

1 **Interannual climate variability data improves niche estimates in species** 2 **distribution models**

3
4 Dirk Nikolaus Karger^{1*}, Bianca Saladin¹, Rafael O. Wüest-Karpati¹, Catherine H. Graham¹,
5 Damaris Zurell^{1,2}, Lidong Mo^{1,3}, Niklaus E. Zimmermann¹

6
7 ¹Swiss Federal Research Institute WSL, Zürcherstrasse 111, 8903 Birmensdorf, Switzerland

8 ²University of Potsdam, Am Neuen Palais 10, 14469 Potsdam, Germany

9 ³Swiss Federal Institute of Technology in Zurich, Department of Environmental Systems
10 Science, Universitätstrasse 16, 8092 Zürich, Switzerland

11 *corresponding author: dirk.karger@wsl.ch

12

13 **Abstract**

14 **Aim**

15 Climate is an essential element of species' niche estimates in many current ecological
16 applications such as species distribution models (SDMs). Climate predictors are often used in
17 the form of long-term mean values. Yet, climate can also be described as spatial or temporal
18 variability for variables like temperature or precipitation. Such variability, spatial or temporal,
19 offers additional insights into niche properties. Here, we test to what degree spatial variability
20 and long-term temporal variability in temperature and precipitation improve SDM predictions
21 globally.

22 **Location**

23 Global.

24 **Time period**

25 1979-2013

26 **Major taxa studies**

27 Mammal, Amphibians, Reptiles

28 **Methods**

29 We use three different SDM algorithms, and a set of 833 amphibian, 779 reptile, and 2211
30 mammal species to quantify the effect of spatial and temporal climate variability in SDMs. All

31 SDMs were cross-validated and assessed for their performance using the Area under the Curve
32 (AUC) and the True Skill Statistic (TSS).

33 **Results**

34 Mean performance of SDMs with climatic means as predictors was TSS=0.71 and AUC=0.90.
35 The inclusion of spatial variability offers a significant gain in SDM performance (mean
36 TSS=0.74, mean AUC=0.92), as does the inclusion of temporal variability (mean TSS=0.80,
37 mean AUC=0.94). Including both spatial and temporal variability in SDMs shows similarly
38 high TSS and AUC scores.

39

40 **Main conclusions**

41 Accounting for temporal rather than spatial variability in climate improved the SDM prediction
42 especially in exotherm groups such as amphibians and reptiles, while for endothermic mammals
43 no such improvement was observed. These results indicate that more detailed information about
44 temporal climate variability offers a highly promising avenue for improving niche estimates
45 and calls for a new set of standard bioclimatic predictors in SDM research.

46 **Introduction**

47 Climate is known to influence species' distributions (Woodward & Woodward, 1987) across
48 different spatial and temporal scales, thus, detecting the impact of climate on species depends
49 to a large degree on the spatial and temporal scale at which it is assessed (Wiens, 1989; Rahbek,
50 2005). While the effect of spatial variability in climate on species distributions has received
51 heightened attention in recent years due to the ever increasing spatial resolution of freely
52 available climate data (e.g. Hijmans *et al.*, 2005; Fick & Hijmans, 2017; Karger *et al.*, 2017),
53 analyses of the effect of temporal climate variability on species ranges have been much less
54 abundant (Zimmermann *et al.*, 2009). Analytically, an increase in resolution in one dimension
55 often comes at the cost of decreased resolution in the other dimension due to computational
56 limitations (Hourdin *et al.*, 2017; Schär *et al.*, 2019). However, a focus on ever increasing
57 spatial resolution may leave time-dependent phenomena undetected (Wiens, 1989). This is
58 especially of concern since one of the major components of climate change is an increase in
59 climate variability and – in consequence – an increase of extremes (Rahmstorf & Coumou,
60 2011; Seneviratne *et al.*, 2012). Increasing frequencies and severities of extreme events may
61 cause greater physiological stress and may thus result in rapid responses in many species with
62 likely severe consequences for their spatial distribution (Reyer *et al.*, 2013; Alexander *et al.*,
63 2015).

64 The spatial ranges of species are commonly estimated using empirical species distribution
65 models (SDMs), sometimes also termed bioclimatic envelope or habitat suitability models
66 (Guisan & Zimmermann, 2000; Guisan & Thuiller, 2005). SDMs characterize the
67 environmental niche of a species (Hutchinson, 1957) usually with respect to a few key
68 environmental factors, such as temperature and precipitation. It has become common practice
69 to use a limited set of climate variables as predictor variables (Araújo & Guisan, 2006) based
70 on long-term means (climatologies) alone (Ashcroft *et al.*, 2011). Such an aggregation of
71 climate variability into long-term climatological means fully removes information on the
72 temporal signal, including inter-annual variability. Species are known to strongly differ in
73 degree to which they can tolerate climatic extremes, and this affects their life cycles, coping
74 strategies through functional adaptations and, ultimately, their spatial distribution. Yet when
75 using long term climatic means, our capacity to distinguish effects from differences in climate
76 variability on species' distributions is basically removed.

77 Climatologies do not only smooth out temporal variabilities in climate but also reduce spatial
78 variability. Spatial climate heterogeneity as a result of small-scale topography and other factors
79 are not represented in gridded datasets of coarse spatial grain. Coarse spatial grains cannot

80 resolve the richness in topography, and thus climate, environment, and habitats, that are
81 essential for quantifying species' environmental niches (Stein *et al.*, 2014; Stein & Kreft, 2015).
82 Such misrepresentation of spatial heterogeneity when representing or aggregating climate
83 predictors at coarse grain might more strongly impact niche estimates in the tropics compared
84 to temperate or boreal zones (Janzen, 1967). In the tropics, species generally experience a lower
85 degree of intra- and interannual climatic variation due to the rather stable environmental
86 conditions they encounter throughout the year (Janzen, 1967; Wiens, 1989). In temperate
87 climates however, the conditions a species experiences are much more variable due to the larger
88 intra- and interannual variation in climate (Janzen, 1967). Species occurring in tropical
89 ecosystems, therefore often have a much narrower climatic niche (Stevens, 1989; Cadena *et al.*,
90 2012). In turn, this also implies that the influence of temporal variability might be greater in
91 areas where species are not well adapted to variation in climate. Therefore, along large-scale
92 geographic gradients both spatial and temporal variability can become important in estimations
93 of a species environmental niche.

94 Climate does not only influence the distribution of species, but also has a profound impact on
95 how specific traits evolve over time as adaptations to climate itself (Kozak & Wiens, 2010;
96 Rolland *et al.*, 2018; Liu *et al.*, 2020). While climate is an important factor in the diversification
97 of species (Liu *et al.*, 2020), many adaptations can also be directly linked to environmental
98 factors. A prominent example is the evolution of endothermy, which allows to some degree, the
99 decoupling of a species internal temperature from that of its surrounding habitat (McNab, 1978;
100 Ruben, 1995), which in turn leads to different responses of species to a climatic factor. Hence,
101 overall, spatial and temporal variabilities may not only act as species range determinants in
102 isolation, but also interact with each other. With climatic data becoming available at
103 increasingly higher spatial and temporal resolution, the opportunity arises to generate an
104 improved understanding of the role of spatial and temporal climatic variability on the
105 distribution of species. Here, we evaluate if considering temporal, and spatial variation in
106 addition to classical coarse-grained climate mean values improves the performance of SDMs
107 when using coarse-grained species distribution data.

108 Based on the potential effects of spatial and temporal climate variability on species discussed
109 before, we hypothesize that

- 110 i) both the inclusion of spatial and temporal variability positively affect the
111 performance of SDMs,
- 112 ii) the performance of ectotherm SDMs increases more strongly when accounting for
113 spatial and temporal variability than the performance of endotherm SDMs, and

114 iii) SDMs for tropical and mountain species will benefit more strongly from including
115 variability than SDMs of species from other habitats.

116 We test these hypotheses by modelling the distribution of 833 amphibian, 779 reptile, and 2211
117 mammal species as a function of current climate using four different predictor groups composed
118 of different combinations of input variables: mean climate, spatial climatic variability and
119 temporal (interannual) climatic variability.

120 **Methods**

121 **Species data**

122 We used global distribution maps provided by the Amphibian, Mammal, and Reptile Red List
123 Assessment (IUCN, 2016). Grid cells within the distribution range of each species were
124 converted to 0.5° grid cells, which is close to 50 km at the equator, a resolution suggested as
125 appropriate (Hurlbert & Jetz, 2007) and often used (Fritz & Rahbek, 2012; Zurell *et al.*, 2018;
126 Thuiller *et al.*, 2019) when gridding polygon range maps at the global scale. Grid cells
127 intersecting with a range map polygon were assigned as presence cells, while those not
128 intersecting were treated as absence cells. We only considered species for which the presences
129 cover at least 72 0.5° grid cells so that a minimum of six data points per predictor variable
130 (including quadratic terms) was available for model building. We also removed domestic and
131 aquatic species.

132 **Climate predictor groups**

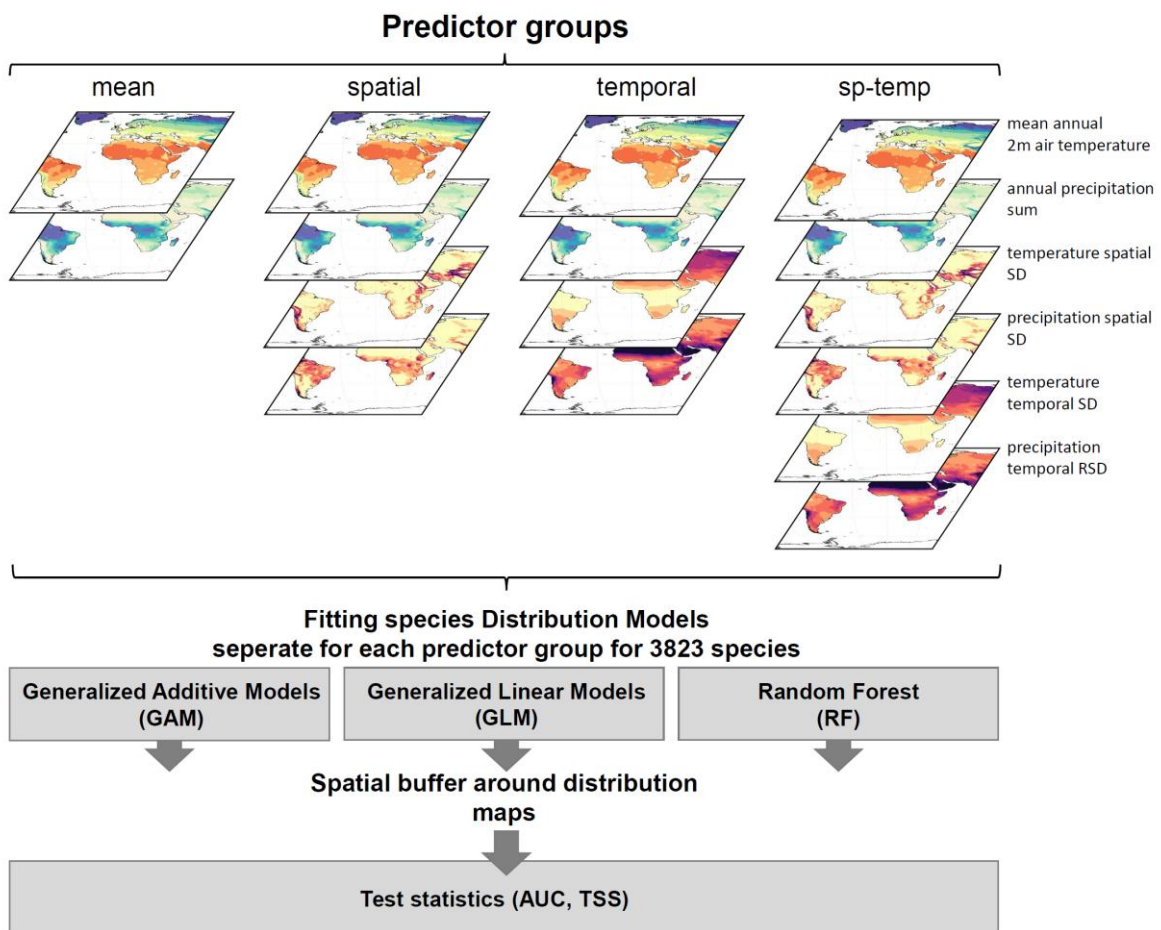
133 We used global climate data from CHELSA V1.2 (Karger *et al.*, 2017a,b) and built several
134 groups of predictors (Fig. 1, Table 1) by aggregating CHELSA to the 0.5° grid of the species
135 data by taking the mean of all 30 arc second grid cells overlapping with a 0.5° grid cell. To
136 calculate sub-grid heterogeneity of a climatic variable (hereafter: spatial) within a 0.5° grid cell,
137 we used the standard deviation of all CHELSA 30 arc second grid cells overlapping with 0.5°
138 grid cells. To calculate the interannual variability (hereafter: temporal) we calculated the
139 standard deviation of mean annual 2m air temperature for each year from 1979 to 2013 from
140 CHELSA V1.2 per grid cell. For temporal precipitation variability we used the relative standard
141 deviation (temporal RSD, equivalent to the coefficient of variation) of the annual precipitation
142 sum across all years from 1979 to 2013 from CHELSA V1.2 per grid cell. Based on the data
143 aggregated as explained above, we generated four different groups of predictors for annual

144 temperature and precipitation, with different combinations of spatial and temporal variabilities
145 (Table 1).

146 **Table 1.** Characterization of the four predictor groups used with the respective variables
 147 included in each group as well as the temporal or spatial unit over which they were aggregated.
 148 All variables are based on CHELSA V1.2 (Karger *et al.*, 2017a).

Predictor group	variables included	aggregation unit
mean	mean annual 2m air temperature 1979-2013	-
	mean annual precipitation sum 1979-2013	-
spatial	mean annual 2m air temperature 1979-2013	-
	mean annual precipitation sum 1979-2013	-
	standard deviation mean annual 2m air temperature 1979-2013	all 0.0083334° grid cells within a 0.5° grid cell
	standard deviation mean annual precipitation sum 1979-2013	all 0.0083334° grid cells within a 0.5° grid cell
	coefficient of variation mean annual precipitation sum 1979-2013	all years from 1979-2013
temporal	mean annual 2m air temperature 1979-2013	-
	mean annual precipitation sum 1979-2013	-
	standard deviation mean annual 2m air temperature 1979-2013	all years from 1979-2013
	coefficient of variation mean annual precipitation sum 1979-2013	all years from 1979-2013
	coefficient of variation mean annual precipitation sum 1979-2013	all years from 1979-2013
sp-temp	mean annual 2m air temperature 1979-2013	-
	mean annual precipitation sum 1979-2013	-
	standard deviation mean annual 2m air temperature 1979-2013	all 0.0083334° grid cells within a 0.5° grid cell
	standard deviation mean annual precipitation sum 1979-2013	all 0.0083334° grid cells within a 0.5° grid cell
	standard deviation mean annual 2m air temperature 1979-2013	all years from 1979-2013
	coefficient of variation mean annual precipitation sum 1979-2013	all years from 1979-2013
	coefficient of variation mean annual precipitation sum 1979-2013	all years from 1979-2013

149



150

151 **Fig. 1.** Schematic representation of the analytical setup. Four predictor groups were formed
152 and three algorithms for species distribution models (SDMs) were fitted from range maps for
153 3823 species of mammals, amphibians, and reptiles. The different SDMs were predicted
154 spatially and their predictive performance assessed within a buffer of 3000 km around observed
155 ranges, using the area under the curve (AUC) and the true skill statistic (TSS) as performance
156 measures.

157

158 **Species distribution modelling**

159 We used three algorithms to relate presences and absences with the selected environmental
160 predictor sets: Generalized Linear models (GLM) (Nelder & Wedderburn, 1972), Generalized
161 Additive Models (GAM) (Hastie & Tibshirani, 1990), and Random Forests (RF) (Breiman,
162 2001). GLMs were run using linear and quadratic terms, GAMs were run using thin plate splines
163 setting an upper limit of 4 degrees of freedom ($k=5$). In both cases, we set weights such that the
164 sum of weights of presences equaled the sum of weights of absences (Barbet-Massin *et al.*,

165 2012). A classification RF was fitted using 1500 trees, while sub-sampling was restricted to
166 contain equal numbers of presences and absences.

167 To assess model performance, we tested SDM predictions only within a buffer around each
168 species' range polygon. By doing so we account for biogeographic history and explicitly test
169 how well a model predicts the actual range of a species rather than how well it also makes
170 predictions far outside a species' range, yet with suitable climate. We applied a buffer of
171 3000km around each range polygon and fitted and tested SDMs only within this extent.

172 We evaluated the predictive performance of the SDMs using repeated split-sample tests: we
173 split the data repeatedly into 80% training and 20% test data, fitted the model on the training
174 data, and predicted it to the test data. This procedure was repeated 30 times, while we recorded
175 predictive performance of each repeat. Predictive performance was assessed using a) the true
176 skills statistic (TSS) (Allouche *et al.*, 2006), after thresholding the predictions into
177 presence/absence using a TSS-optimized threshold, and b) the area under the curve (AUC)
178 (Swets, 1988). We provide the full SDM description following the ODMAP protocol (Zurell *et*
179 *al.*, 2020)(Zurell *et al.* 2020) in Appendix S2.

180 **Performance tests of predictor groups**

181 We used a linear mixed effects model (Bates *et al.*, 2015) with either TSS or AUC as response
182 variable and the predictor group as fixed effects together with the SDM algorithm (GLM, GAM,
183 RF) and the species identity as random effects. Adding the type of SDM (GLM, GAM, or RF)
184 as random effect on the intercept considers that algorithms can perform differently well (e.g.
185 have a different mean performance between AUC or TSS, Thuiller *et al.*, 2019). To always
186 compare the same species, but modeled with different sets of predictor groups, we also added
187 the identity of the species as random affect to the intercept. To check if there are differences in
188 SDM performance across climatologies, we ran a paired Wilcoxon test. By this, we tested if
189 one climatology performs better than another.

190 All analyses have been performed using the R language for statistical computing (R Core Team,
191 2015, version 3.6.1), the R packages raster (Hijmans & van Etten, 2014), mgcv (Wood & Wood,
192 2015), and randomForest (randomForest: Breiman and Cutler's Random Forests for
193 Classification and Regression).

194 **Spatial performance of different predictor groups**

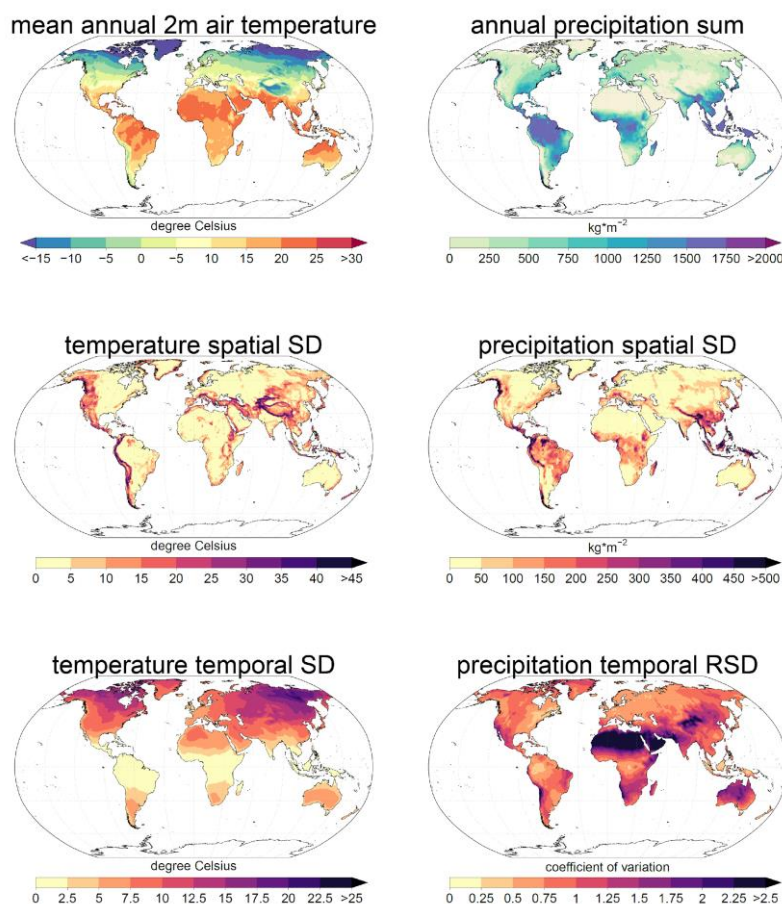
195 To test if different predictor groups have different performances in different regions, we used
196 the gridded range map at 0.5° resolution from IUCN and assigned the value of the respective

197 test metric (TSS, AUC) to the entire range in which a species is present. All ranges were then
198 stacked and the mean of all TSS and AUC values covering a 0.5° grid cell calculated.

199 Results

200 Spatial patterns of the predictor groups

201 While mean annual 2m air temperatures and annual precipitation sums were generally higher
202 in the tropics and decrease towards the poles (Fig. 2, upper), the spatial SD of these two
203 variables is usually highest in mountainous terrain (Fig. 2, middle). Interannual variability
204 (temporal SD) of temperature is generally higher in the northern hemisphere compared to the
205 southern hemisphere, and increases from tropics to continental arctic or boreal areas. Variability
206 (temporal RSD) of precipitation is more idiosyncratic, with lowest values estimated in desert
207 areas.



208
209 **Fig. 2.** Spatio-temporal variation in 2m air temperature and precipitation used as predictors in
210 the different SDMs based on CHELSA V1.2. Mean annual values (upper row) show the annual
211 mean for temperature, and the mean annual sum for precipitation averaged over the years 1979-
212 2013 and aggregated to 0.5° from a 30 arc second spatial grain by taking the mean of a 0.5°
213 grid cell. Spatial variation (middle) indicates the standard deviation (SD) of all temperature

214 values of a 30 arc second grid of temperature or precipitation overlapping with a 0.5° grid cell.
215 Temporal variation (lower row) shows the standard deviation (SD) of temperature over years
216 between 1979-2013, and the relative standard deviation (RSD) calculated as the coefficient of
217 variation for precipitation over the same time period.

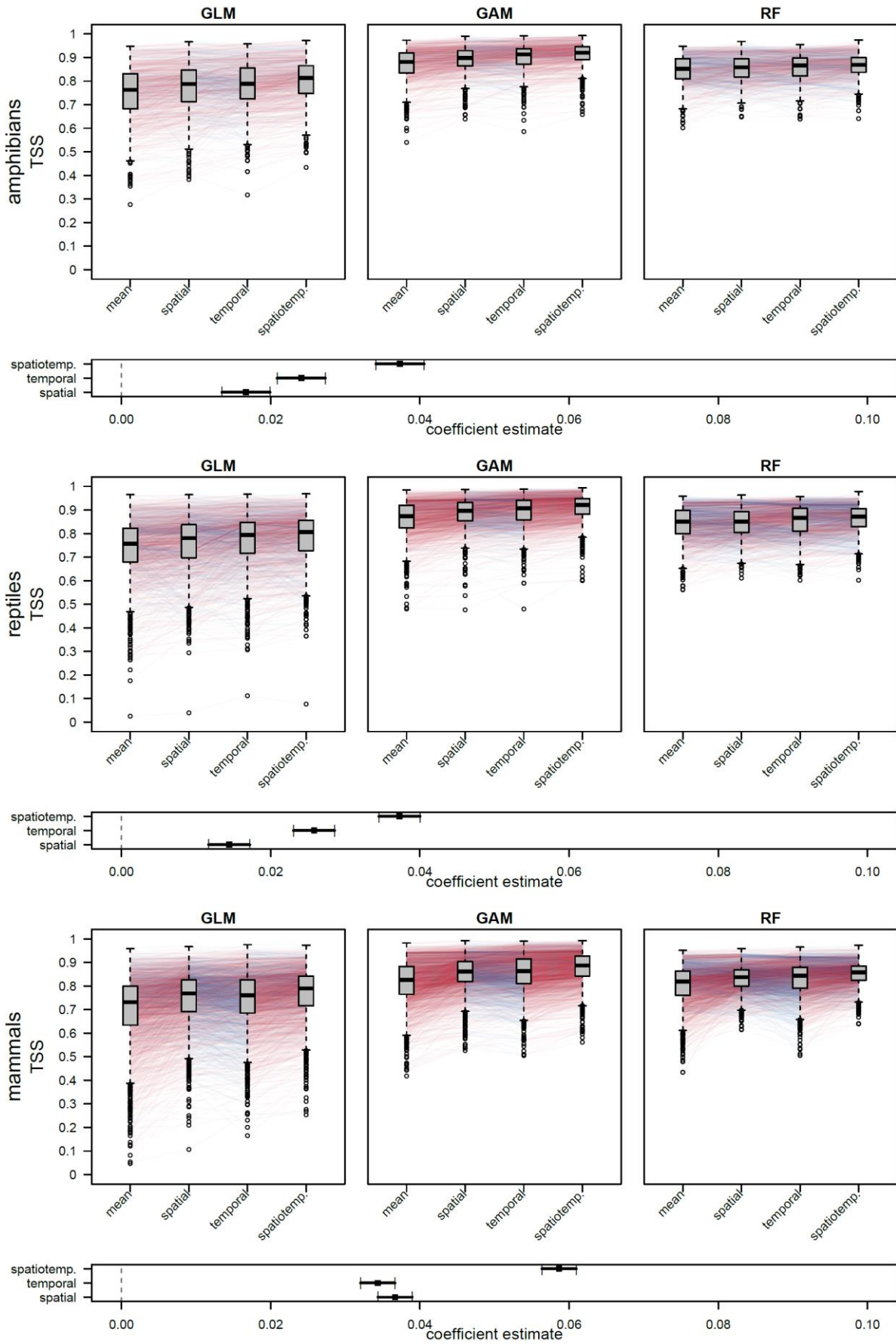
218

219 **Performance scores of the SDMs with different predictor groups**

220 Overall the predictive performance of the SDMs was high with an average AUC of 0.92 and
221 ranging on from 0.90 to 0.95 between different groups of predictors, SDMs, and climatologies.
222 For TSS, values averaged 0.75 with a minimum 0.68 and a maximum of 0.82 for the different
223 predictor groups.

224 SDMs based on mean climate predictors performed worst among all groups, with average AUC
225 and TSS scores of 0.90 and 0.71, respectively (GAM: 0.91; 0.73, GLM: 0.90; 0.73, RF: 0.90;
226 0.68). SDMs based on mean climate predictors plus spatial predictors performed slightly better,
227 with average AUC and TSS scores of 0.92 and 0.74 (GAM: 0.93; 0.77, GLM: 0.92; 0.76, RF:
228 0.91; 0.70). SDMs based on mean climate predictors plus temporal predictors performed
229 slightly better, with average AUC and TSS scores of 0.94 and 0.80 (GAM: 0.94; 0.81, GLM:
230 0.94; 0.81, RF: 0.94; 0.77). SDMs containing mean climate predictors plus spatial and temporal
231 predictors performed similar as the SDMs with mean and temporal predictors, with average
232 AUC and TSS scores of 0.94 and 0.80 (GAM: 0.95; 0.82, GLM: 0.93; 0.81, RF: 0.94; 0.77).

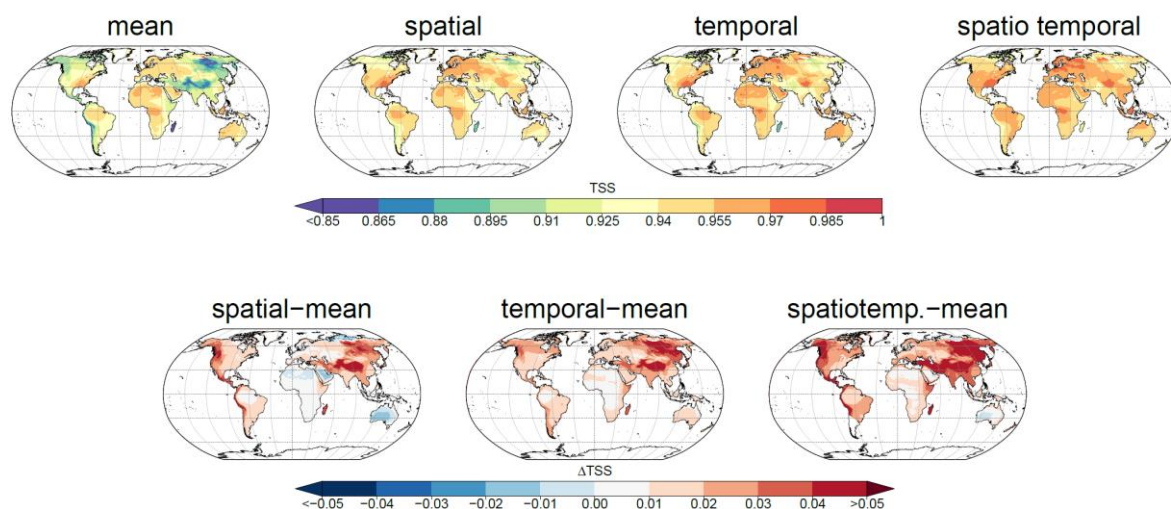
233 The results of the linear mixed effects model to assess the SDM performance with different
234 predictor groups showed that adding predictors that account for either spatial or temporal
235 variation increased predictive performance of models across all groups of vertebrates. Models
236 based on the temporal predictor group outperformed models based on the spatial predictor
237 group for amphibians and reptiles, but not for mammals (equal performance). Models that
238 included predictors that accounted for both spatial and temporal variation (sp-temp predictor
239 group) performed best across all vertebrate groups. Fig. 3 illustrates these results using effect-
240 size plots (below boxplots) for TSS, while results for AUC are equivalent (see Supplemental
241 Figure S1).



243 **Fig. 3.** Comparison of the performance of three different SDM algorithms (GLM = Generalized
244 linear model, GAM = Generalized additive model, RF = Random Forests) calculated with four
245 different sets of predictors for amphibians, reptiles, and mammals measured by the True Skill
246 Statistic (TSS). Colored lines connect pairs of SDMs based on different predictor sets for the
247 same species, with red and blue lines indicating pairs in which TSS values increased and
248 decreased between predictor groups from left to right. Plots below the boxplots shows the
249 coefficient estimates of a linear mixed effects model with TSS as response, the groups (mean,
250 spatial, temporal, sp-temp) as predictor, and the model (GLM, GAM, RF) as well as the species
251 ID as random effects. Coefficients are in relation to the performance of SDMs with the predictor
252 set: mean.

253 Spatial comparison

254 The performance of SDMs is highly variable across the globe (Fig. 4). The mean predictor
255 group generally performed worst in mountainous terrain, such as the Andes or the Himalayas,
256 but also Madagascar showed low TSS and AUC scores (Fig. 4, Supplementary Fig. S2 for
257 AUC). Including spatial variability in temperature and precipitation in SDMs improved the
258 models in these areas, but showed a slight decline in performance in desert and arctic areas (Fig.
259 4: TSS differences spatial-mean). Adding temporal variability to the models containing mean
260 predictors resulted in improved SDM performance in almost all areas (Fig. 4: temporal-mean).
261 Including all spatial and temporal predictors resulted in a slight improvement in the spatial
262 model accuracies compared to including the temporal group with the mean predictor group (Fig.
263 4: spatio temporal), yet the improvement compared to mean plus temporal SDM were small.
264



266 **Fig 4.** Spatial variation in mean TSS values per grid cell and TSS differences between models
267 using different predictor groups. The upper row illustrates TSS averaged for all mammals,
268 reptiles, and amphibians modeled for the four models using different predictor groups. The
269 lower row illustrates the averaged TSS difference among all SDMs when adding either spatial,
270 temporal or both spatial and temporal (spatiotemp.) predictors to SDMs based on mean
271 predictors only.

272 **Discussion**

273 Including temporal variability of predictors into broad-scale SDMs leads to a greater
274 improvement of model performance than the inclusion of sub-grain spatial variability of these
275 predictors. These findings suggest that especially the inclusion of interannual climate variability
276 has a large potential of improving the estimation of niche characteristics across a large range of
277 taxa. Including temporal predictor variability increased the performance of SDMs in almost all
278 areas across the globe, though to differing degrees. Especially prominent is the increase in areas
279 with marked seasonality such as in tropical monsoon climates, tropical wet and dry climate, or
280 areas that receive very infrequent precipitation such as the Horn of Africa (Beck *et al.*, 2018).
281 Temporal variability does also increase the performance of SDMs in mountainous regions
282 potentially indicating that temporal variability in a climate variable is also capable to capture
283 the niche limitations that are otherwise captured by spatial heterogeneity. One reason for the
284 performance gain when including temporal variability is that it expresses the degree of climatic
285 extremes which can physiologically limit the distribution of species (Zimmermann *et al.*, 2009).
286 Although, the degree to which extremes are represented in such variability predictors certainly
287 depends on the temporal resolution of the climatic input dataset. In the case presented here, we
288 used interannual variation, which means that extreme events are restricted to extremely dry or
289 wet years, or extremely hot or cold years. Using more detailed temporal analyses would allow
290 to refine the representation of climatic extremes further.

291 As expected, the inclusion of the spatial variability improves SDMs mainly in mountainous
292 areas where climate is extremely heterogeneous over short distances. The improvement was
293 specifically strong in tropical mountains where species usually occur in narrow elevational
294 bands with little or no intra-annual variability (Janzen, 1967; Ghalambor *et al.*, 2006). In
295 topographically less heterogeneous terrain however, we observed a decline in the predictive
296 power of SDMs. Almost all over Africa, Australia, and the low elevation parts of Eurasia, and
297 North America spatial variability has no effect, or even a negative effect on the performance of
298 SDMs. In these areas spatial heterogeneity is low and inclusion of spatial variability in climate
299 predictors seems biologically unimportant, which leads to a decrease in their performance

300 (Loehle & LeBlanc, 1996; Davis *et al.*, 1998; Vaughan & Ormerod, 2003; Dormann *et al.*,
301 2012).

302

303 The increase in SDM performance is however not equal across the three taxonomic groups
304 analyzed here. While amphibians and reptiles show a significantly higher SDM performance of
305 the temporal predictor group over the spatial predictor group, mammal SDMs do not
306 significantly differ when either spatial or temporal predictors are added to the mean predictor
307 group. This difference might be explained by the differences in physiology between these
308 groups. All three groups have evolved differently in response to their environment, with
309 ectothermic groups being much less adaptable to climatic variations than endothermic groups
310 (Rolland *et al.*, 2018). Such evolved differences in physiology ultimately affect how organisms
311 interact with and are constrained by their environment (Buckley *et al.*, 2012). Ectothermic
312 species for example cannot buffer climate variation as well as endothermic species (Clusella-
313 Trullas *et al.*, 2011; Sunday *et al.*, 2011; Hoffmann *et al.*, 2013; Gunderson & Stillman, 2015)
314 which have evolved the physiological capacity to regulate temperatures to some extent (Pither,
315 2003). When building SDMs from climate means alone, thus neglecting the temporal dimension
316 of predictors, we miss out on important climatic constraint especially for endothermic species
317 distributions, ultimately limiting the accuracy of niche estimations (Zimmermann *et al.*, 2009).
318 Model formulation and parametrization certainly plays a role in the observed differences
319 between predictor groups. More predictors in a model usually lead to a better overall fit of a
320 model (Brun *et al.*, 2019) which can partly explain the increase in predictive power when the
321 predictors based on mean climate are complemented with either spatial or temporal variability.
322 As both, the spatial and the temporal predictor groups have the same number of variables, this
323 effect does not hold when comparing these two. Combining mean with spatial and temporal
324 predictor groups however, lead to an additional improvement. At this point however, the
325 parametrization of has not yet plateaued (Randin *et al.*, 2006; Chala *et al.*, 2016; Brun *et al.*,
326 2019; Gregor *et al.*, 2019) and model performance still increases when using both spatial and
327 temporal variability as predictors. Using different SDM algorithms mainly affects the absolute
328 performance of the SDMs in terms of the specific test metric (AUC, TSS). However, it did not
329 affect the relative difference in model performance between SDMs calculated from different
330 predictor groups.

331 With an increasing need in biodiversity modeling for current, past, and future predictions a
332 better understanding of the climatic predictors that quantify the ecological niche of a species is
333 needed. Here, we show that specifically the inclusion of temporal variability offers a promising

334 improvement in modelling the current distribution of species. Yet, also the inclusion of spatial
335 (sub-grain) variabilities can improve model accuracies, primarily mountains and most clearly
336 in tropical mountains. In summary, we anticipate that a more detailed inclusion of the temporal
337 variability of climate variables offers a highly promising avenue for improving species
338 distribution modelling in the future.

339 **Data Accessibility Statement**

340 The data that support the findings of this study are openly available in EnviDat (envidat.ch) at
341 <http://doi.org/XXXXXX>. Codes related to this study will be available on Zenodo at
342 <http://doi.org/YYYYYYYY>

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353 **Author contributions:**

354 D.N.K. and N.E.Z. developed the idea with input from all co-authors, D.N.K., L.M. and R.O.W.
355 implemented the species distribution modelling, B.S. and D.N.K. analyzed the results further,
356 D.N.K. wrote the first draft of the manuscript, and all authors contributed equally to the
357 revisions.

358 **Biosketch:**

359 Dirk Nikolaus Karger is a senior researcher at the Swiss Federal Research Institute WSL and
360 mainly interested in the impact climate has on global ecosystems and species. The author
361 consortium binds a strong interest in species distribution modelling.

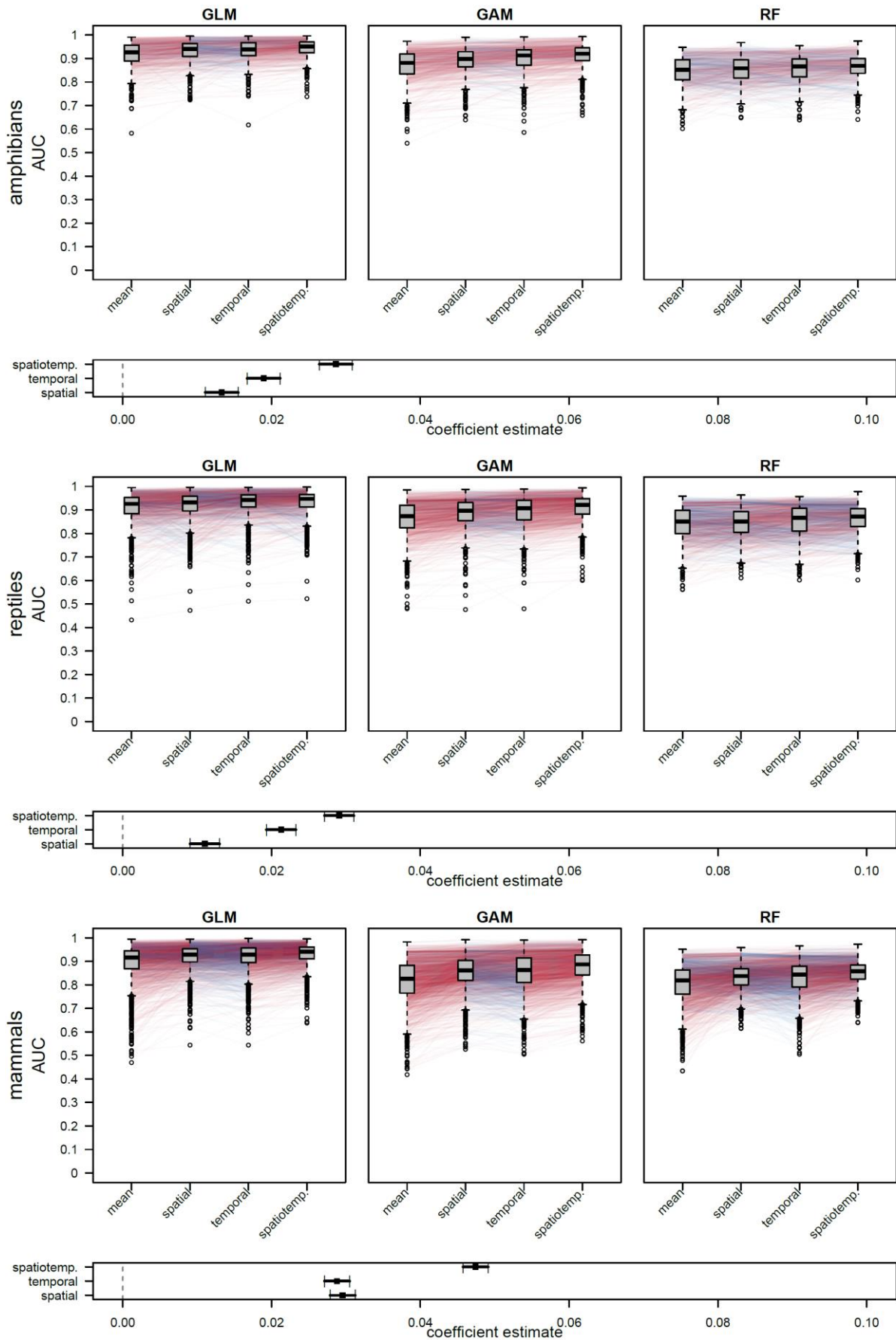
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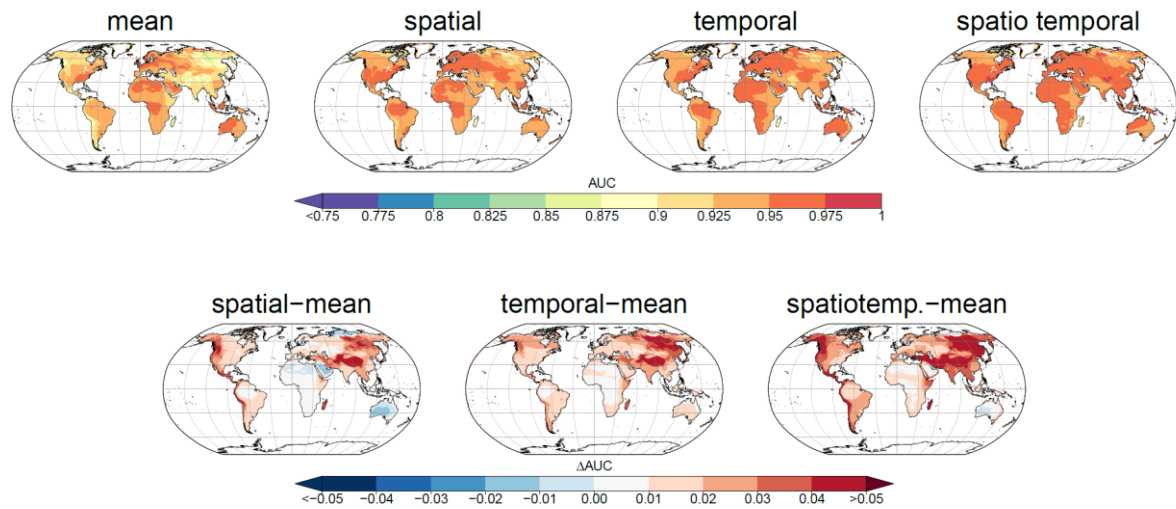
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523 **Appendices**



525 **Fig. S1.** Comparison of the performance of three different SDM algorithms (GLM =
526 Generalized linear model, GAM = Generalized additive model, RF = Random Forests)
527 calculated with four different sets of predictors for amphibians, reptiles, and mammals
528 measured by the Area Under the Curve (AUC). Colored lines connect pairs of SDMs based on
529 different predictor sets for the same species, with red and blue lines indicating pairs in which
530 AUC values increased and decreased between predictor groups from left to right. Plots below
531 the boxplots shows the coefficient estimates of a linear mixed effects model with AUC as
532 response, the groups (mean, spatial, temporal, spatiotemp.) as predictor, and the model (GLM,
533 GAM, RF) as well as the species ID as random effects. Coefficients are in relation to the
534 performance of SDMs with the predictor set: mean.
535



536

537 **Fig S2.** Spatial variation in mean AUC values per grid cell and AUC differences between
538 models using different predictor groups. The upper row illustrates AUC averaged for all
539 mammals, reptiles, and amphibians modeled for the four models using different predictor
540 groups. The lower row illustrates the averaged AUC difference among all SDMs when adding
541 either spatial, temporal or both spatial and temporal (spatiotemp.) predictors to SDMs based on
542 mean predictors only.

543