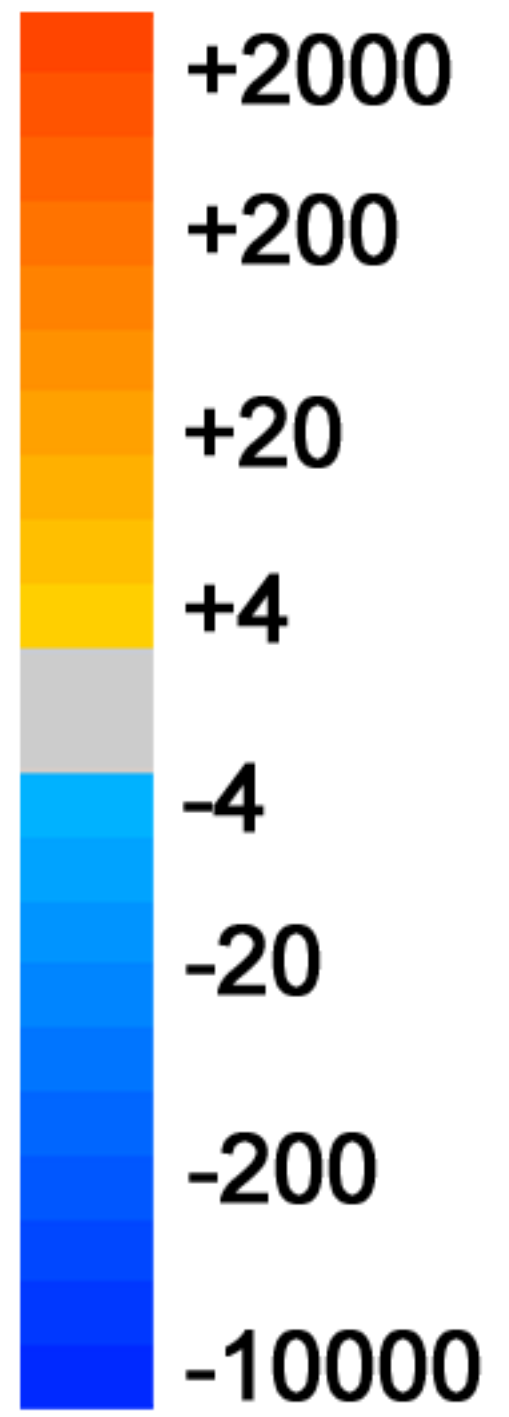
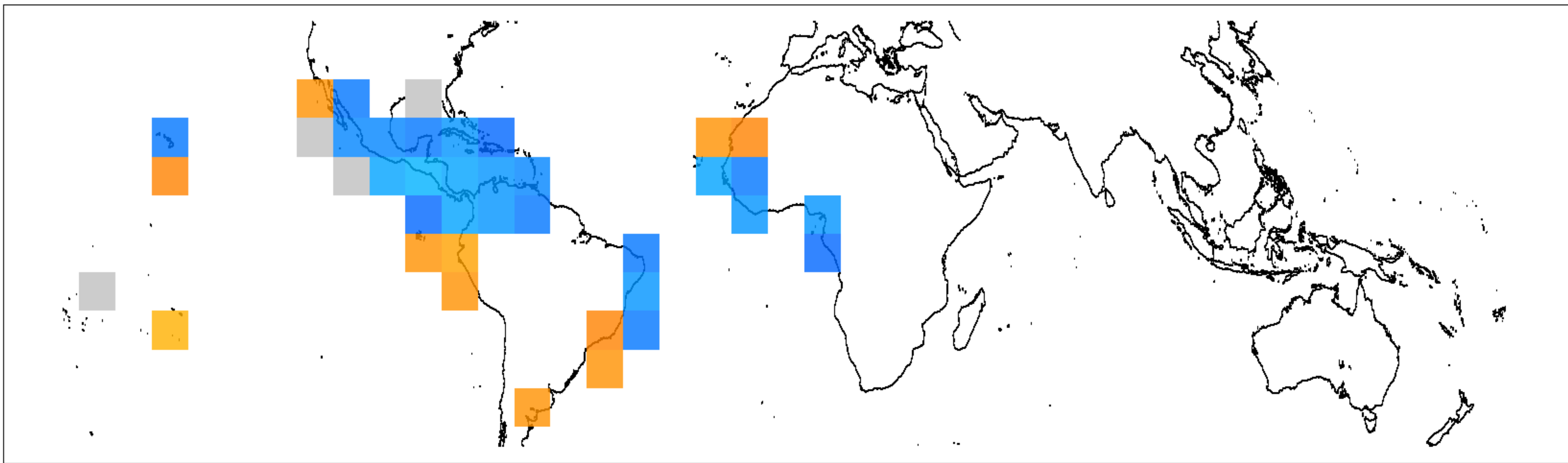




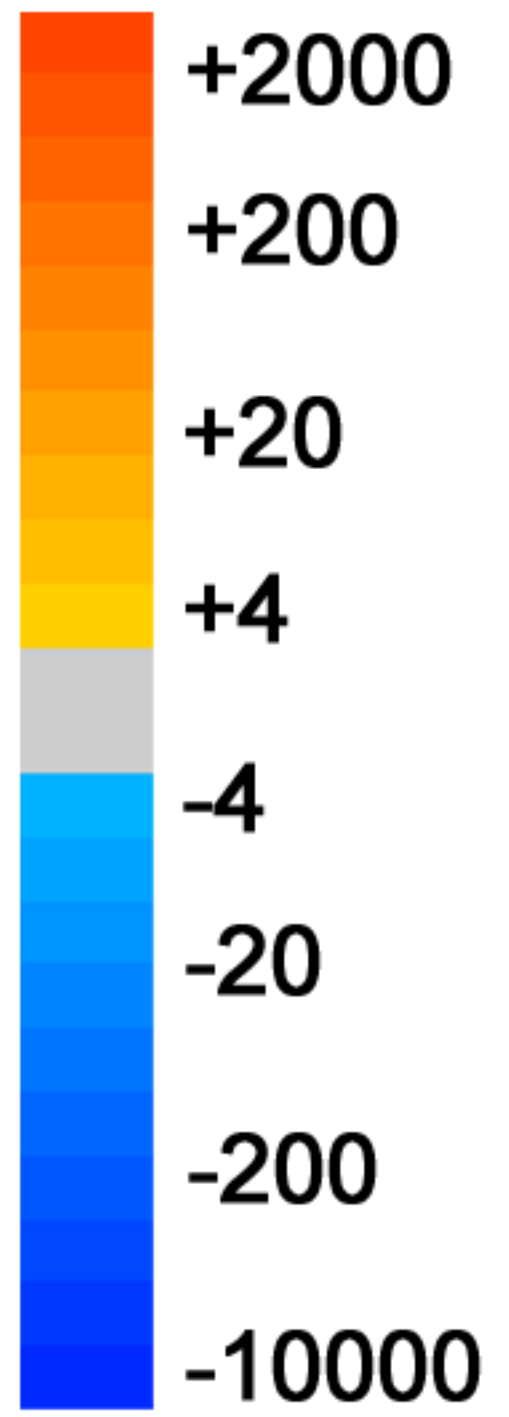
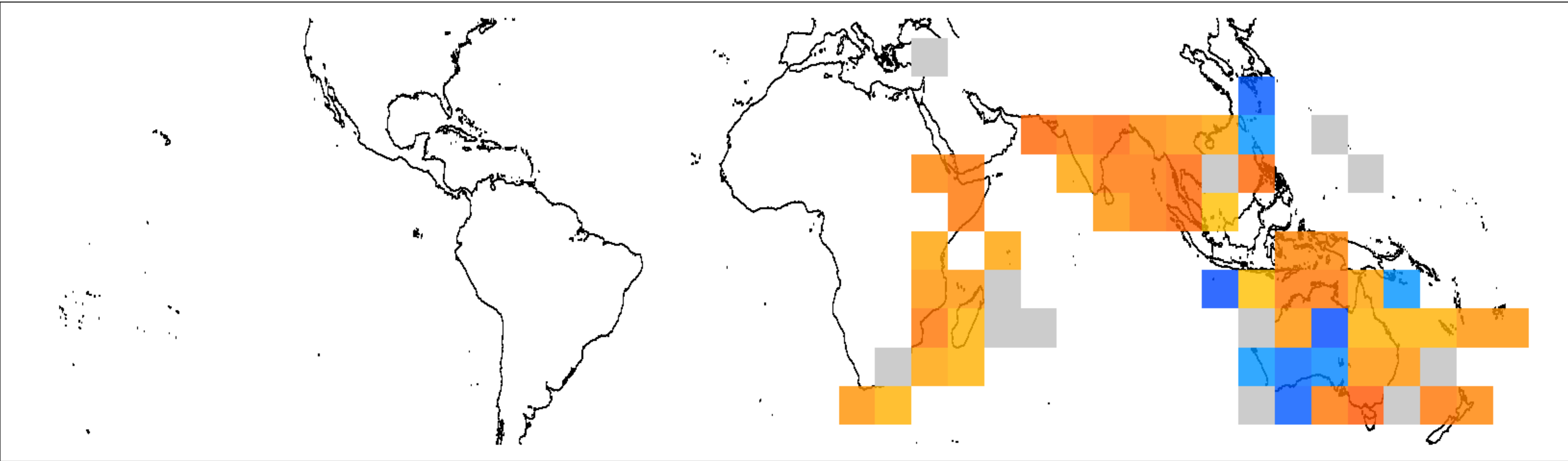
Change in occupied coastline (km)



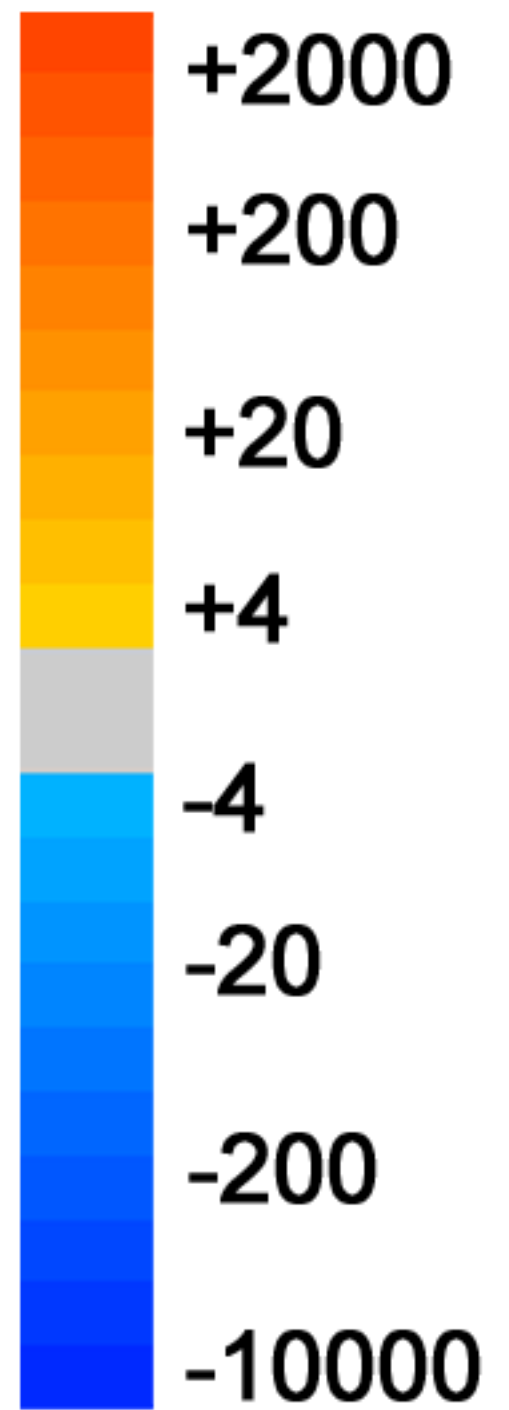
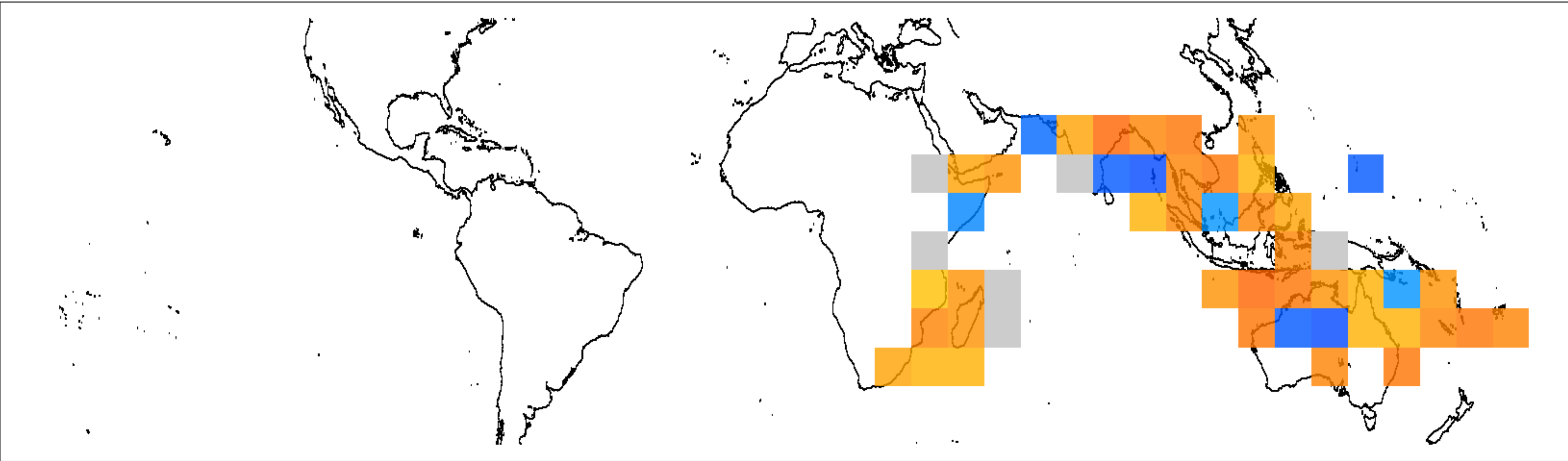
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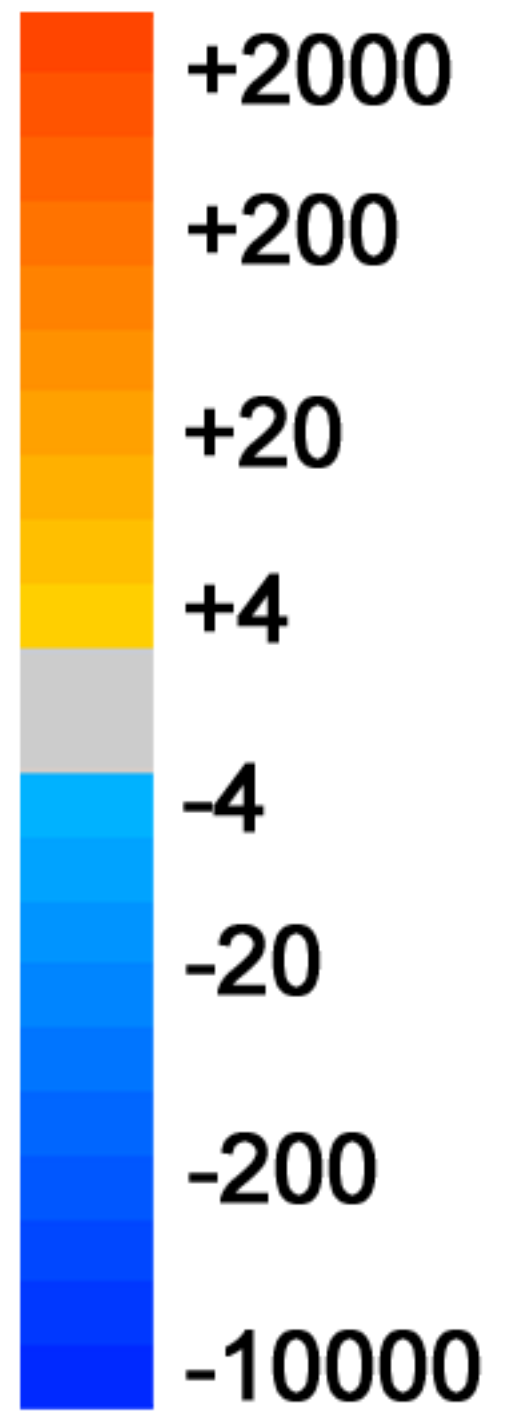
Change in occupied coastline (km)



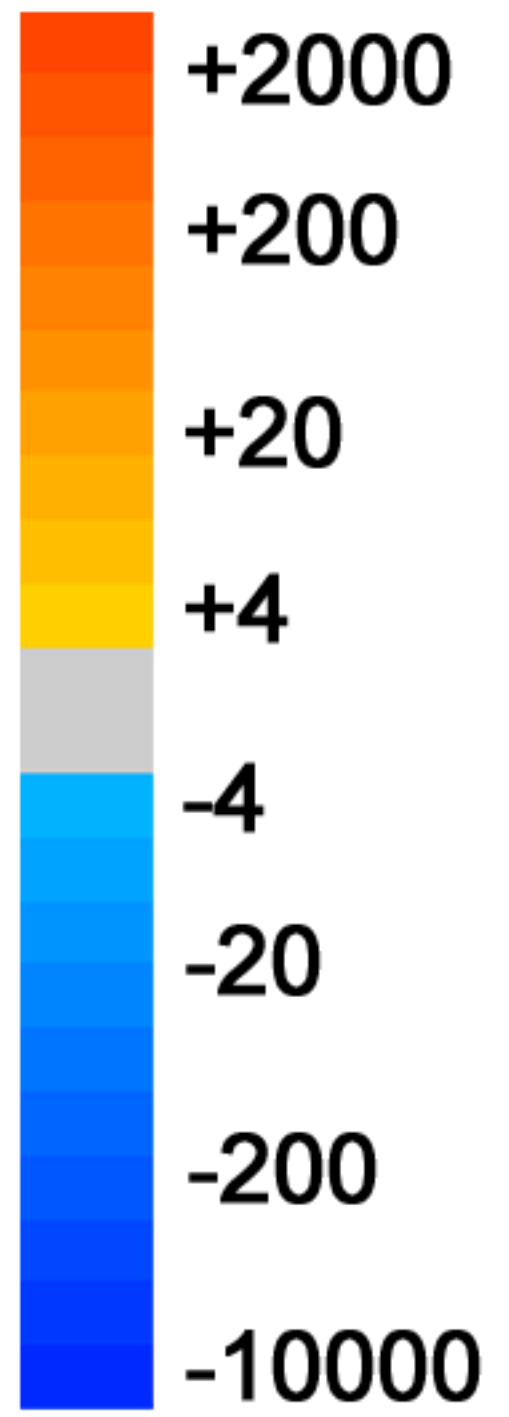
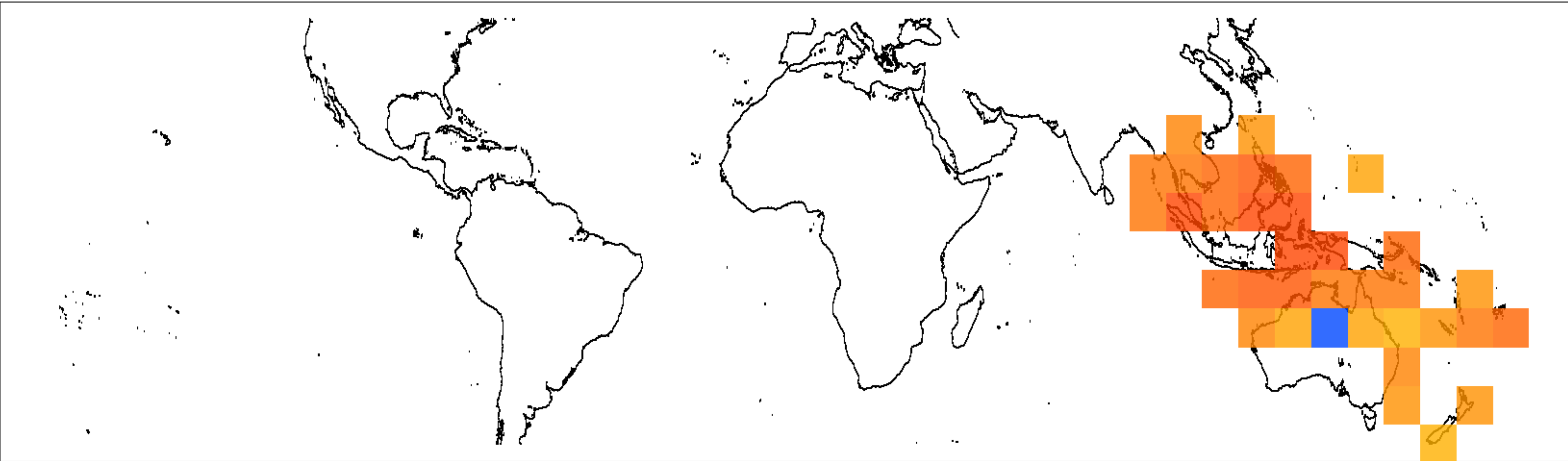
Change in occupied coastline (km)



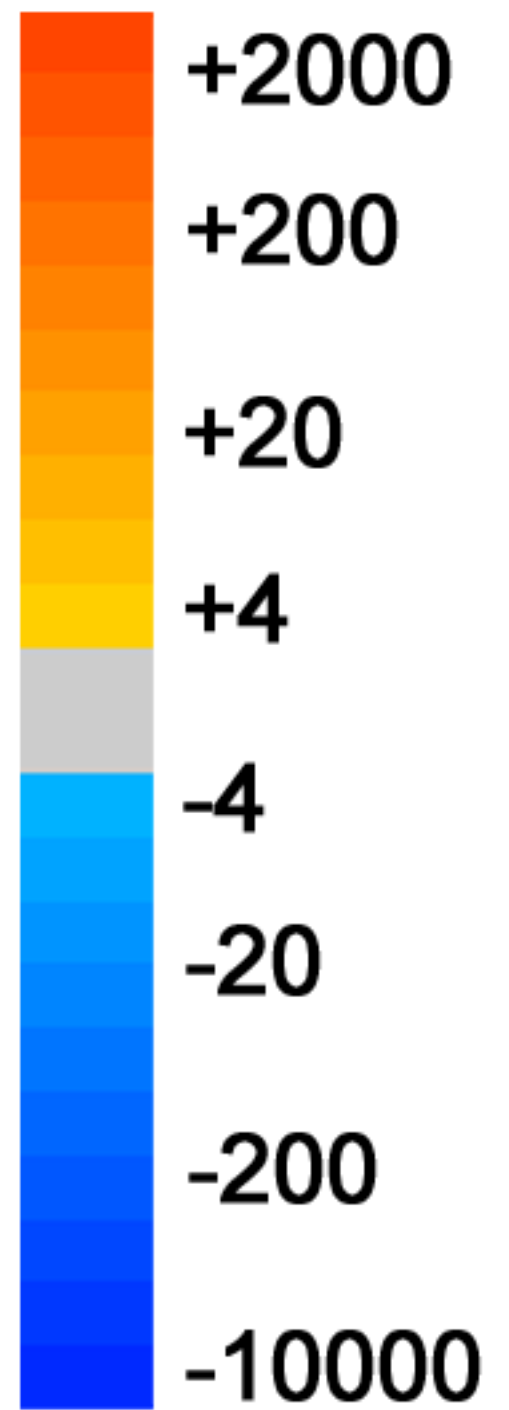
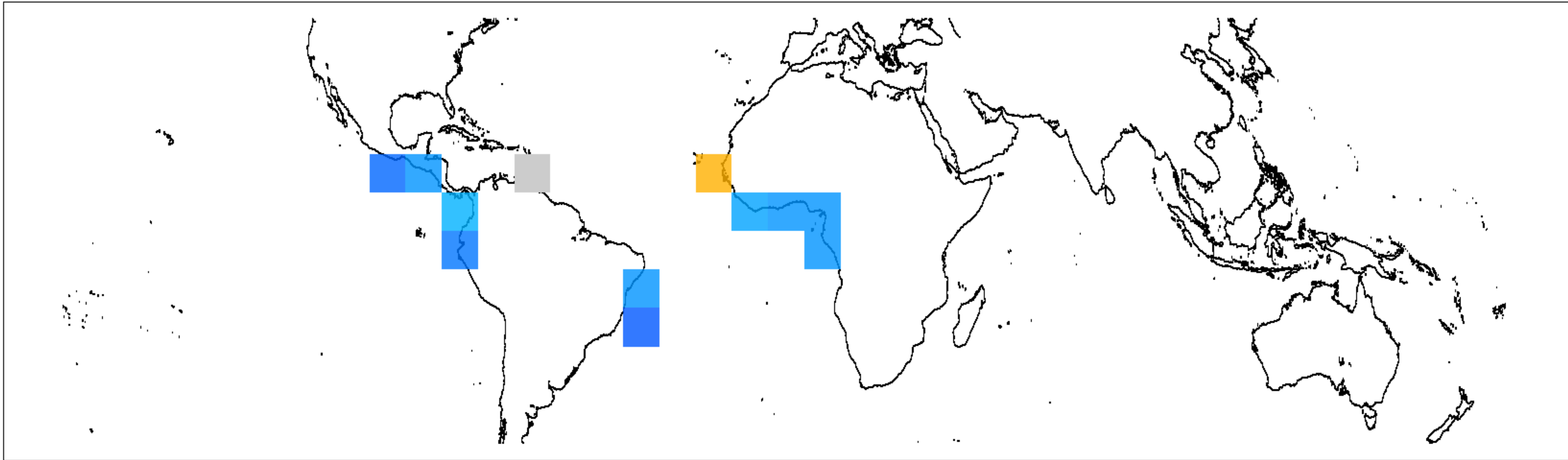
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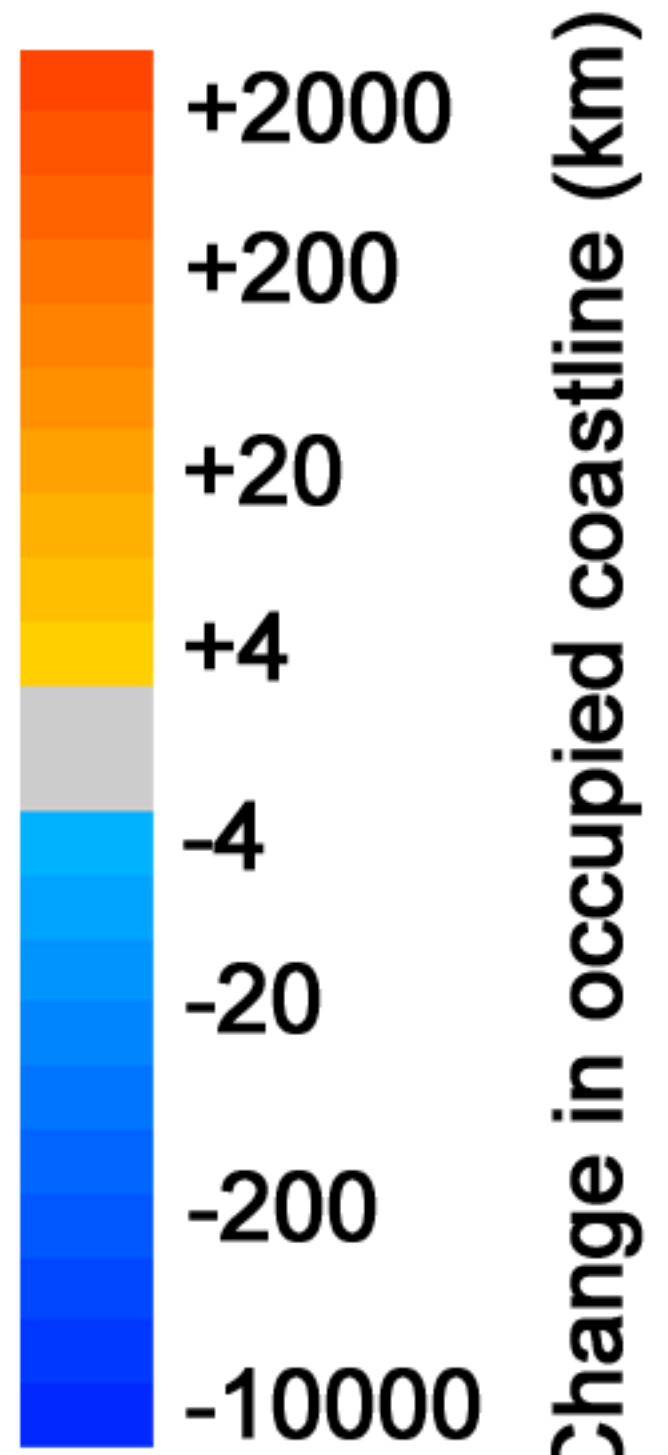
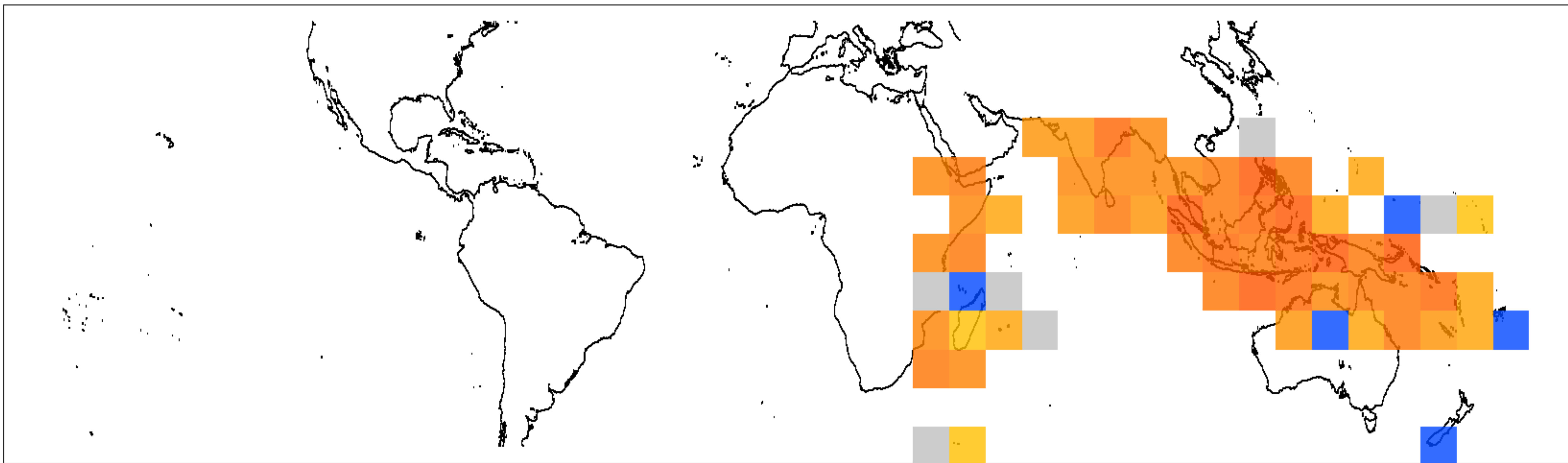
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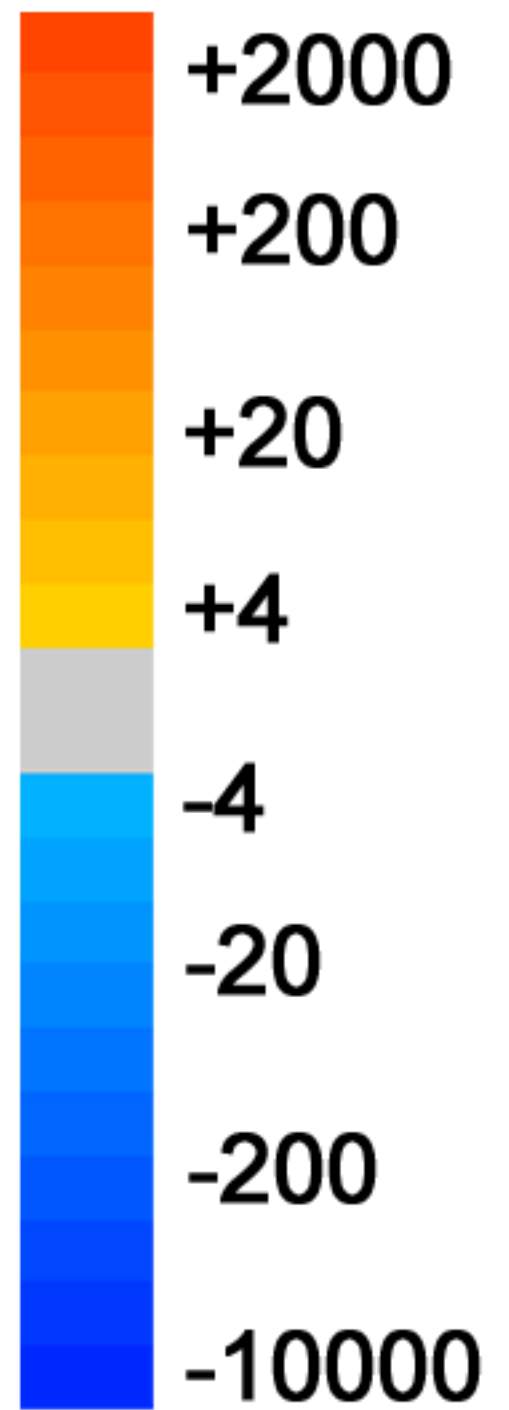
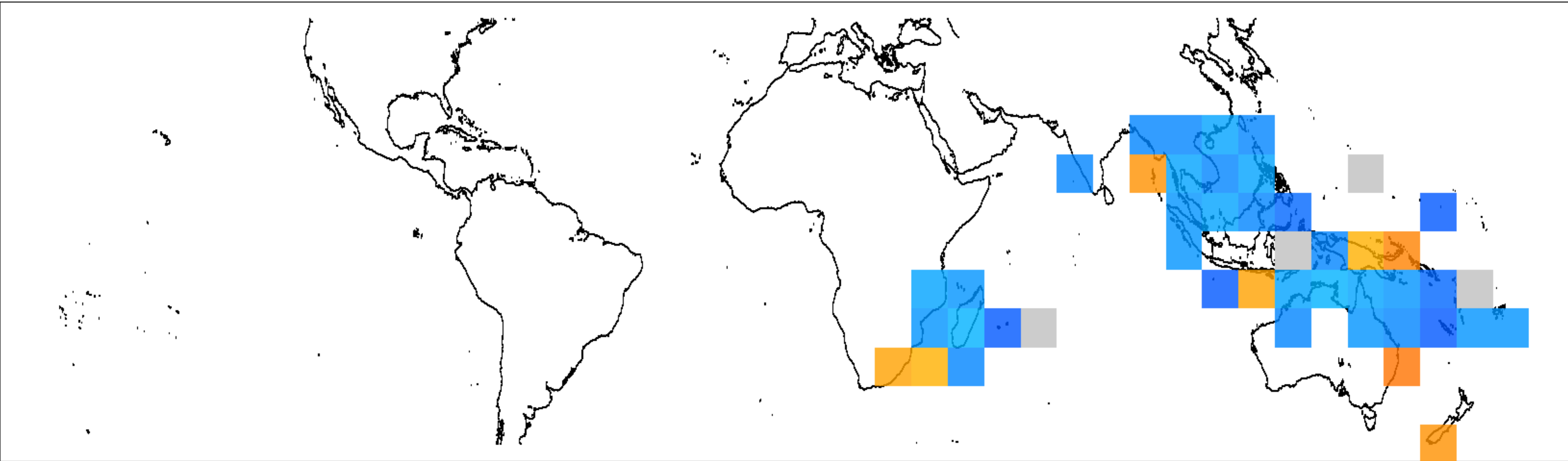


Change in occupied coastline (km)

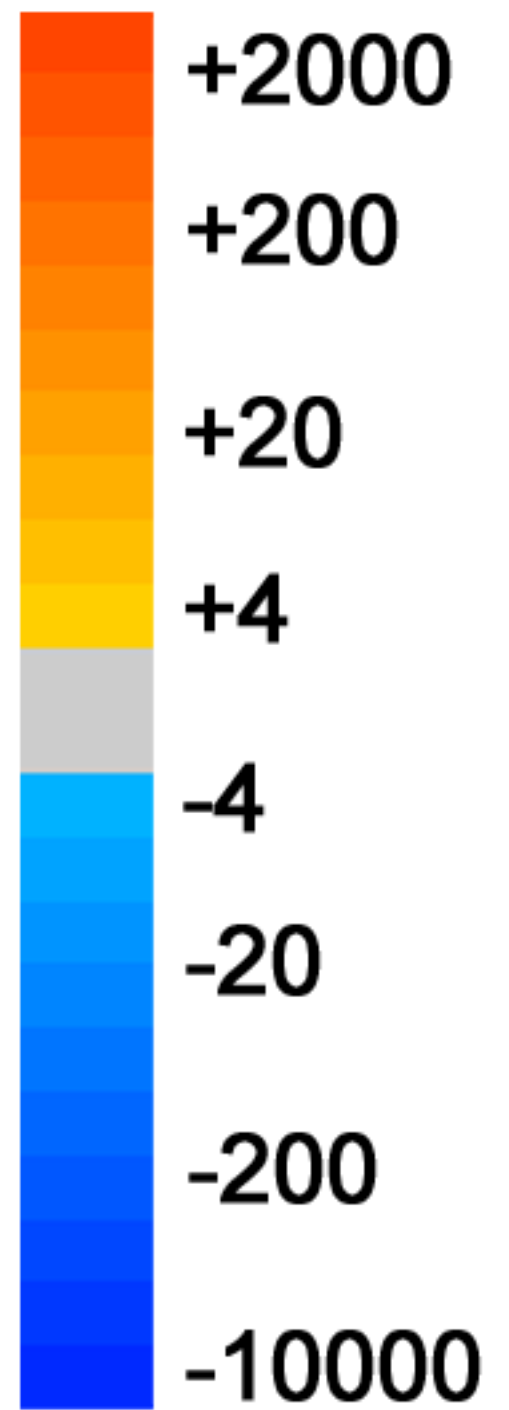
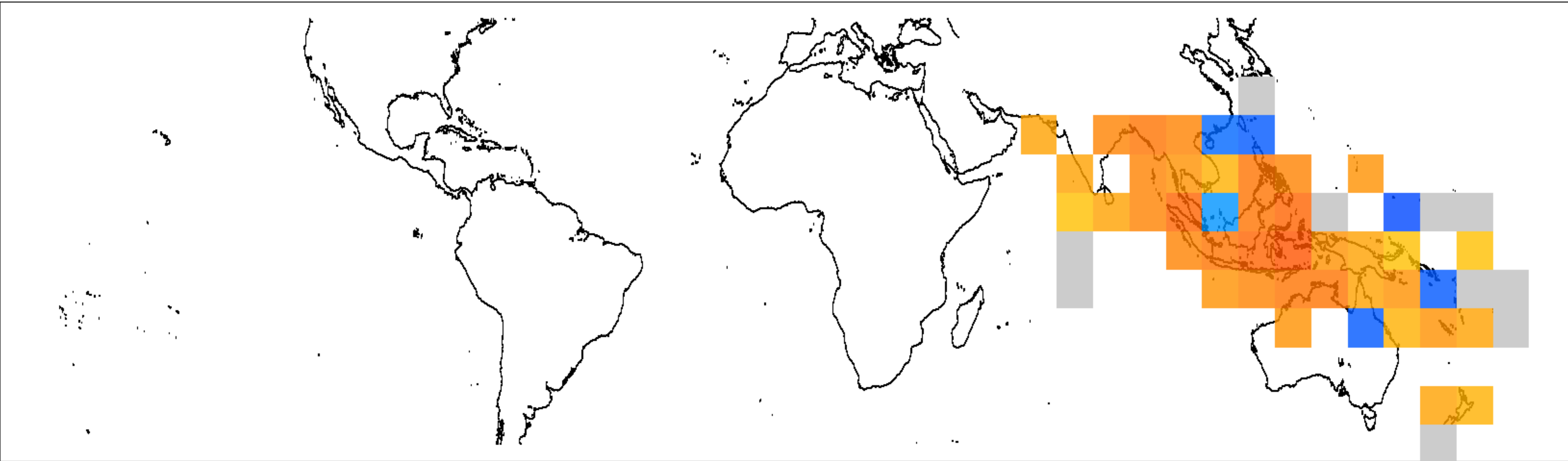


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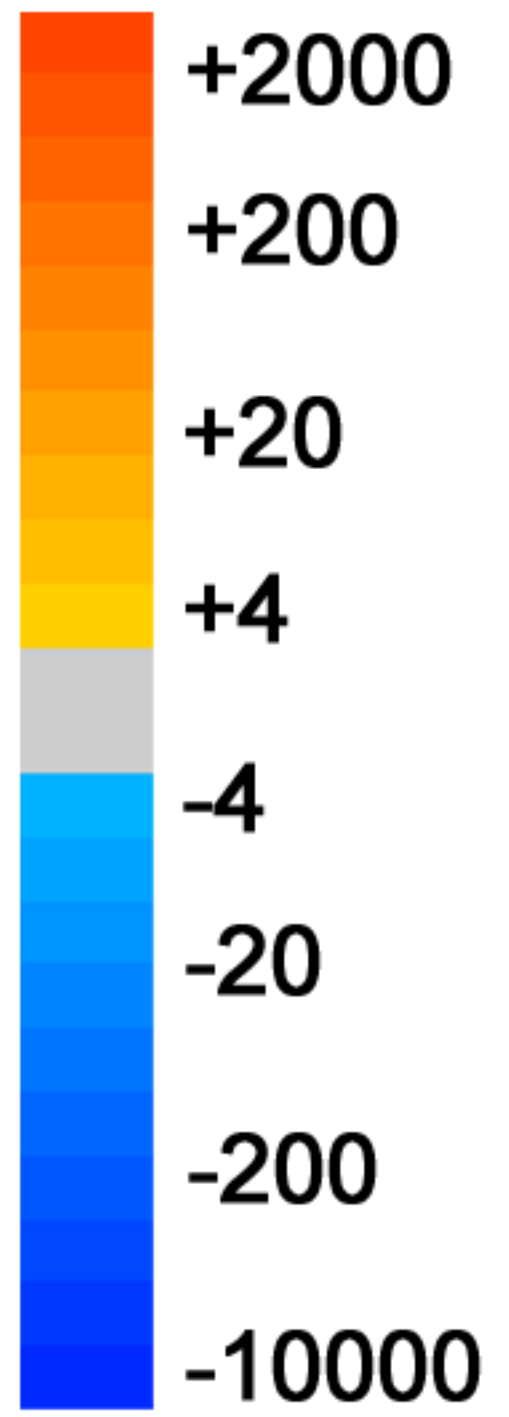
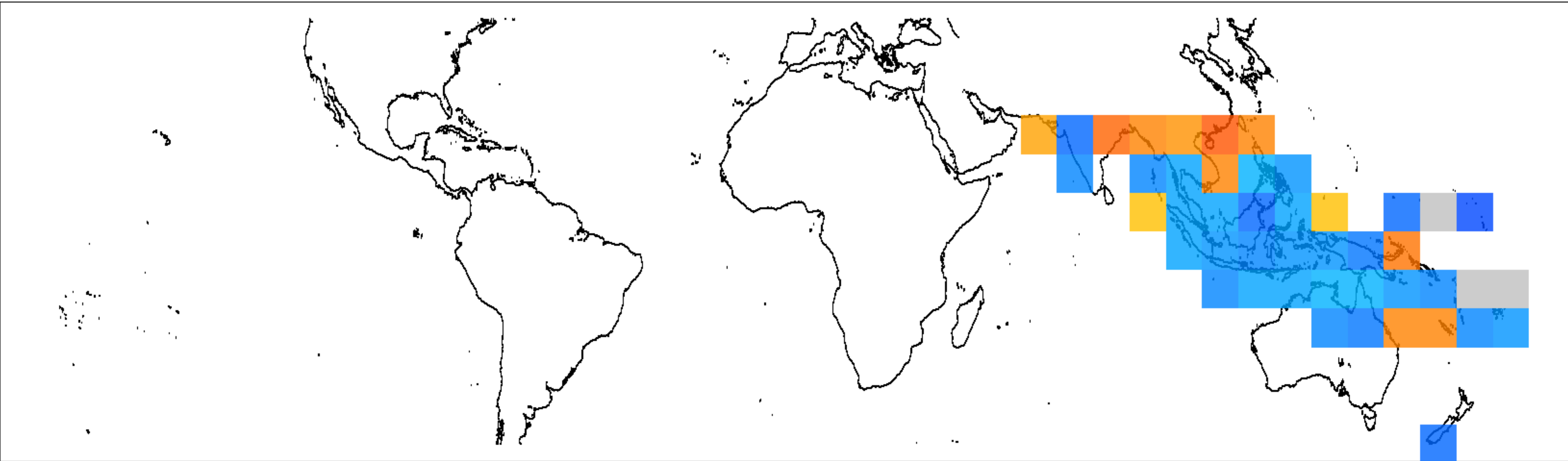




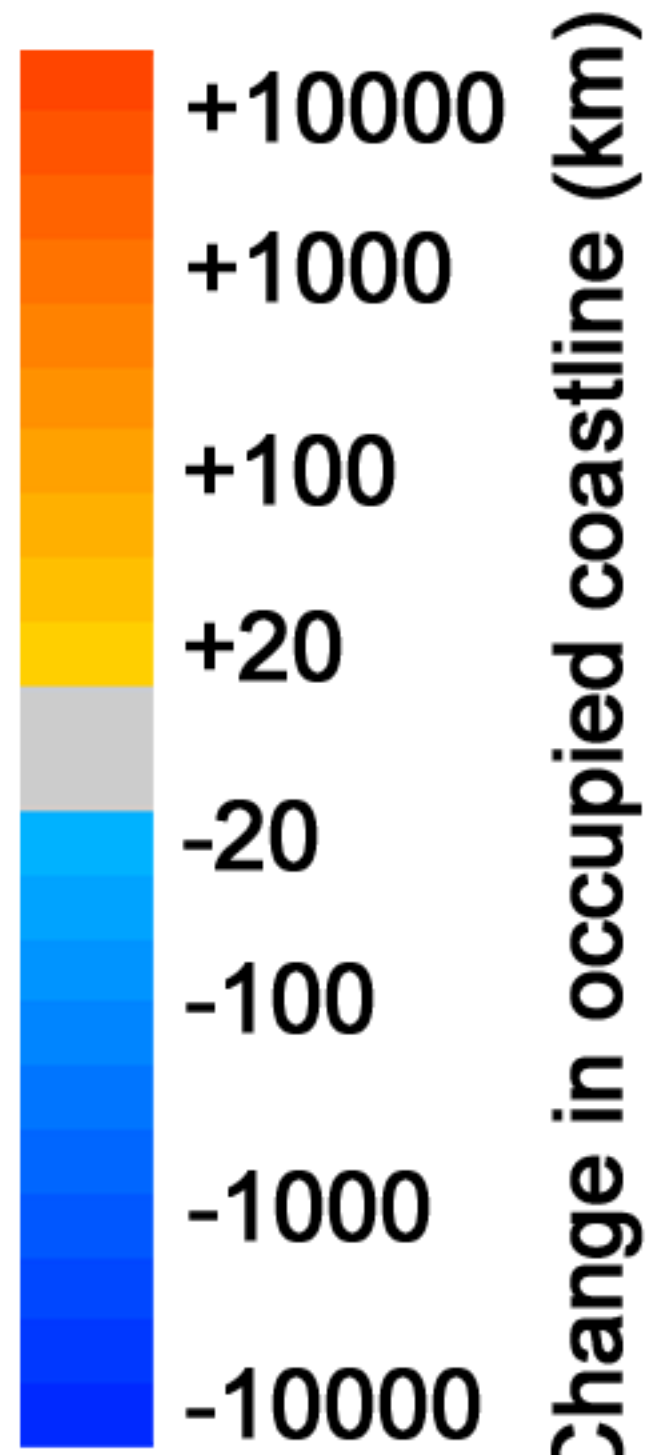
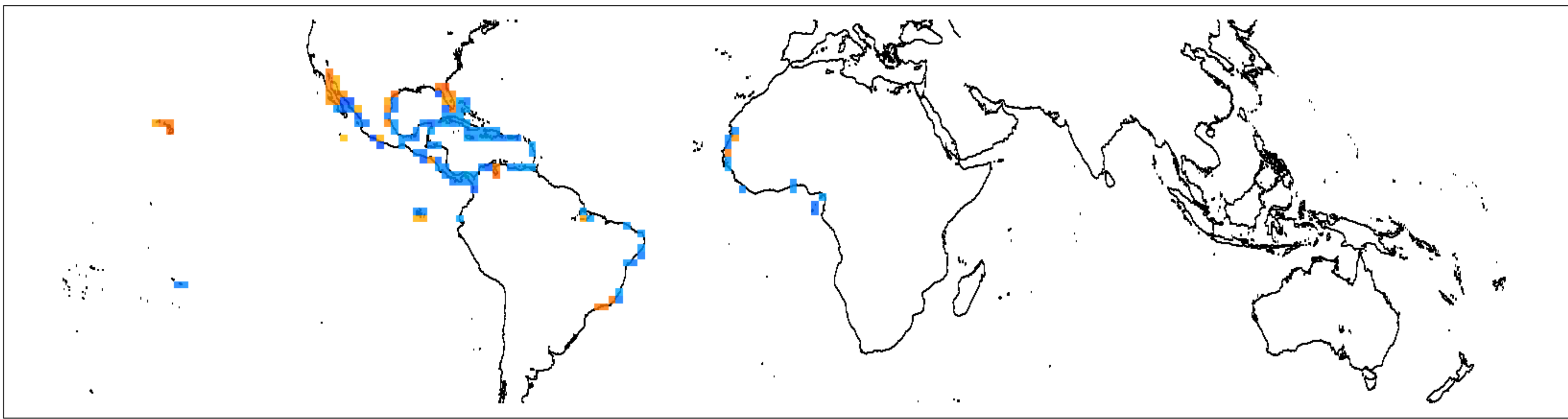
Change in occupied coastline (km)

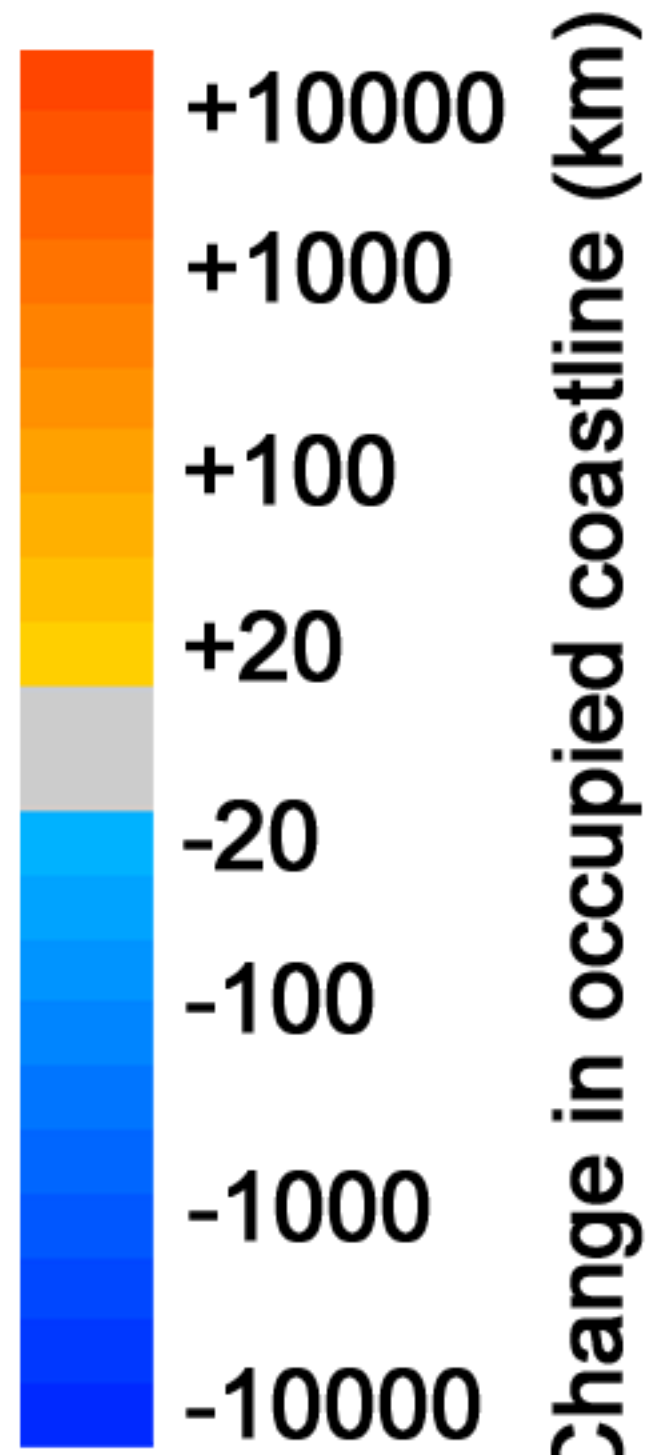
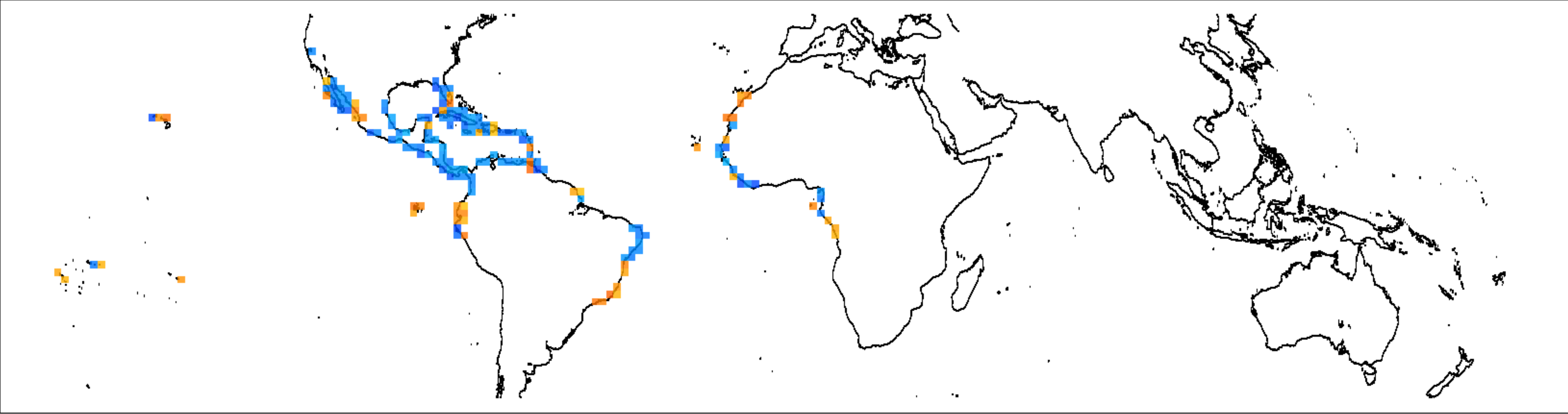


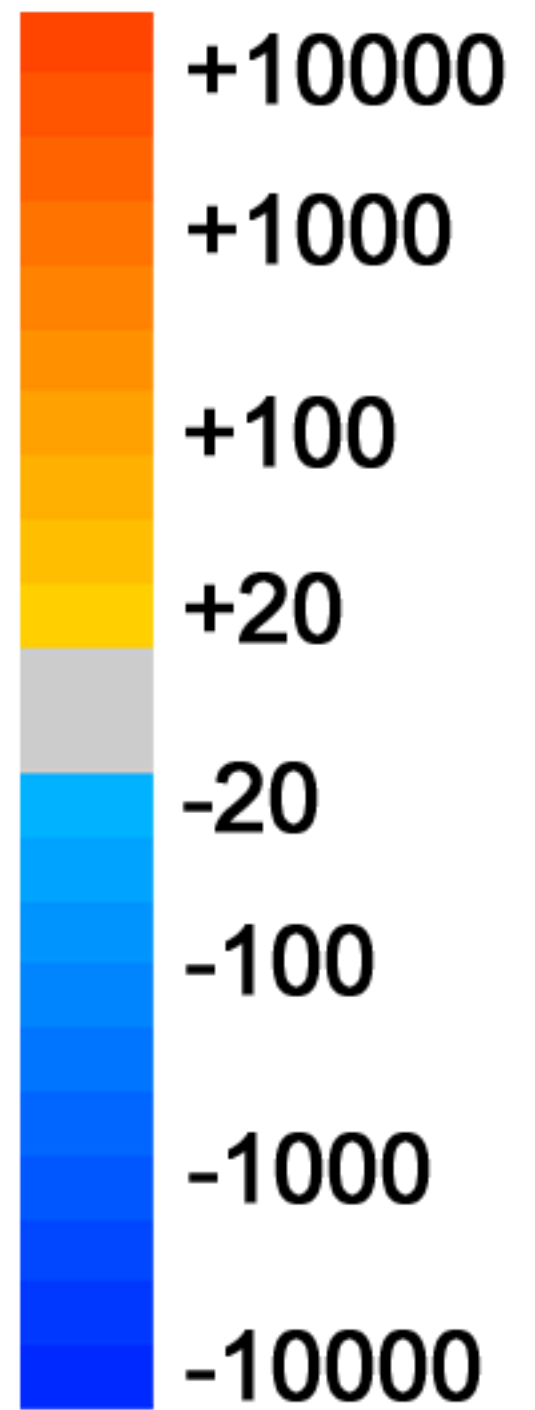
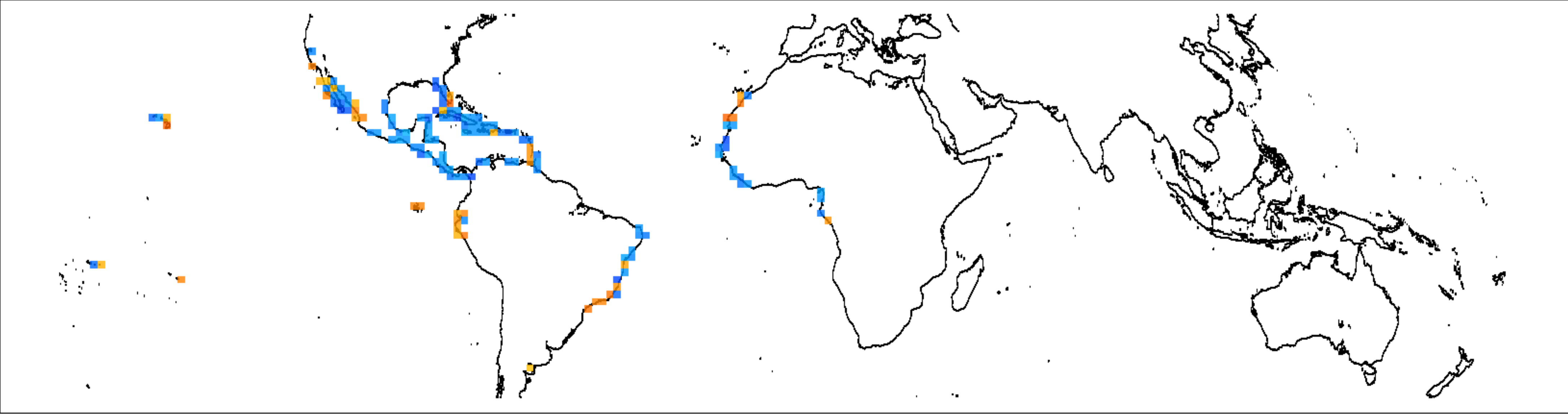
Change in occupied coastline (km)



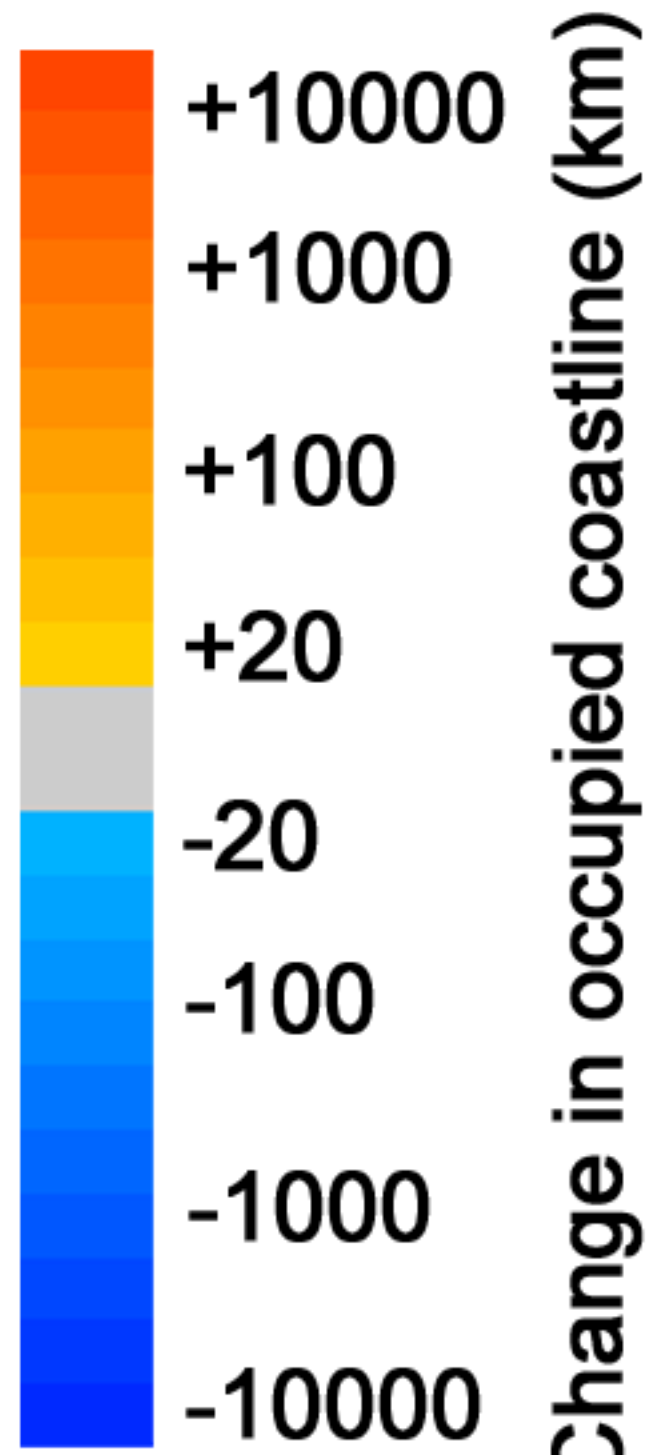
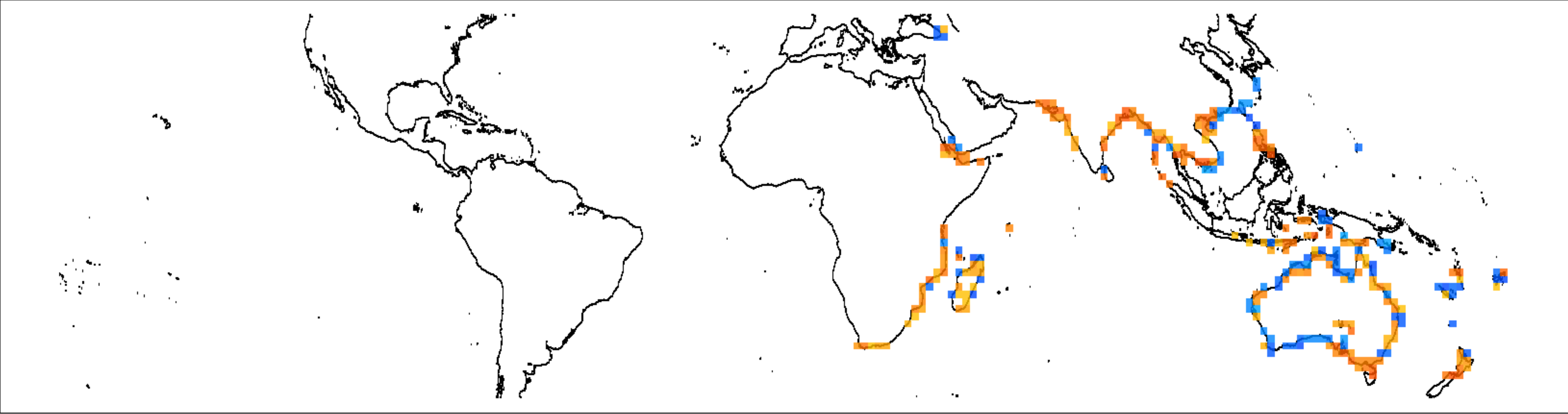
Change in occupied coastline (km)

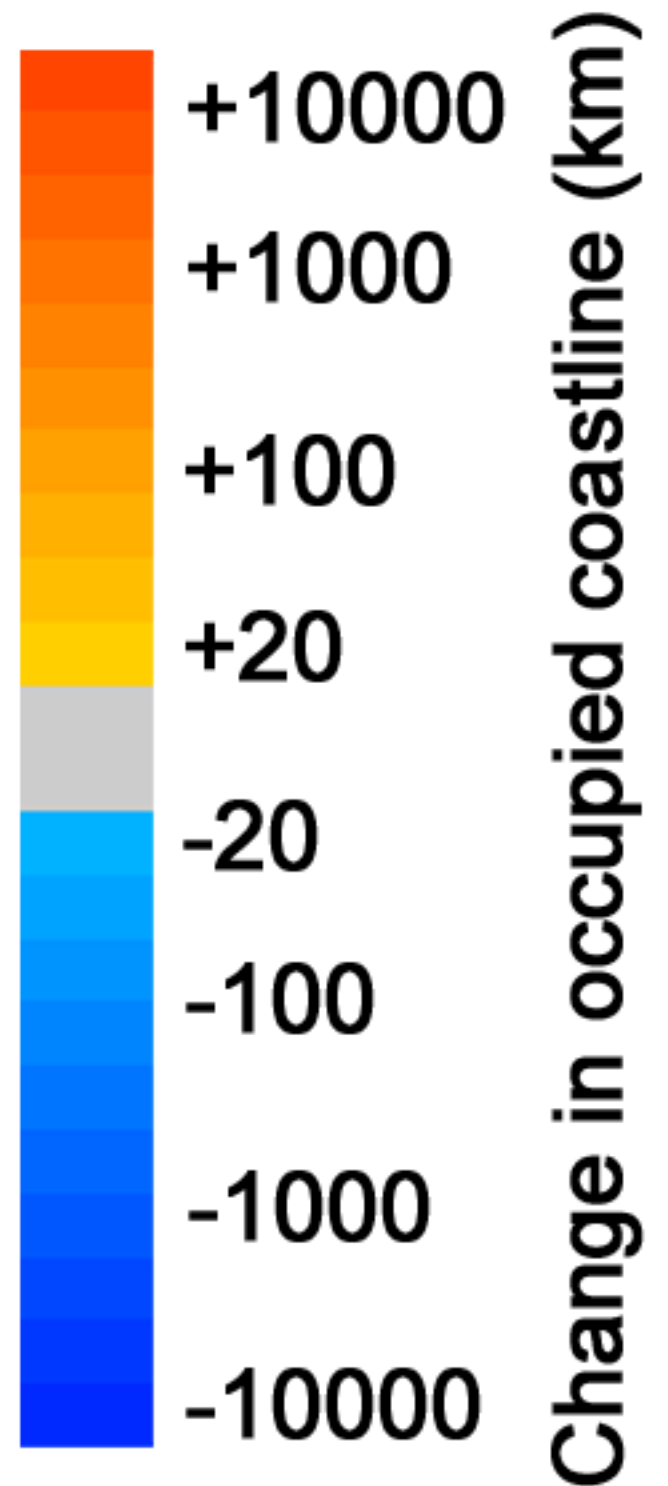
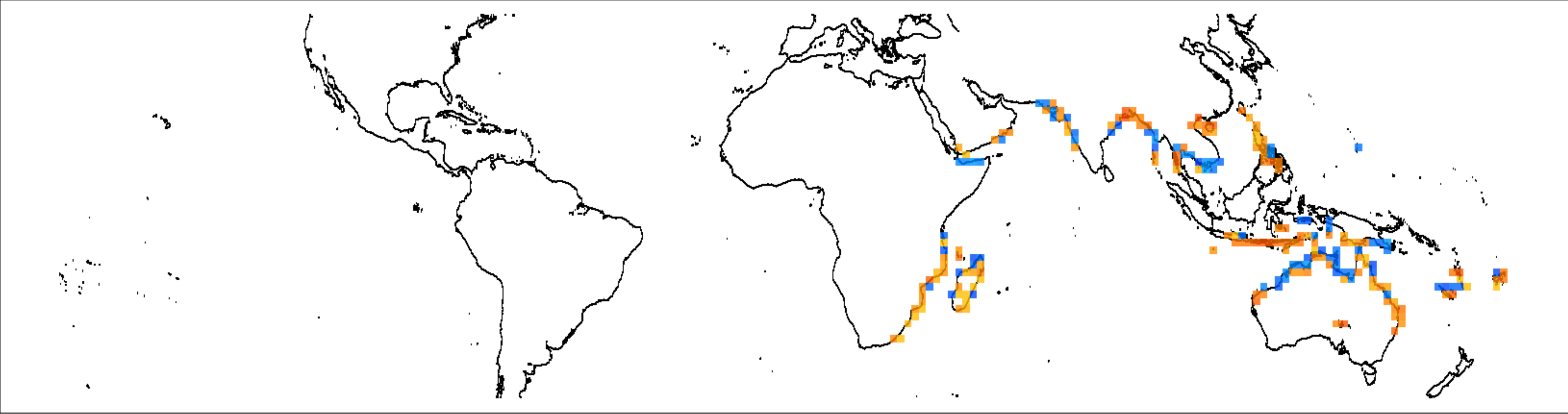


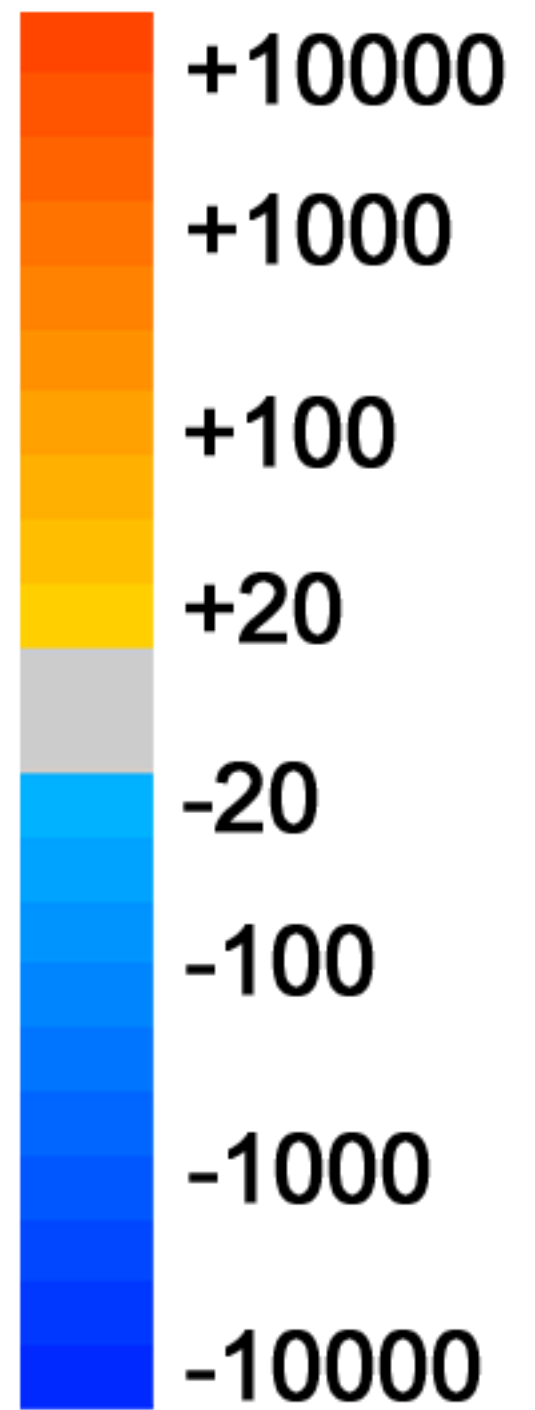
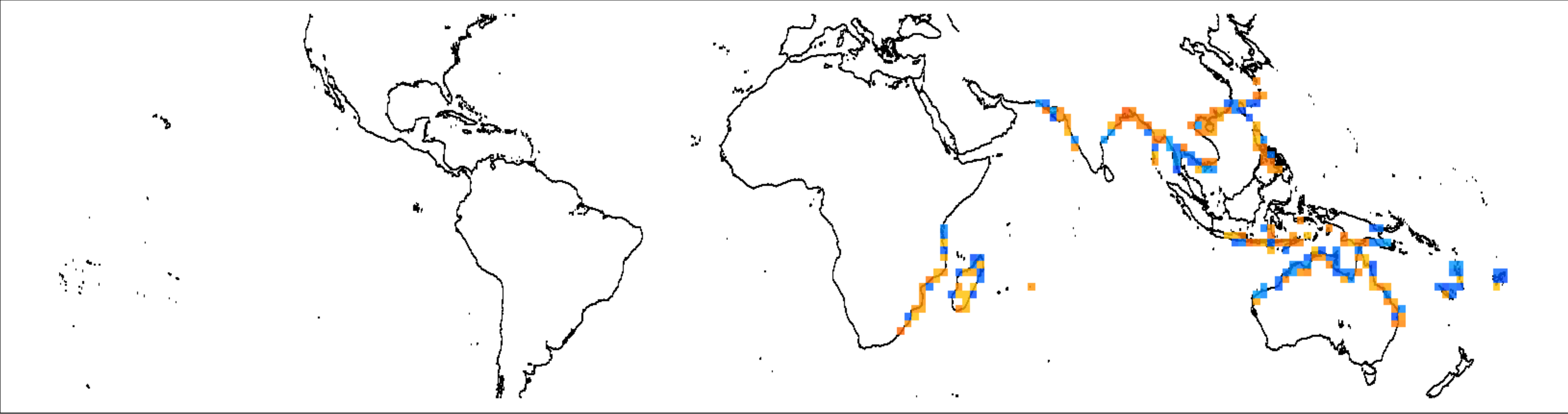




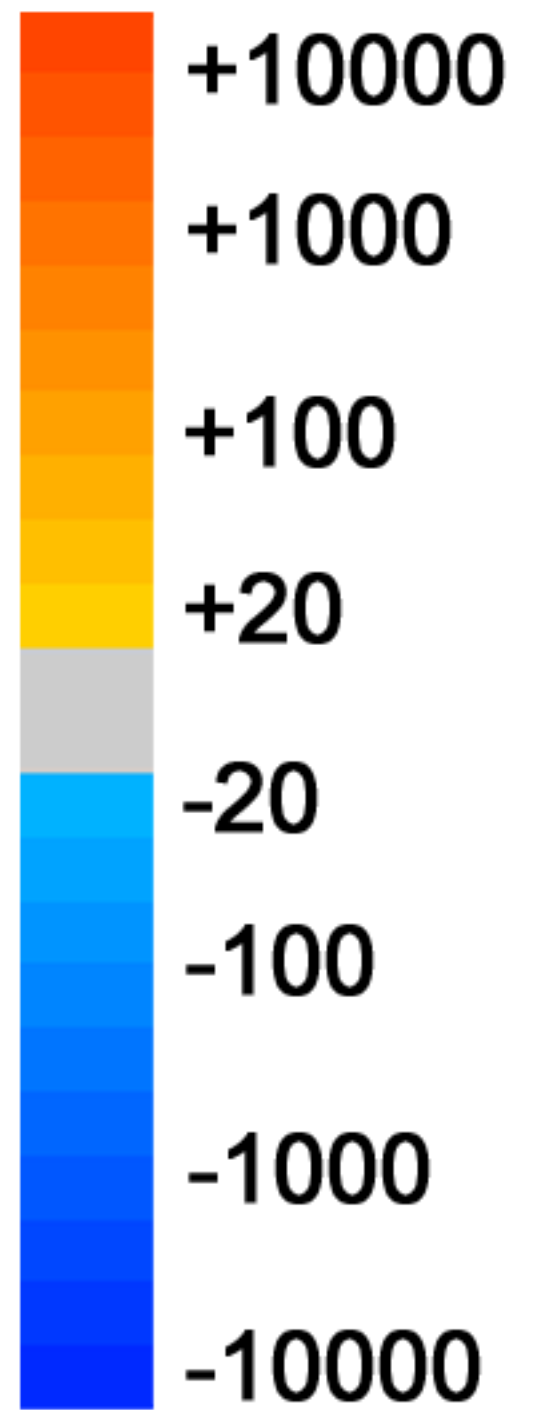
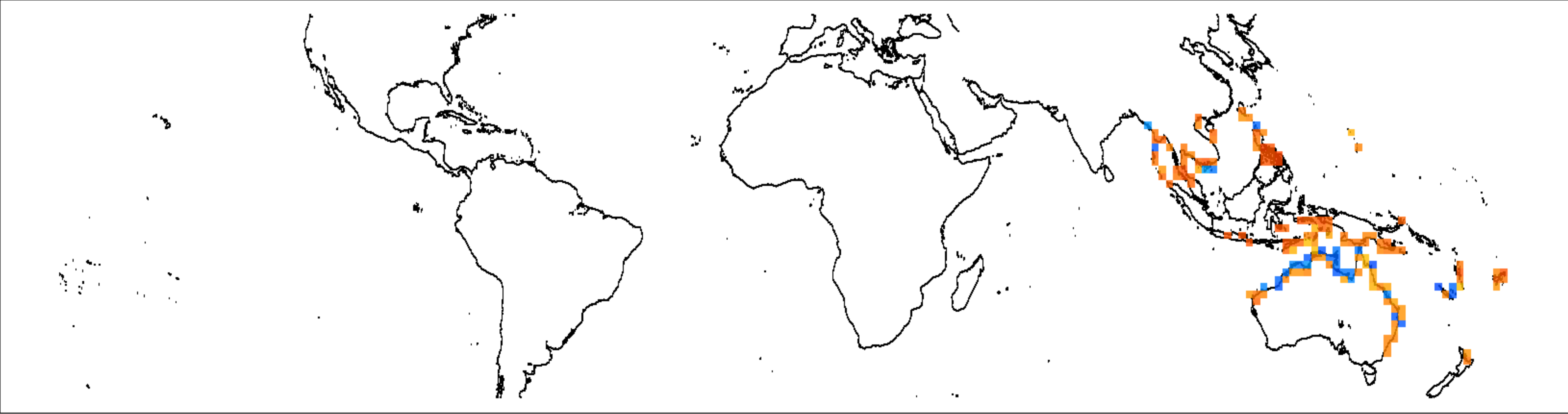
Change in occupied coastline (km)



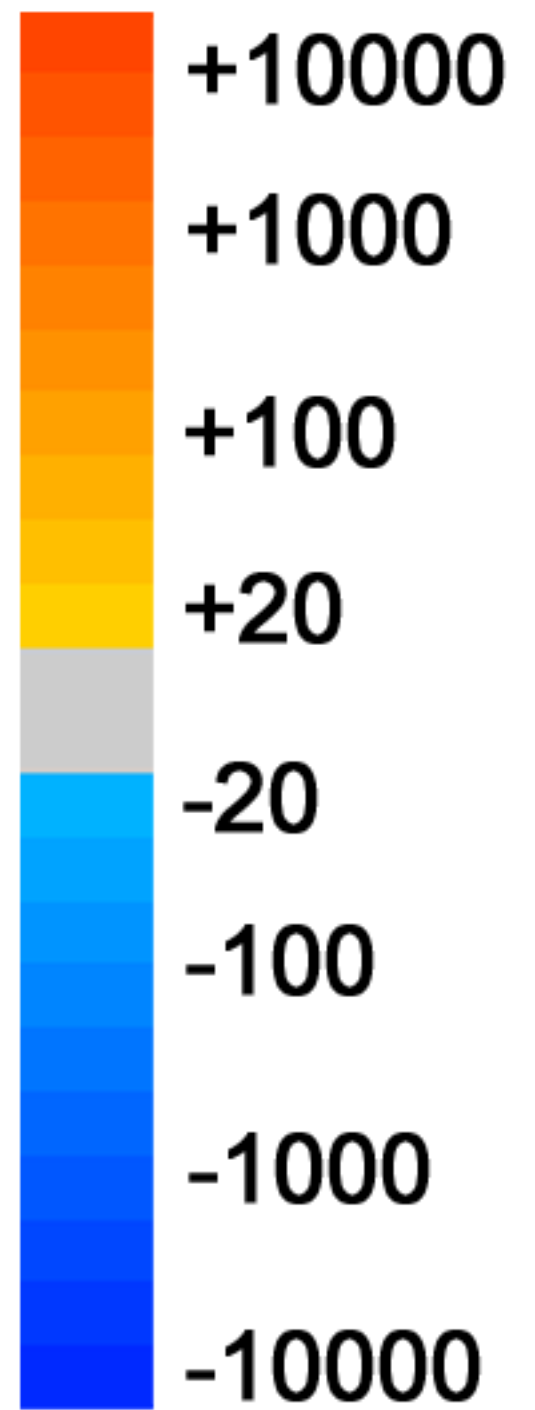
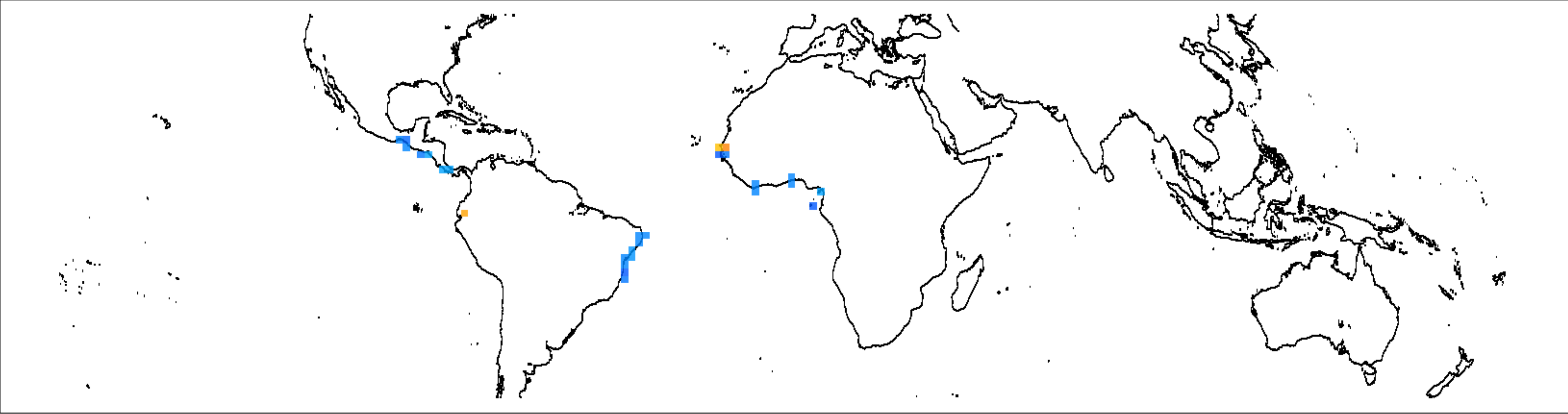




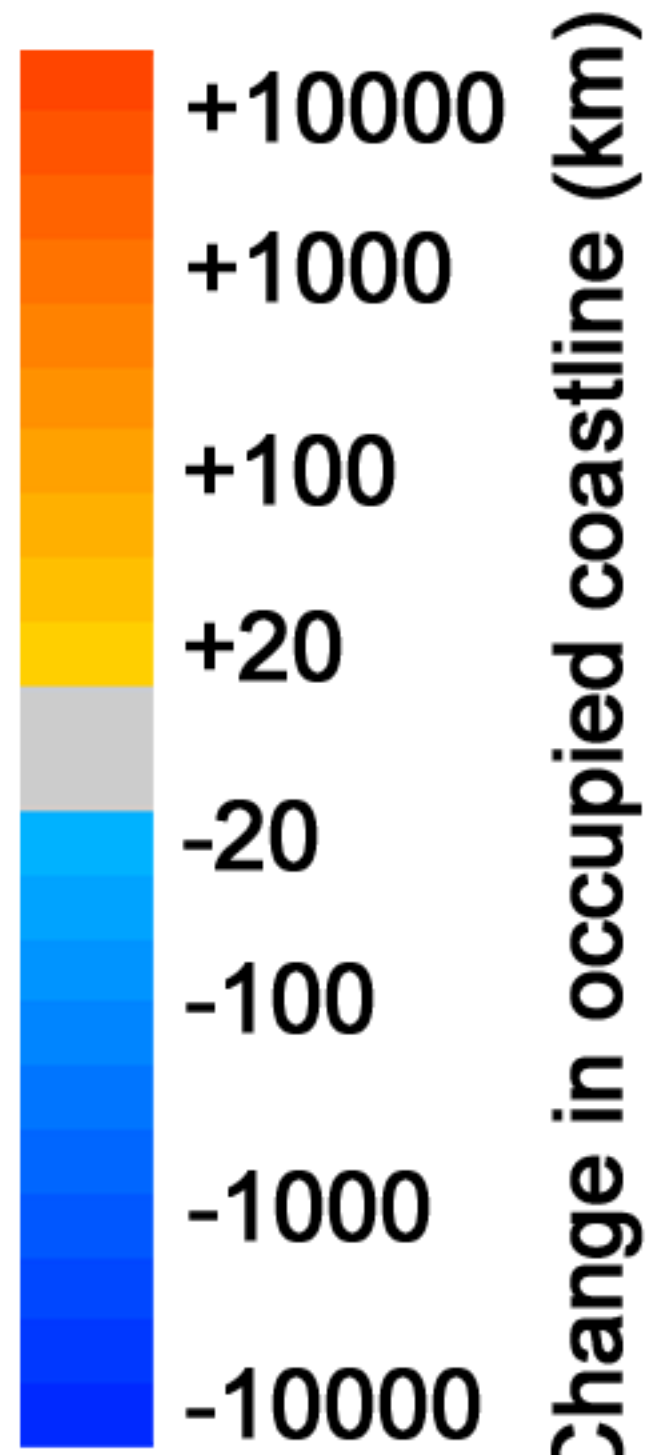
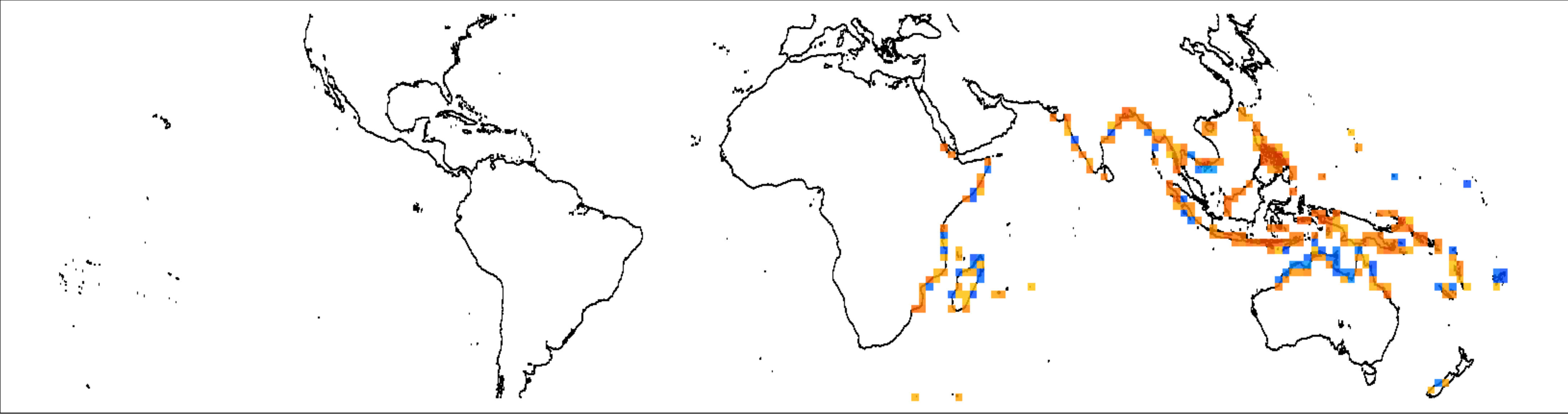
Change in occupied coastline (km)

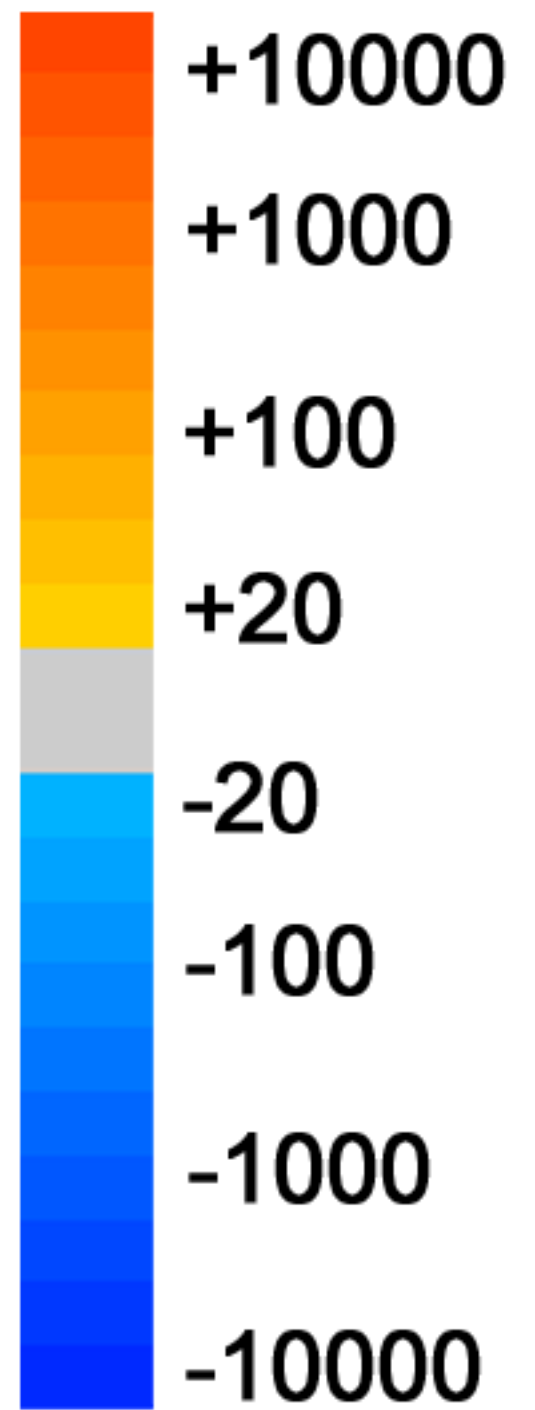
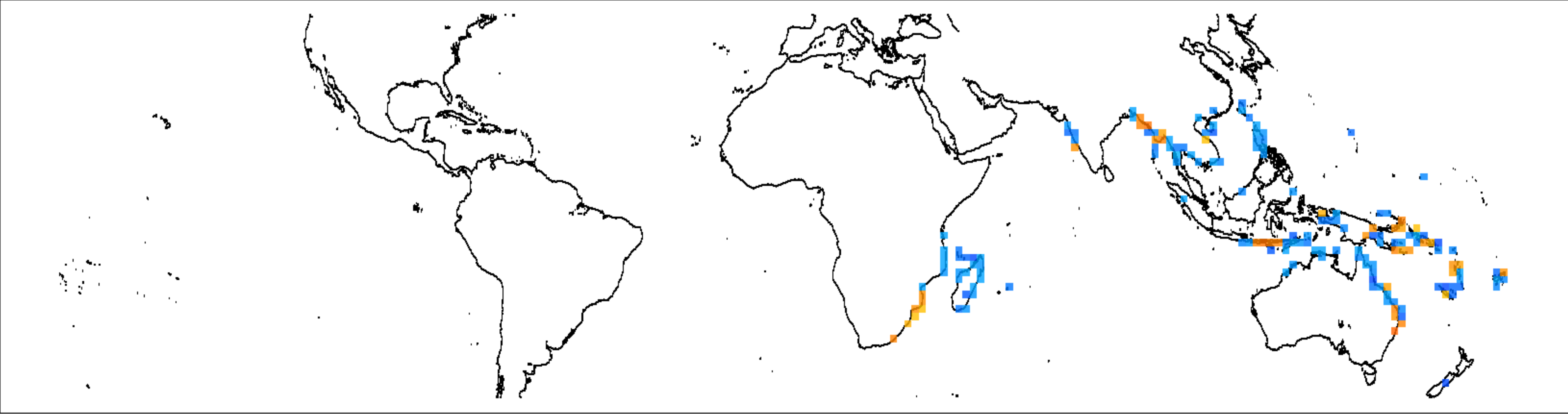


Change in occupied coastline (km)



Change in occupied coastline (km)





Change in occupied coastline (km)

