

Supplementary Information

S1 Methods

S1.0.1 Bumble bee records

We used a large continental-wide bumble bee data-set [1] that, before any filtering, comprises 649,407 specimen records from 46 species and spans 1805 – 2020. With this data-set, we follow the *Bombus* taxonomy of Williams *et al.* [2], including the lumping of *B. sonorus* with *B. pensylvanicus* and *B. californicus* with *B. fervidus*. We also follow the taxonomic changes in *Alpinobombus* proposed by Williams *et al.* [3] and the recent split of *B. occidentalis* along the 57th parallel into *B. occidentalis* (south) and *B. mckayi* (north) [4]. These records have been compiled from a variety of collections and sources with reputable origin. These data have been used extensively for analyses of bumble bee trends [5–7].

S1.0.2 Spatial and temporal classification of bee occurrence

To construct sites, we overlaid a grid across North America. We considered three spatial resolutions: $50 \times 50\text{km}$, $100 \times 100\text{km}$, and $250 \times 250\text{km}$. We present results for $100 \times 100\text{km}$ in the main text and the others in the Supplementary Material. We split records (which span 1901 – 2020) into six, 20 year “eras,” each of which we further divided into four, 5 year “time intervals” wherein, at each site, a bumble bee species could have been observed (detection=1) or not observed (detection=0).

Given the unstructured, presence-only nature of our data, we do not know which of the five year time intervals actually contained “visit(s),” wherein a collector actually sampled a given site. Consequently, we have to infer non-detections (detection=0). We do

so by first identifying site \times time interval combinations where visits to sites to collect or observe bumble bees were known to have occurred. If *any* bumble bee species had been detected at a given site during a given time interval, we know that a bumble bee sampling event (or “visit”) took place. We assume that any other species of bumble bee, if present, could have been detected on that occasion at that site, thereby setting detection status to 0 for those species. This approach excludes site \times time interval combinations for which no bumble bees was recorded and past work using simulated data has shown that this approach produces non-biased estimates of species’ occupancy [8]. A similar approach has also been used in other previous work [9]. Importantly, however, this method is only valid if collectors sample bees across *Bombus*, rather than only collecting target species. Historical data likely comprises a mix of specimens from such community collections and targeted collections. Simulation work suggests that as long as $\sim 50\%$ of the sampling events targeted entire communities, inferring non-detections in this manner yields non-biased estimates of species occupancy [see 10]. Using a strict definition of a sampling event (observations that occurred in the same day within $1km$ of one other) we estimated that 49.54% of sampling events in our data-set contained two or more species which suggests that at least 50% of the sampling events targeted more than one species, as some community sampling events only collect a single species.

We model each species only over the sites that we infer to be plausibly within that species’ range. To construct a species’ range, we trace a convex hull around all sites containing observations of that species, regardless of when those observations occurred, and consider all sites within the resultant polygon to be within that species’ range. By only modeling each species over the sites at which it could plausibly occur, we generate meaningful estimates of occurrence, while also ensuring that effects of climate and floral resources are only based on the relevant sets of sites and values of environmental variables.

S1.0.3 Climate data

We compile climatic variables using CHELSA high resolution climate data for earth [11, 12], which contains monthly global temperature and precipitation values at a spatial resolution of 1×1 km. To calculate the maximum temperature at a given site in a given era, we calculate the average maximum temperature (using only data for July and August, as these months will often record the highest temperature in the year) across all of the 1×1 km cells within that site and across all the years within that era. To calculate the mean precipitation, we similarly average monthly mean precipitation (for all 12 months) across the same cells and years. Because the climate data records are only available until 2016, climate values in our final era are based on 15 years of data (2001-2016) rather than the full 20 years.

S1.0.4 Floral resource data

To quantify floral resources for bees, we combine classifications of land use estimates for the Holocene (HYDE) [13] with floral resource scores for bees [14]. Land use estimates for the Holocene spans 10000 BCE - 2015 CE worldwide. From 1900s to 2000, HYDE provides land-use categories on a decade basis and from 2000 to 2015, yearly. HYDE's spatial resolution is 5 arc minutes which is approximately 9.26 Km at the equator and 4.6 Km at latitude 60. HYDE land use categories contain, for example, cropland, urban, rangeland, wild-remote woodlands [13]. While these categories are useful for understanding the form that land conversion has taken over the past century, it is unclear how transitions between these categories might impact bees. Koh *et al.* [14] quantified expert knowledge to estimate bee abundance based on land uses, including a variety of crops and other land types such as pasture and forest, using the Cropland Data Layer (CDL) from 2008. Using these values of floral resources does not allow for temporal variation in floral resources

per se (i.e., the value of 'corn' does not change through time). Variation in floral resources through time stems from changes in land values from HYDE. The Cropland Data Layer, produced by the National Agricultural Statistics Service (NASS), provides geo-referenced crop land cover data for the continental United States at a 30m resolution.

We overlay the HYDE land-use map with the CDL map to obtain the categories of the CDL that geographically overlap with the HYDE categories for 2008. Then for each HYDE category, we calculate the average floral resources reported by Koh *et al.* [14]. Koh *et al.* [14] leveraged expert opinion to create a range of floral resources availability for 45 land-use cover types from the CDL. We add floral resources for spring, summer, and fall to provide an overall metric of floral resources through the season, as these are more relevant for bumble bees, which have long flight periods. While Koh *et al.* [14] also produced expert estimates for nesting resources, we only used floral resources here as these are more likely to apply to all bumble bee species. By overlaying the HYDE land-use map and the CDL map, we are implicitly assuming that the floral resources provided by a given crop are consistent across the continent and have been through the last century; an assumption that is probably not true. However, we believe that this metric still likely captures a coarse estimate of available floral resources.

S1.1 Occupancy models

We assume that the probability that species i is detected at site j in era k , x_{ijk} , is drawn from a Bernoulli distribution (0 or 1) with probability (y_{ijk}),

$$x_{ijk} \sim \text{Bernoulli}(y_{ijk}) \tag{S1}$$

where y_{ijk} is the product of detection probability (p_{ijk}) and the unknown, but true occupancy state, z_{ijk} ,

$$y_{ijk} = p_{ijk} * z_{ijk} \quad (S2)$$

The true but unknown site occupancy for species i at site j , z_{ijk} is equal to 1 if that site is occupied and 0 if it is not. We assume that this true site occupancy is drawn from a Bernoulli distribution with mean equal to the species' occupancy probability at that site,

$$z_{ijk} \sim \text{Bernoulli}(\psi_{ijk}) \quad (S3)$$

Both occupancy probability, ψ , and detection probability, p , can be formulated as functions of covariates, and we do this in two different ways for the former.

First, to test for genus-wide temporal trends in bumble bee occupancy (Q1), we consider a simple model wherein we model "era" directly. Specifically, we model occupancy as

$$\begin{aligned} \text{logit}(\psi_{ijk}) = & \psi_0 + \\ & \psi_{\text{species}}[i] + \\ & \psi_{\text{area}} \times \text{area}[j] + \\ & \psi_{\text{era}}[i] \times k \end{aligned} \quad (S4)$$

Here, ψ_0 denotes mean occupancy, $\psi_{\text{species}}[i]$ denotes a species-specific random effect, ψ_{area} denotes a fixed effect of site area to account for the fact that some sites are truncated by water and smaller (area[j] denotes the area of site j), and $\psi_{\text{era}}[i]$ denotes a species-specific effect of era. We call this the **Era model**.

Second, we consider a model wherein we replace the effect of era in the above model with era-level environmental predictors (Q2). Specifically, we include site-averaged max-

imum temperature, site-averaged precipitation, and site-averaged floral cover, such that
our model for occupancy becomes

$$\begin{aligned}
\text{logit}(\psi_{ijk}) = & \psi_0 + \\
& \psi_{\text{species}}[i] + \\
& \psi_{\text{area}} \times \text{area}[j] + \\
& \psi_{\text{temp}}[i] \times \text{temp}[j, k] + \\
& \psi_{\text{temp2}} \times \text{temp}[j, k]^2 + \\
& \psi_{\text{precip}}[i] \times \text{precip}[j, k] + \\
& \psi_{\text{floral}}[i] \times \text{floral}[j, k]
\end{aligned} \tag{S5}$$

Here, ψ_0 , $\psi_{\text{species}}[i]$, and ψ_{area} are as defined above in Eq. S4 and $\psi_{\text{temp}}[i]$, $\psi_{\text{precip}}[i]$, and $\psi_{\text{floral}}[i]$ denote species-specific linear effects of temperature, precipitation, and floral resources, respectively and ψ_{temp2} denotes a quadratic effect of temperature (not species-specific). We call this the **Environmental model**.

We assume that species-specific slopes in both of the above models are normally distributed about some mean. Specifically,

$$\begin{aligned}
\psi_{\text{era}}[i] & \sim \mathcal{N}(\mu_{\psi_{\text{era}}}, \sigma_{\psi_{\text{era}}}) \\
\psi_{\text{temp}}[i] & \sim \mathcal{N}(\mu_{\psi_{\text{temp}}}, \sigma_{\psi_{\text{temp}}}) \\
\psi_{\text{precip}}[i] & \sim \mathcal{N}(\mu_{\psi_{\text{precip}}}, \sigma_{\psi_{\text{precip}}}) \\
\psi_{\text{floral}}[i] & \sim \mathcal{N}(\mu_{\psi_{\text{floral}}}, \sigma_{\psi_{\text{floral}}}),
\end{aligned} \tag{S6}$$

where $\mu_{\psi_{\text{era}}}$, $\mu_{\psi_{\text{temp}}}$, $\mu_{\psi_{\text{precip}}}$, $\mu_{\psi_{\text{floral}}}$ denote the mean effect of each corresponding predictor, across species, and σ terms denote the variances about these means.

118 In both of the above models, we model detection probability as

$$\text{logit}(p_{ijk}) = p_0 + p_{\text{site.era}}[j, k] \quad (\text{S7})$$

119 where p_0 denotes the mean detection probability and $p_{\text{site}}[j, k]$ denotes a site-specific ran-
120 dom effect that is era-specific. This latter term allows detection to vary relatively inde-
121 pendently across sites and between eras. Specifically, we assume

$$p_{\text{site.era}}[j, k] \sim \mathcal{N}(\mu_{p_{\text{site.era}}}, \sigma_{p_{\text{site.era}}}). \quad (\text{S8})$$

122 In addition, we ran our “era” model without splitting *B. occidentalis* into *B. occidentalis*
123 and *B. mckayi* to assess the effect this species split has on their trend through time.

124 We fit models in JAGS [15] and assess model convergence both by visually inspecting
125 chains and checking The Gelman-Rubin statistic (we ensured that $R_{\text{hat}} < 1.1$ for
126 all parameters). We use flat, uninformative priors for all parameters and ran models
127 for 20,000 iterations, discarding the first 10,000 iterations and thinning by 10 across 3
128 chains. For all analysis we used R V4.0.4 [16]. For spatial manipulations we used the
129 packages `raster` [17], `rgeos` [18], `maptools` [19], `rgdal` [20], `sp` [21], `spatstat` [22]; for
130 data manipulation we used `stringr` [23] and `data.table` [24]; for running models, we
131 used `rjags` [25], `R2jags` [26], and `runjags` [27].

132 S2 Supplementary Results

133 At a spatial resolution of 50×50 km, our final data-set contained 224,262 bee records
134 across 2228 sites and six 20 year time intervals. This translates into 521993 unique species
135 \times site \times time interval combinations. Site-era combinations were less well sampled, given
136 the smaller spatial scale with the same data, with each receiving, on average, 1.3 visits

across 4 time intervals (Figs. S11) and 5.2 positive species observations (Fig. S9) across 2.6 species (Fig. S13). Mean precipitation increased an average of 0.36kg/m² per month, mean maximum temperature increased 0.82°C, and mean floral resources decreased by -0.02).

At a resolution of 250×250km, our final data-set contained 240,561 bee records across 294 sites and six 20 year time intervals. This translated into 23800 unique species × site × observations. Site-era combinations were well sampled, with each receiving, on average, 2.5 visits across 4 time intervals (Figs. S12) and 27.9 positive species detections (Fig. S10) across 6.3 species (Fig. S14). Mean precipitation increased an average of 0.36kg/m² per month, mean maximum temperature increased 0.91°C, and mean floral resources decreased by -0.03).

For our **Era model** with *B. occidentalis* and *B. mckayi* lumped together into a single species, the species' trend through time is estimated as slightly decreasing but with a Bayesian confidence interval that overlaps zero ($\psi_{\text{era},\text{occidentalis}} = -0.104$, 95% BCI=[-0.272, 0.067]). While in the **Era model** with *B. occidentalis* and *B. mckayi* separated, *B. occidentalis* is estimated to be decreasing ($\psi_{\text{era},\text{occidentalis}} = -0.142$, 95% BCI=[-0.318, 0.024]) and *B. mckayi* is estimated to be increasing ($\psi_{\text{era},\text{mckayi}} = 0.345$, 95% BCI=[-0.001, 0.723]).

Results were largely consistent between spatial resolutions. We found that bumble bee occupancy increased slightly through time, decreased significantly with temperature, and was not associated with changes in precipitation or floral resources (Figs. S15). Similarly, we found that species responses varied widely at all spatial scales (Table 1 vs. Tables S3 vs. S4). However, fewer species trends were significantly different from zero at larger spatial scales. At larger spatial scales we were more likely to find occurrences at any given site than at smaller spatial scales and, therefore, we were less likely to identify changes in occupancy through time. Finding that some species are declining at all spatial resolutions we analyzed increases our confidence that the detected declines are real.

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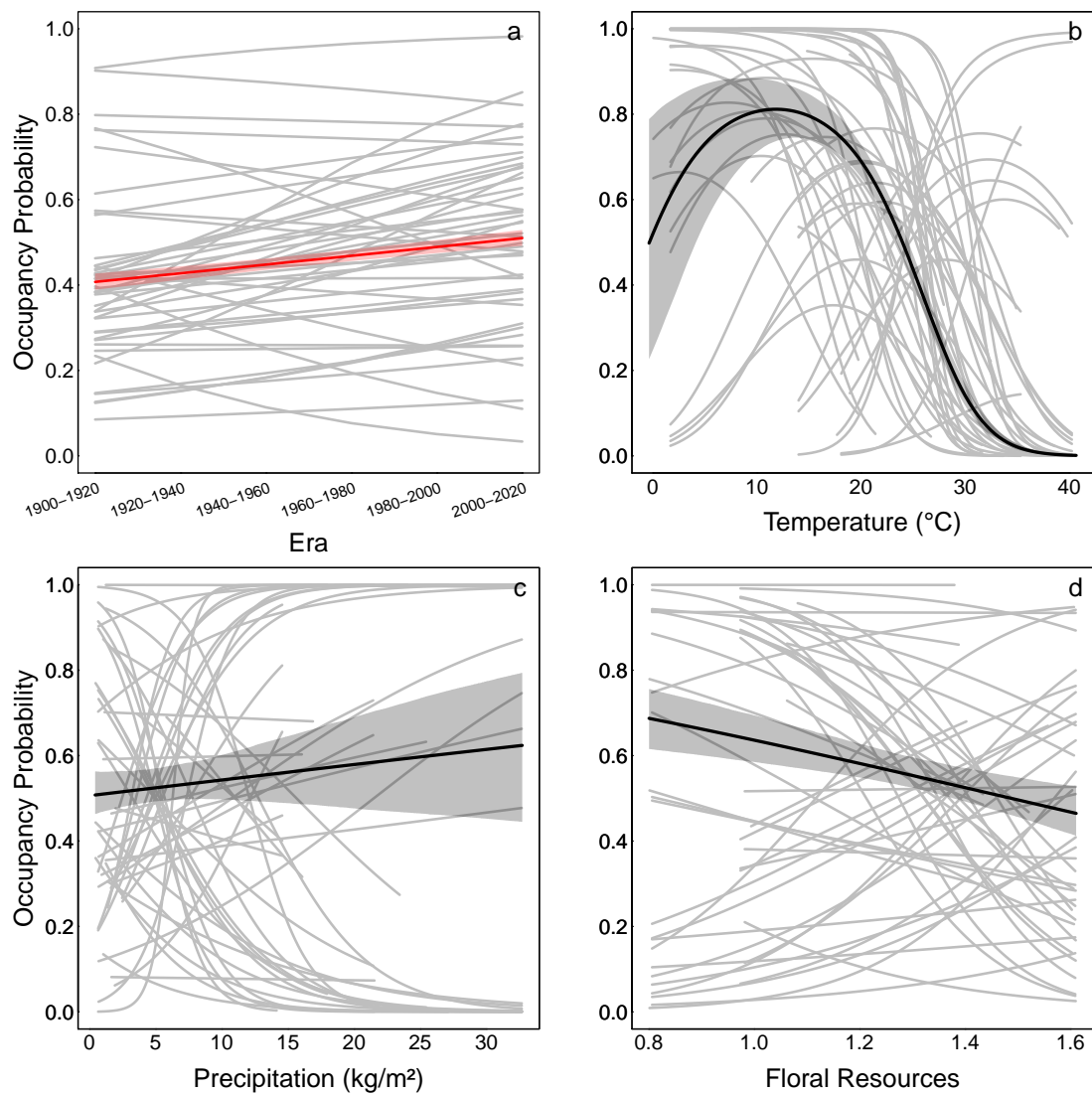


Figure S1: Same as Fig. 1, but with a stricter data filtering; each site needed to have at least 5 records in each of the 20-year eras in order to be included in the analysis. These patterns do not differ qualitatively from those shown in the main text.

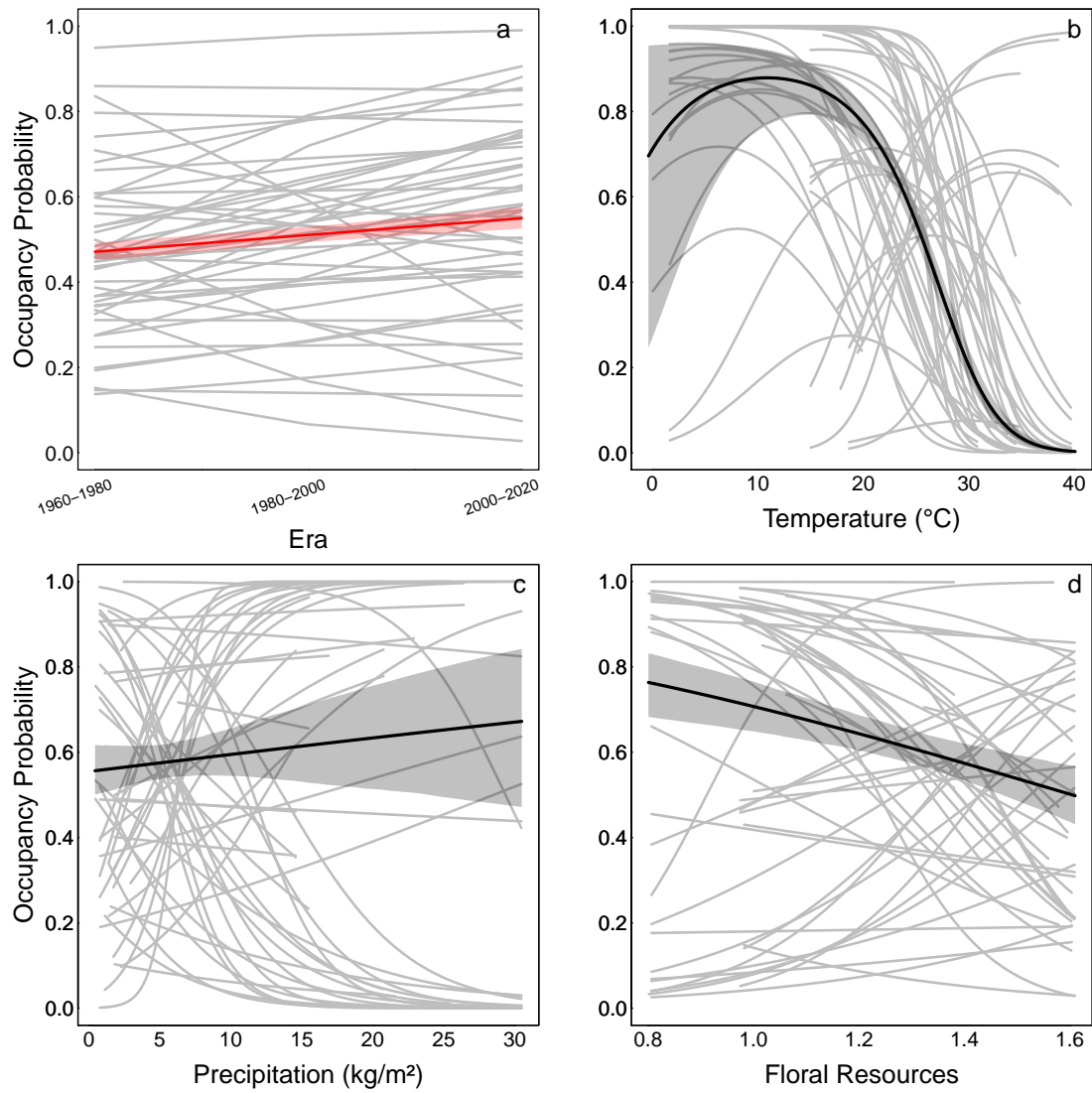


Figure S2: Same as Fig. 1, but limiting to only records collected from 1960 (instead of 1900). These patterns do not differ qualitatively from those shown in the main text.

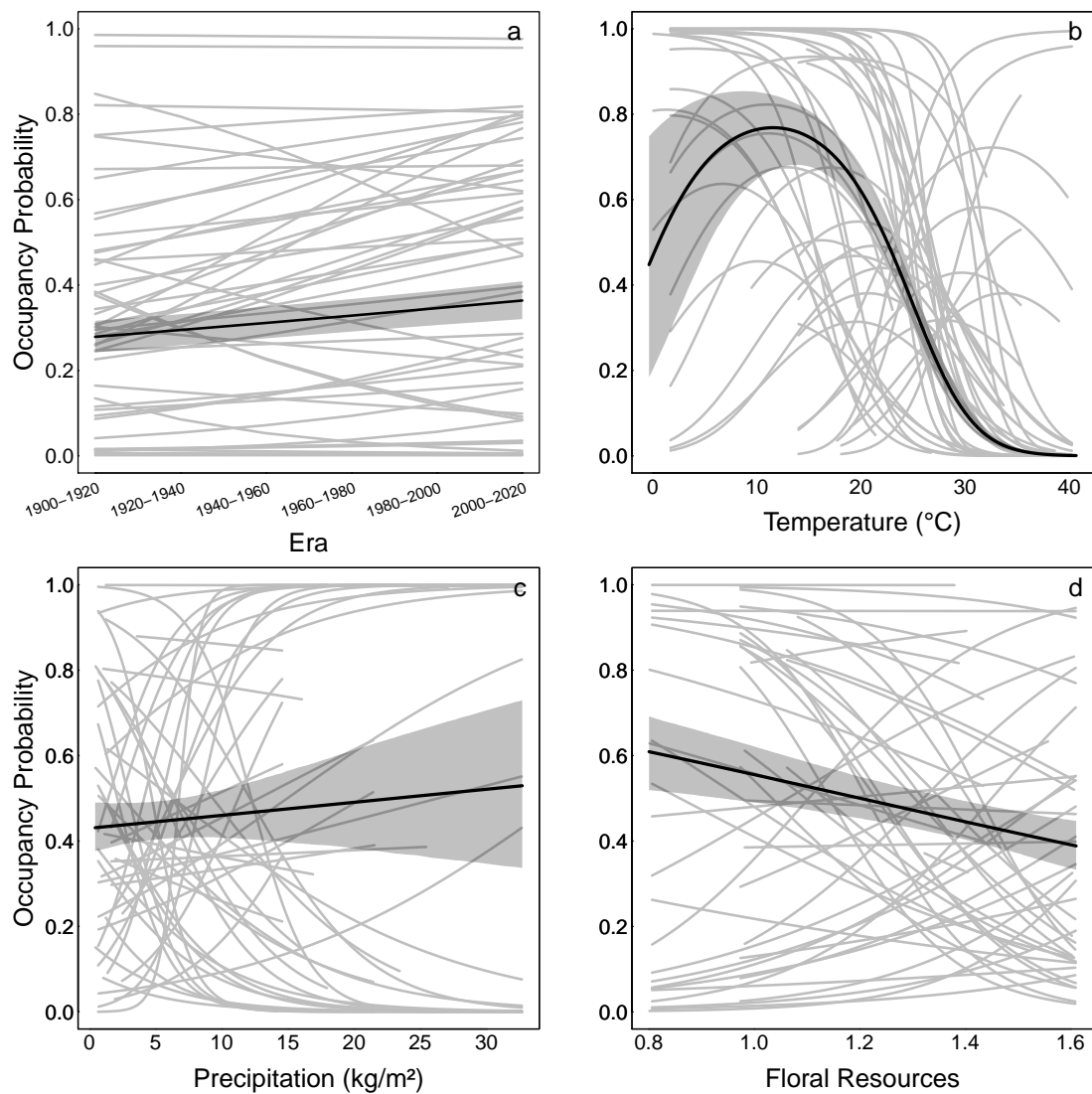


Figure S3: Same as Fig. 1, but combining the era and environmental model into a single combined model with era, temperature, precipitation and floral resources all as predictors. These patterns do not differ qualitatively from those shown in the main text.

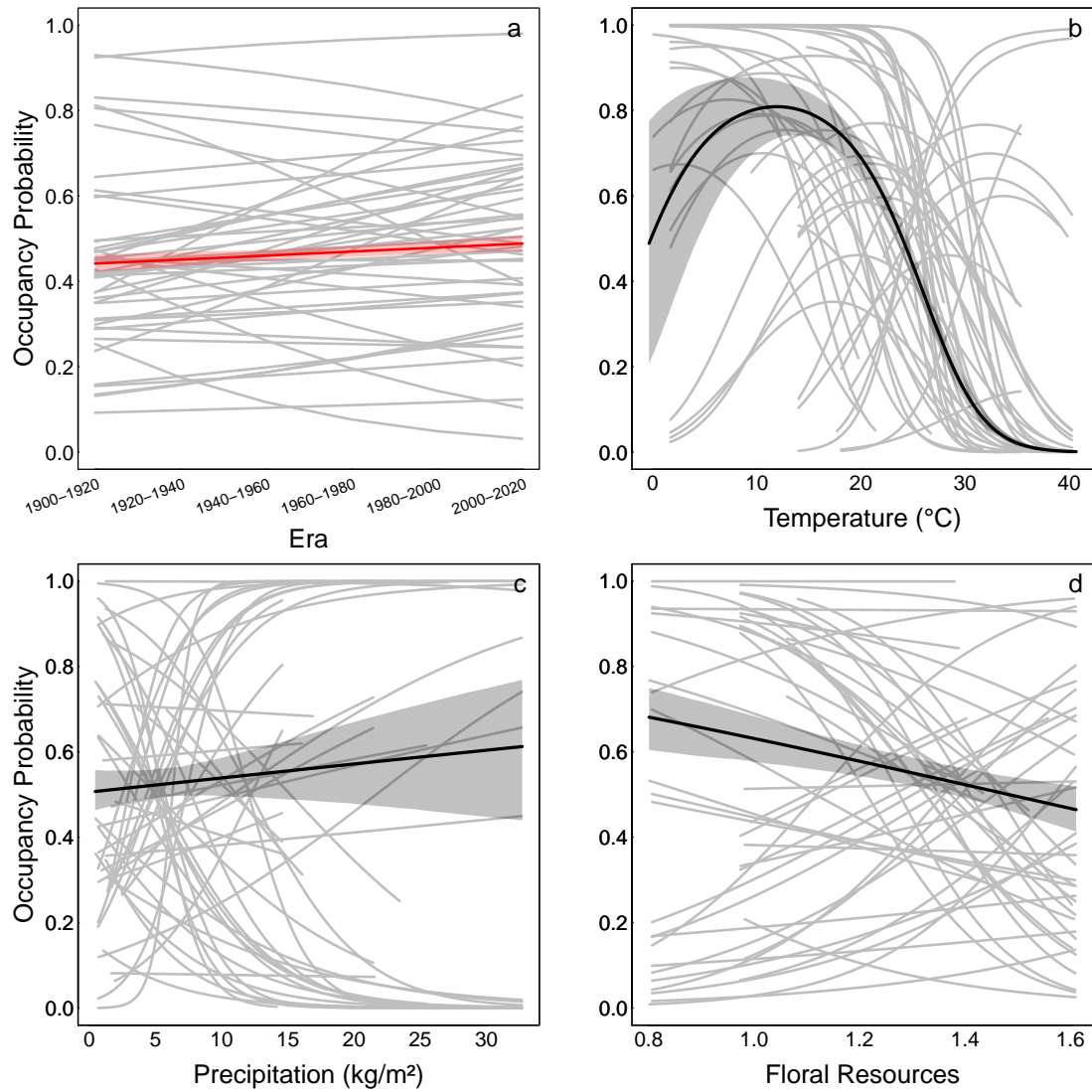


Figure S4: Same as Fig. 1, but here we also include a fixed effect of era on detection. These patterns do not differ qualitatively from those shown in the main text.

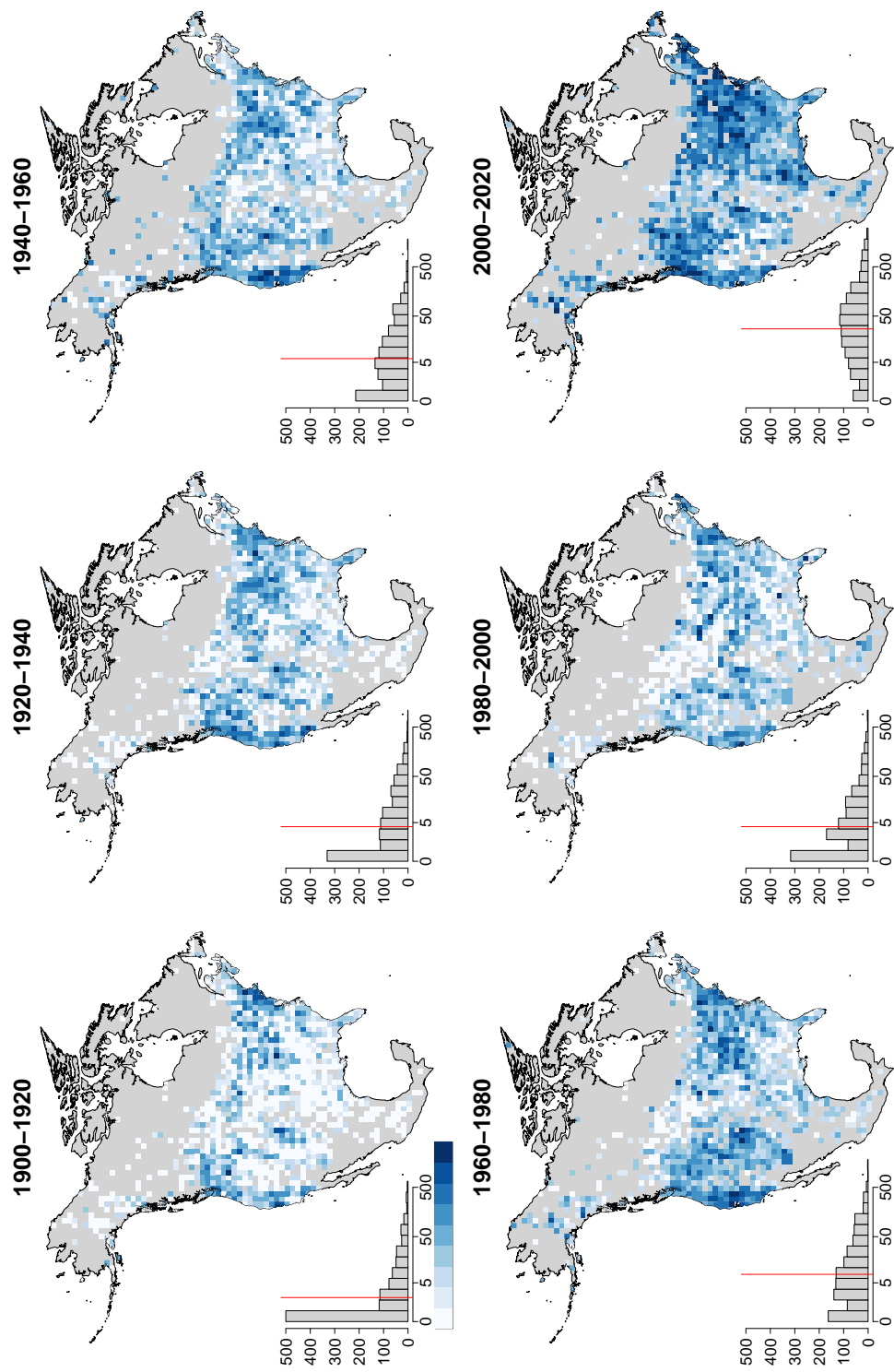


Figure S5: Occurrences per site per era at a site increases through time at a spatial resolution of 100×100 km.

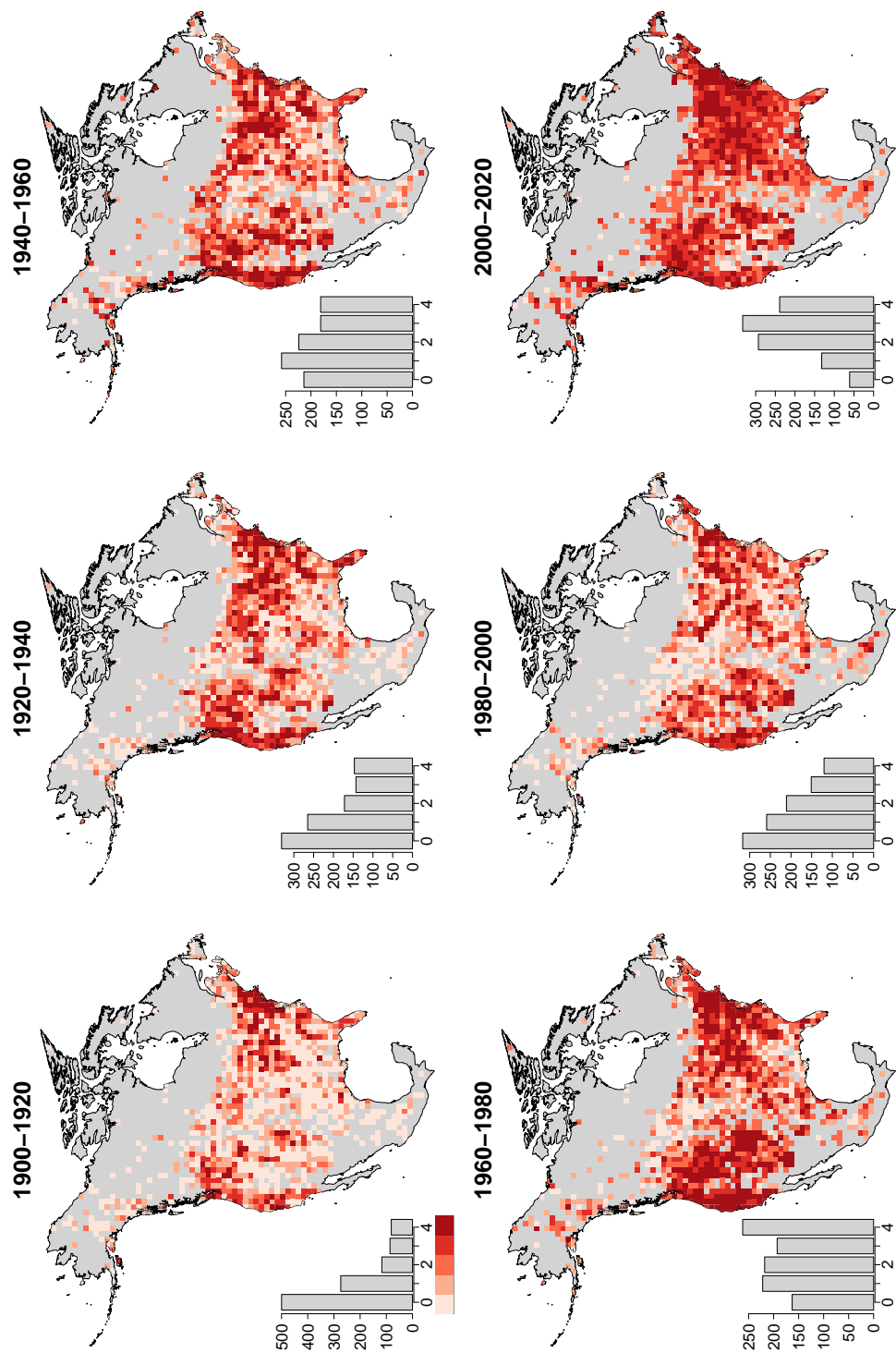


Figure S6: Number of time intervals that received visits, per site per era, at a spatial resolution of 100×100 km.

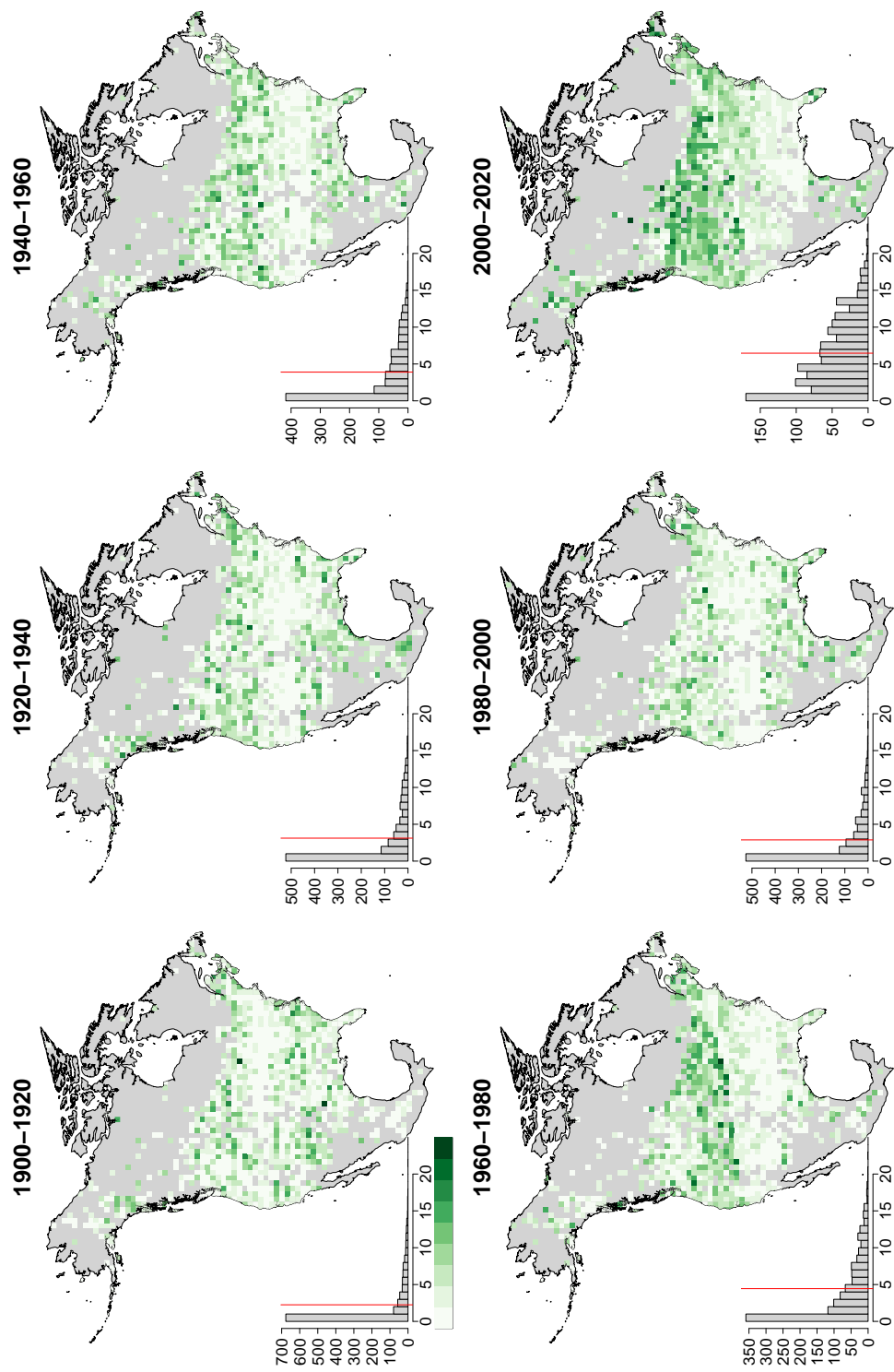


Figure S7: Number of species detected, per site per era, at a spatial resolution of $100 \times 100 \text{ km}$.

Model	Submodel	Parameter	Mean	95% BCI
Era	Occupancy	ψ_0	-0.48	[-0.83, -0.12]
		ψ_{area}	-0.07	[-0.10, -0.04]
		$\mu_{\psi,\text{era}}$	0.08	[0.02, 0.14]
		$\sigma_{\psi,\text{era}}$	0.20	[0.16, 0.26]
		$\sigma_{\psi,\text{species}}$	1.12	[0.88, 1.42]
	Detection	p_0	-0.64	[-0.67, -0.60]
		$\sigma_{p,\text{site.era}}$	0.77	[0.74, 0.79]
Environmental	Occupancy	ψ_0	-0.66	[-1.26, -0.07]
		ψ_{area}	0.11	[0.07, 0.15]
		$\mu_{\psi,\text{temp}}$	-1.57	[-2.17, -0.97]
		ψ_{temp2}	-0.30	[-0.35, -0.25]
		$\mu_{\psi,\text{precip}}$	0.05	[-0.36, 0.45]
		$\mu_{\psi,\text{floral}}$	-0.17	[-0.40, 0.04]
		$\sigma_{\psi,\text{temp}}$	1.94	[1.56, 2.43]
		$\sigma_{\psi,\text{precip}}$	1.32	[1.05, 1.64]
		$\sigma_{\psi,\text{floral}}$	0.70	[0.56, 0.89]
		$\sigma_{\psi,\text{species}}$	2.03	[1.57, 2.62]
	Detection	p_0	-0.70	[-0.74, 0.67]
		$\sigma_{p,\text{site.era}}$	0.85	[0.83, 0.88]

Table S1: Parameter estimates for models run at a spatial resolution of $100 \times 100 \text{ km}$. Bold indicates 95% Bayesian credible intervals that do not overlap zero for parameters that are not constrained to be greater than zero.

Species	$\psi_{\text{era}}[i]$	$\psi_{\text{temp}}[i]$	$\psi_{\text{precip}}[i]$	$\psi_{\text{floral}}[i]$
1 affinis	-0.3 (-0.41, -0.2)	-0.64 (-1.24, -0.08)	-0.41 (-0.89, 0.07)	0.37 (-0.06, 0.8)
2 appositus	0.06 (-0.02, 0.15)	-1.76 (-2.24, -1.35)	-0.47 (-0.73, -0.23)	0.01 (-0.26, 0.26)
3 auricomus	0.13 (0.06, 0.2)	0.23 (-0.05, 0.5)	-0.13 (-0.39, 0.12)	-1.2 (-1.46, -0.96)
4 bifarius	-0.04 (-0.14, 0.07)	-1.18 (-1.49, -0.91)	0.51 (-0.24, 1.64)	0.83 (0.61, 1.07)
5 bimaculatus	0.48 (0.4, 0.57)	-0.54 (-0.88, -0.22)	1.2 (0.9, 1.53)	-0.75 (-1.02, -0.51)
6 bohemicus	-0.22 (-0.29, -0.14)	-1.81 (-2.23, -1.46)	0.06 (-0.18, 0.37)	-0.16 (-0.41, 0.08)
7 borealis	0.11 (0.04, 0.17)	-4.33 (-5.03, -3.7)	0.1 (-0.21, 0.4)	-1.39 (-1.72, -1.09)
8 caliginosus	0.04 (-0.11, 0.18)	-2.29 (-3.2, -1.49)	0.24 (-0.23, 0.71)	-0.97 (-1.58, -0.39)
9 centralis	0.21 (0.13, 0.29)	-0.67 (-0.93, -0.43)	-0.87 (-1.1, -0.65)	0.4 (0.23, 0.57)
10 citrinus	0.07 (0.01, 0.14)	-0.71 (-1.11, -0.34)	0.75 (0.39, 1.12)	0.35 (0.04, 0.67)
11 crotchii	0.13 (-0.07, 0.32)	0.66 (-0.18, 1.58)	-2.37 (-3.26, -1.56)	-1.18 (-2.16, -0.26)
12 cryptarum	0.4 (0.22, 0.58)	-2.71 (-3.71, -1.93)	-1.06 (-1.79, -0.48)	-0.6 (-1.27, -0.03)
13 fervidus	-0.13 (-0.19, -0.07)	-3.61 (-4.17, -3.12)	-1.67 (-1.93, -1.43)	-0.01 (-0.19, 0.17)
14 flavidus	0.22 (0.15, 0.29)	-1.72 (-1.93, -1.52)	0.35 (0.19, 0.5)	0.54 (0.36, 0.72)
15 flavifrons	0.08 (0.01, 0.15)	-1.67 (-1.9, -1.45)	0.11 (-0.06, 0.3)	0.82 (0.66, 0.98)
16 franklini	0.16 (-0.14, 0.48)	-1.86 (-5.11, 1.47)	-0.57 (-1.96, 0.84)	-0.33 (-1.71, 1.03)
17 fraternus	-0.06 (-0.13, 0.01)	2.33 (1.95, 2.73)	0.19 (0, 0.39)	-0.02 (-0.2, 0.14)
18 frigidus	0.11 (0.03, 0.2)	-3.45 (-3.89, -3.05)	-0.96 (-1.24, -0.71)	0.11 (-0.16, 0.38)
19 griseocollis	0.29 (0.23, 0.35)	0.59 (0.36, 0.85)	-0.02 (-0.19, 0.14)	-1.17 (-1.44, -0.95)
20 huntii	0.21 (0.14, 0.29)	-2.03 (-2.49, -1.63)	-1.71 (-1.99, -1.45)	0.36 (0.21, 0.52)
21 impatiens	0.2 (0.14, 0.26)	-0.53 (-0.9, -0.17)	4.77 (4.29, 5.27)	-1.01 (-1.26, -0.77)
22 insularis	0.01 (-0.04, 0.07)	-1.66 (-1.87, -1.47)	-0.64 (-0.78, -0.5)	0.4 (0.27, 0.53)
23 jonellus	0.2 (-0.02, 0.43)	-2.39 (-4.24, -0.82)	-0.93 (-2, 0.95)	-0.25 (-1.51, 0.95)
24 kirbiellus	0.1 (-0.01, 0.2)	-2.62 (-3, -2.27)	-0.73 (-1.11, -0.42)	0.41 (0.1, 0.76)
25 mckayi	0.35 (0, 0.72)	-3.76 (-6.59, -1.43)	-0.33 (-2.15, 2.02)	-0.14 (-1.6, 1.19)
26 melanopygus	0.13 (0.06, 0.21)	-0.44 (-0.61, -0.29)	1.3 (1.01, 1.62)	0.42 (0.27, 0.58)
27 mixtus	0.09 (0.02, 0.15)	-1.47 (-1.66, -1.27)	0.32 (0.16, 0.49)	0.54 (0.38, 0.69)
28 morrisoni	-0.05 (-0.14, 0.05)	0.7 (0.41, 0.99)	-0.86 (-1.23, -0.52)	0.73 (0.5, 1)
29 natvigi	0 (-0.23, 0.22)	-2.56 (-3.54, -1.65)	-0.44 (-1.21, 0.25)	-0.24 (-1.13, 0.57)
30 neoboreus	0.01 (-0.24, 0.25)	-2.78 (-4.12, -1.57)	0.02 (-1.26, 1.53)	-0.49 (-1.63, 0.69)
31 nevadensis	0.24 (0.16, 0.31)	-1.06 (-1.34, -0.81)	-0.74 (-0.93, -0.56)	0.17 (0.04, 0.31)
32 occidentalis	-0.14 (-0.32, 0.02)	-3.29 (-4.05, -2.65)	0.74 (0.06, 1.47)	-0.61 (-0.96, -0.27)
33 pensylvanicus	-0.03 (-0.11, 0.05)	2.33 (2.09, 2.58)	1.44 (1.12, 1.77)	-0.42 (-0.62, -0.24)
34 perplexus	0.3 (0.22, 0.38)	-4.61 (-5.7, -3.5)	2.31 (1.7, 2.97)	0.34 (-0.08, 0.76)
35 polaris	0.07 (-0.11, 0.25)	-3.44 (-4.58, -2.44)	-0.95 (-1.78, -0.2)	-0.31 (-1.31, 0.63)
36 rufocinctus	0.09 (0.04, 0.14)	-2.77 (-3.16, -2.4)	-1.81 (-2.06, -1.58)	-0.17 (-0.32, -0.03)
37 sandersoni	0.23 (0.15, 0.32)	-1.56 (-1.97, -1.15)	0.97 (0.61, 1.35)	0.63 (0.28, 0.99)
38 sitkensis	0.07 (-0.03, 0.17)	-0.71 (-1.04, -0.37)	2.04 (1.59, 2.58)	-0.41 (-0.8, -0.04)
39 suckleyi	-0.33 (-0.42, -0.25)	-0.96 (-1.18, -0.75)	-0.35 (-0.53, -0.2)	0.1 (-0.05, 0.25)
40 sylvicola	0.17 (0.09, 0.25)	-2.07 (-2.31, -1.84)	-0.72 (-0.92, -0.53)	0.9 (0.69, 1.12)
41 ternarius	0.15 (0.08, 0.21)	-4.85 (-5.53, -4.2)	-0.45 (-0.89, -0.03)	-0.8 (-1.12, -0.48)
42 terricola	-0.07 (-0.13, -0.01)	-5.44 (-6.1, -4.83)	1.28 (0.98, 1.59)	-1.38 (-1.68, -1.11)
43 vagans	0.13 (0.07, 0.19)	-2.94 (-3.4, -2.5)	0.97 (0.71, 1.22)	-0.8 (-1.02, -0.59)
44 vandykei	0.22 (0.08, 0.36)	0.83 (0.3, 1.39)	0.27 (-0.04, 0.59)	-0.51 (-0.99, -0.08)
45 variabilis	-0.44 (-0.55, -0.32)	1.12 (0.74, 1.53)	-0.02 (-0.28, 0.24)	-0.54 (-0.76, -0.33)
46 vosnesenskii	0.12 (-0.01, 0.25)	1.9 (1.39, 2.46)	1.78 (1.22, 2.39)	-0.39 (-0.77, -0.02)

Table S2: Species specific parameter estimates for models run at a spatial resolution of $100 \times 100 \text{ km}$. 95% Bayesian credible intervals are presented inside the parenthesis.

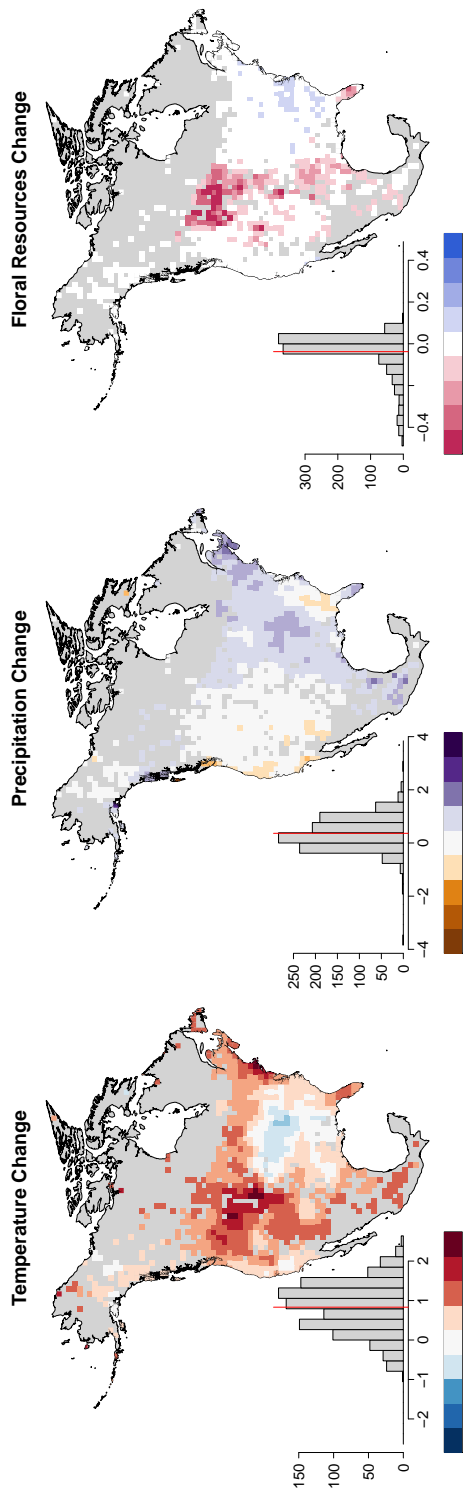


Figure S8: Change in mean temperature, mean precipitation, and mean floral resources, through time at a spatial resolution of 100×100 km.

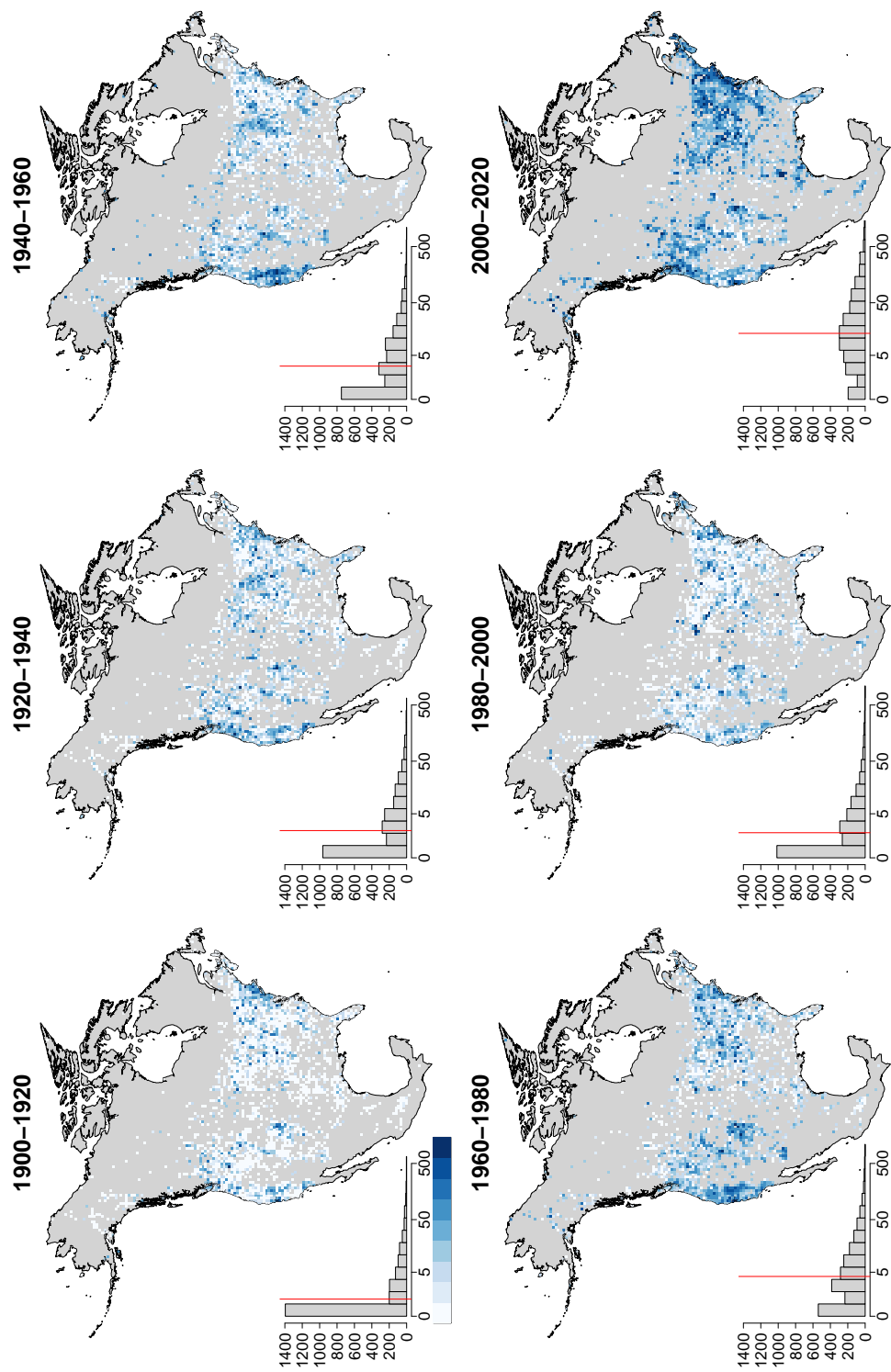


Figure S9: Occurrences per site per era at a site increases through time at a spatial resolution of 50×50 km.

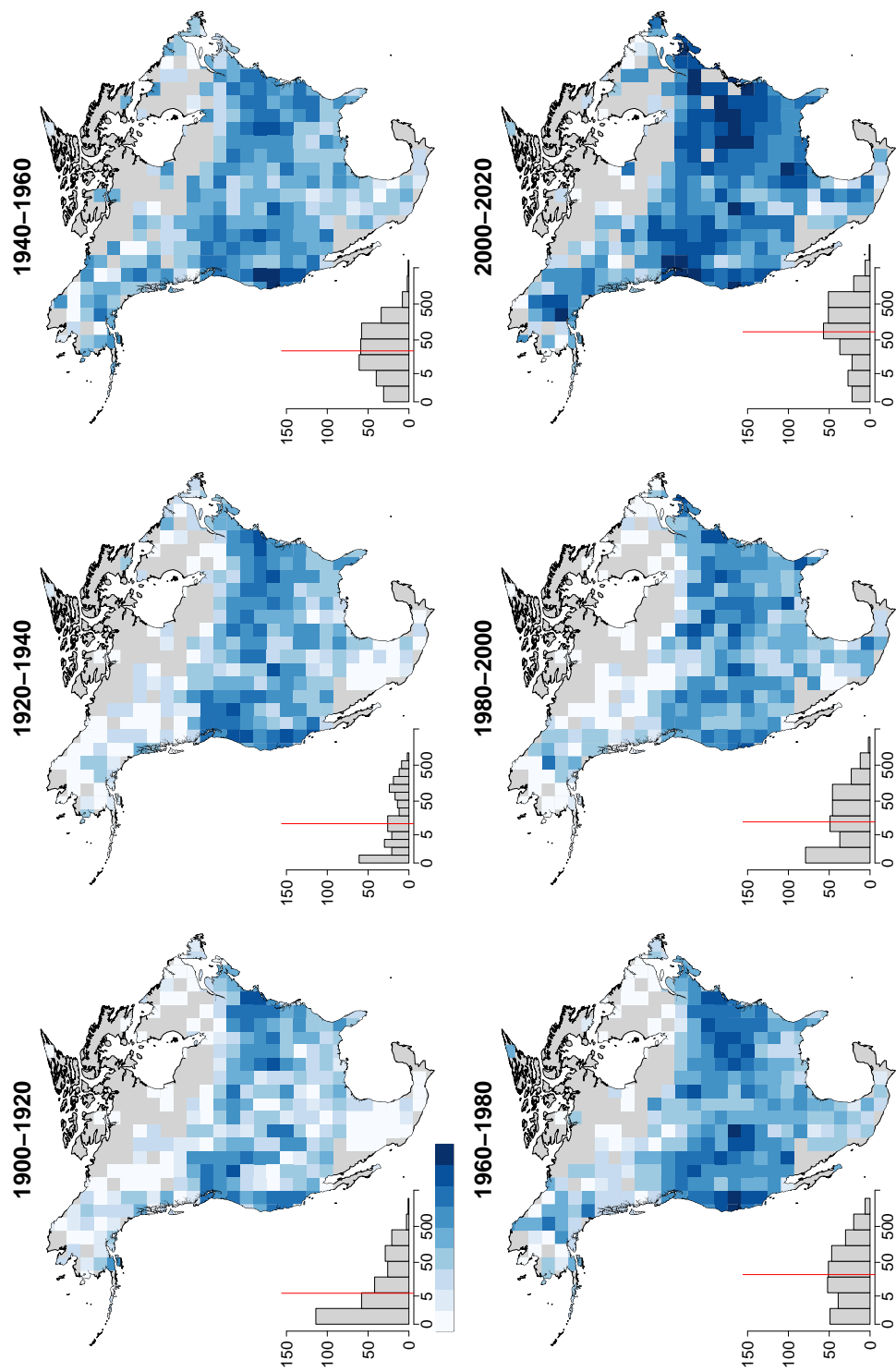


Figure S10: Occurrences per site per era at a site increases through time at a spatial resolution of $250 \times 250 \text{ km}$.

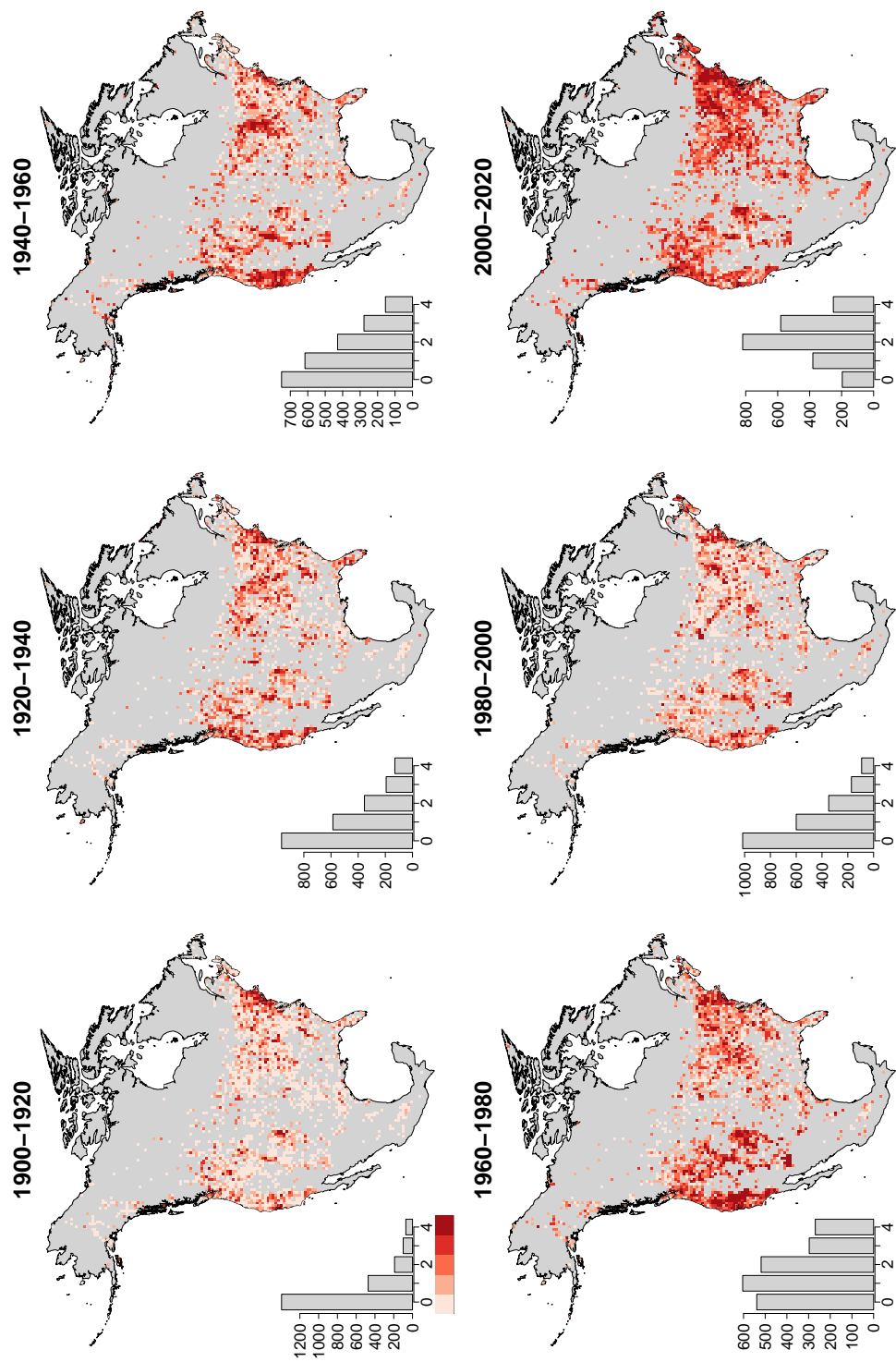


Figure S11: Number of time intervals that received visits, per site per era, at a spatial resolution of $50 \times 50 \text{ km}$.

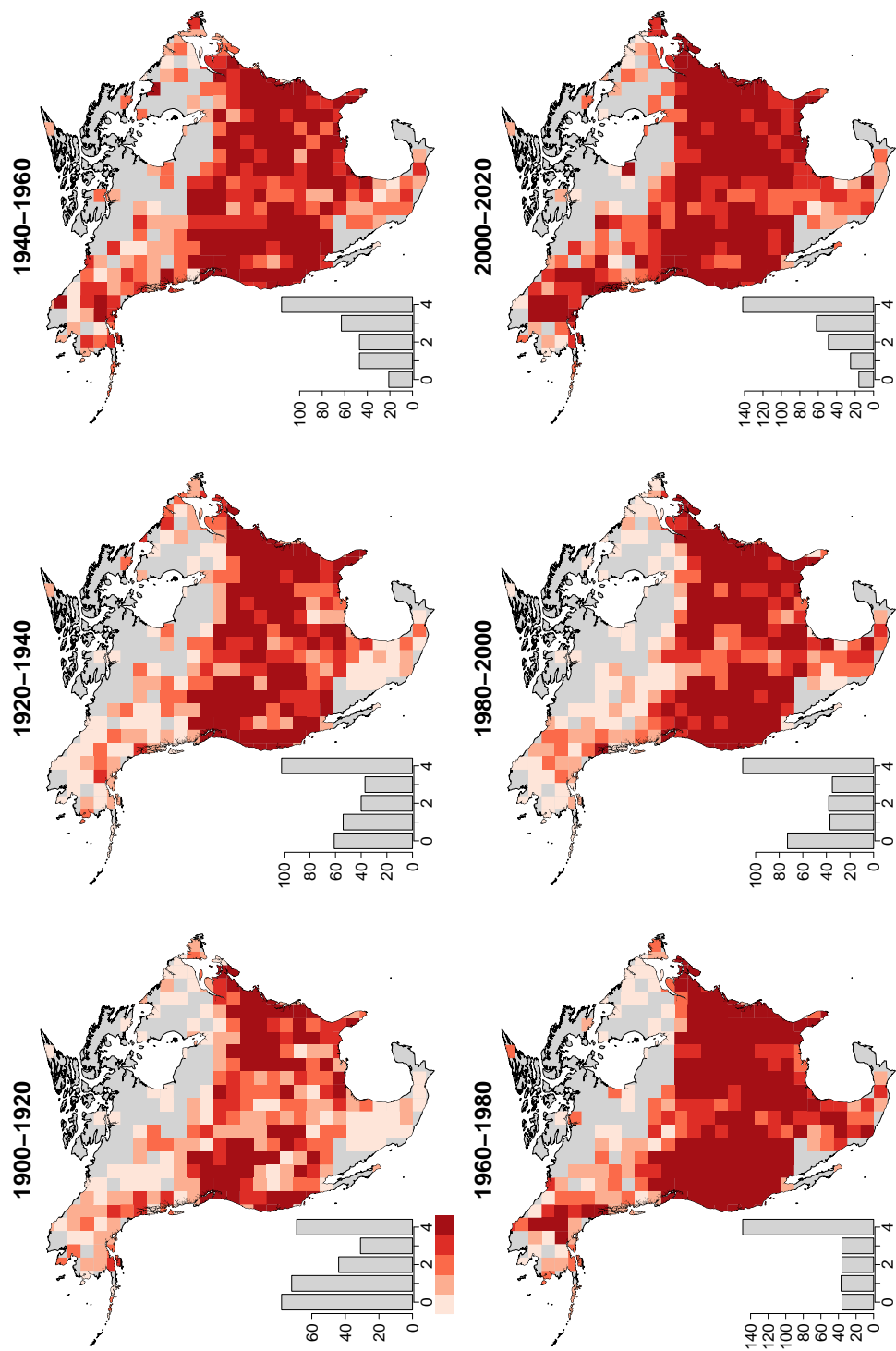


Figure S12: Number of time intervals that received visits, per site per era, at a spatial resolution of 250×250 km.

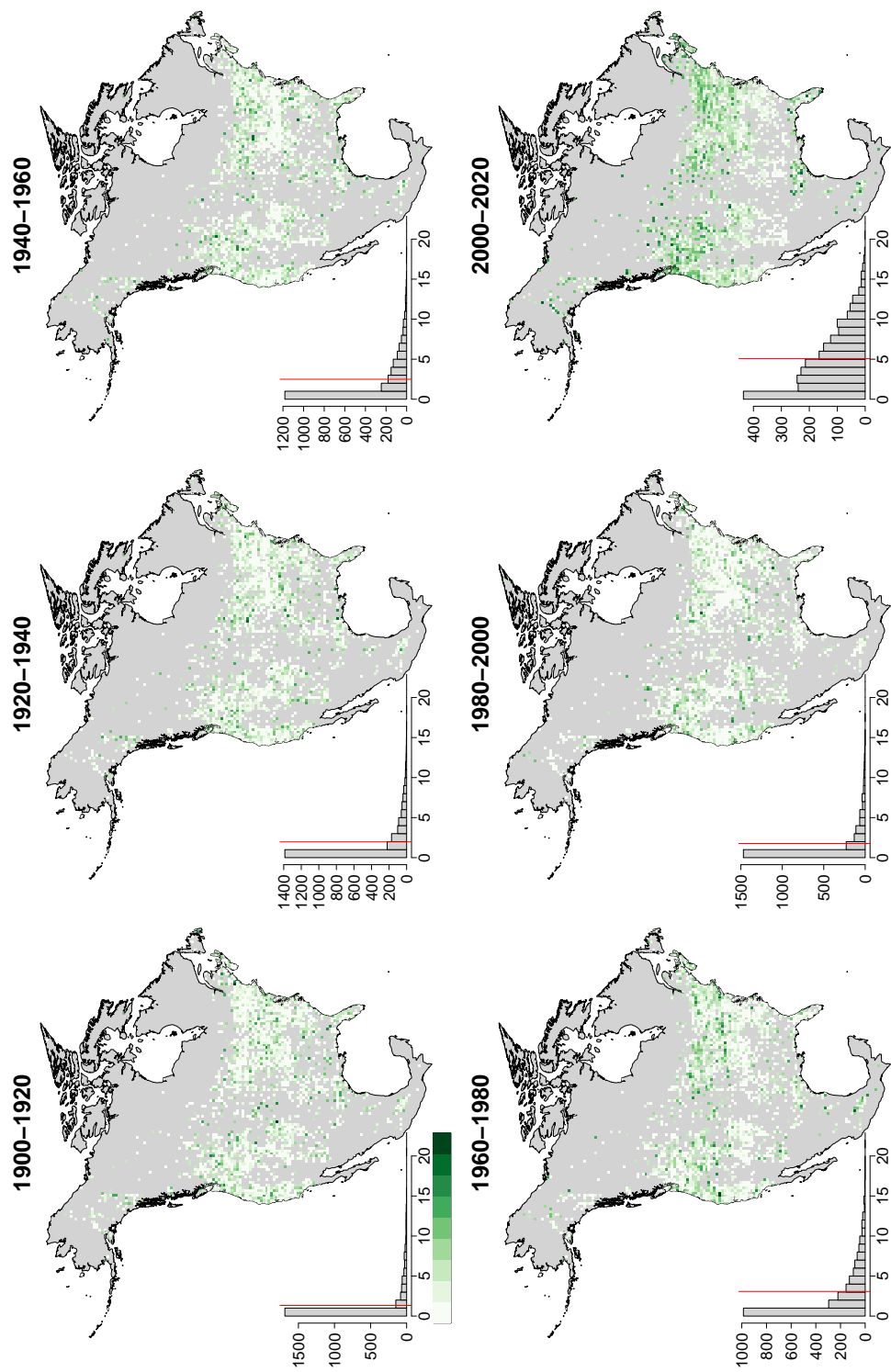


Figure S13: Number of species detected, per site per era, at a spatial resolution of 50×50 km.

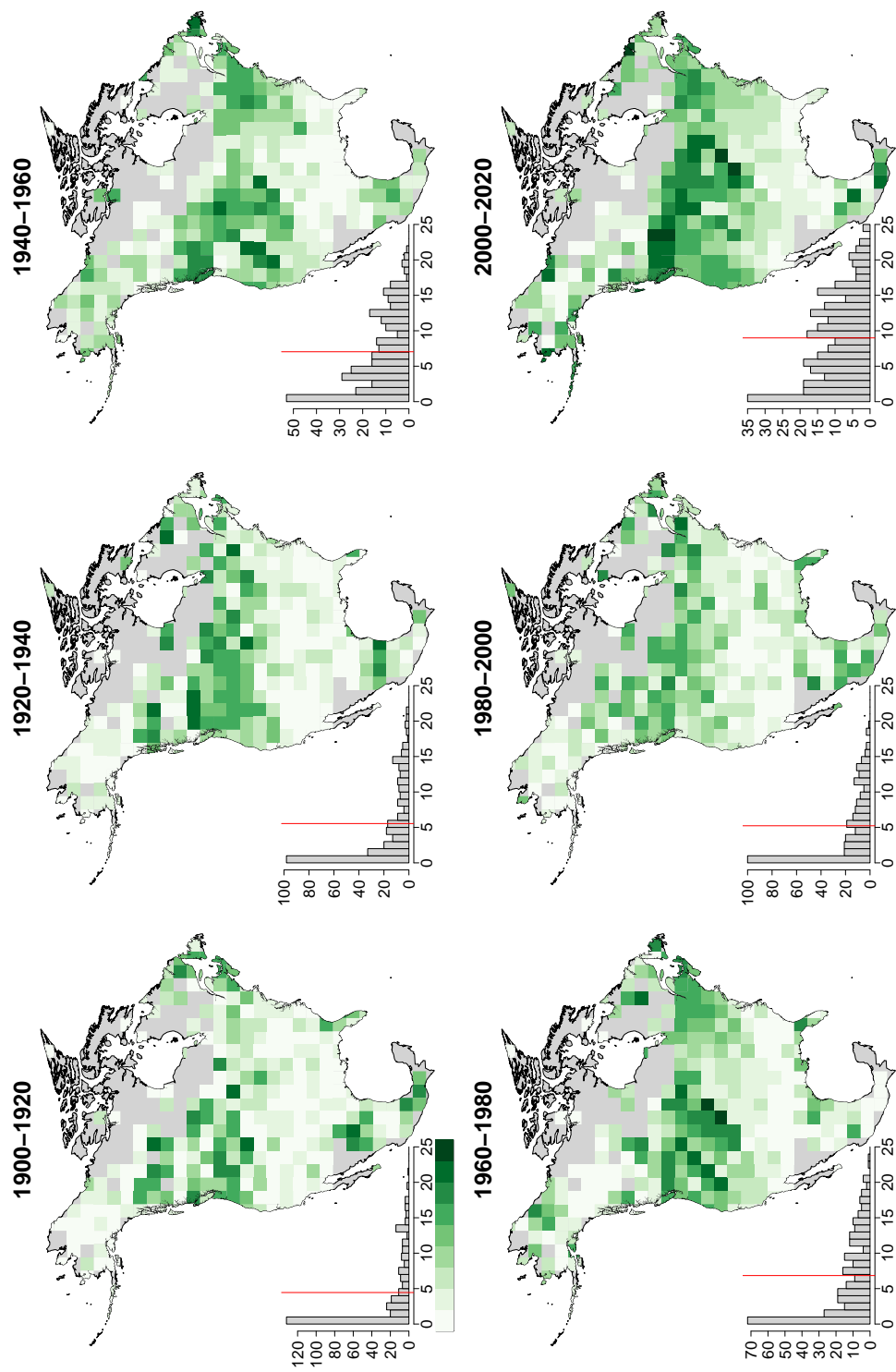


Figure S14: Number of species detected, per site per era, at a spatial resolution of 250×250 km.

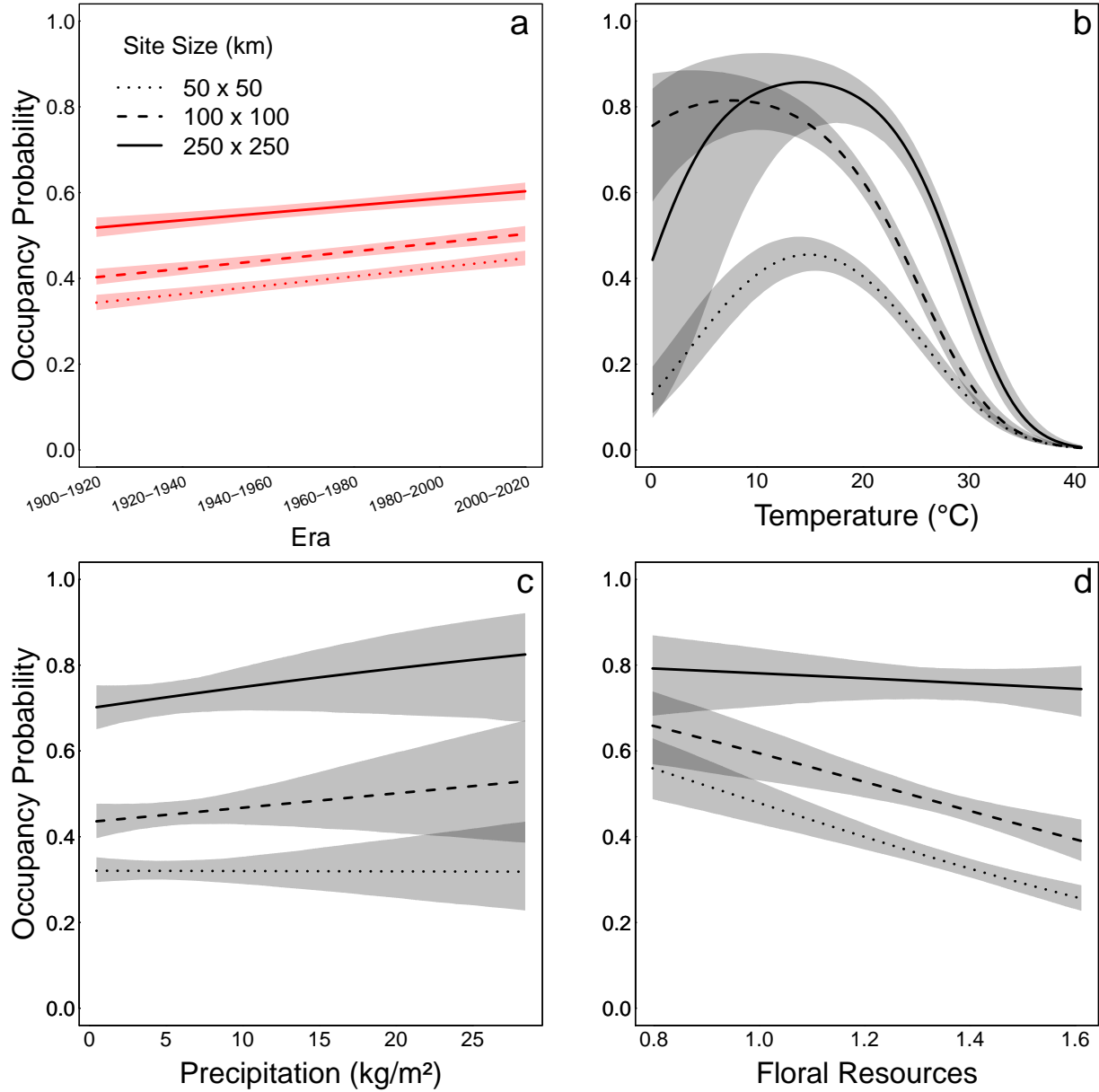


Figure S15: Qualitative occupancy trends are relatively insensitive to the spatial resolution of analysis. Shaded regions denote 95% Bayesian credible intervals. Output in (a) is from our era model and output in (b)-(d) is from our environmental model. To highlight that these are two separate models we have plotted the mean line(s) for the Era model in red and the Environmental model in black.

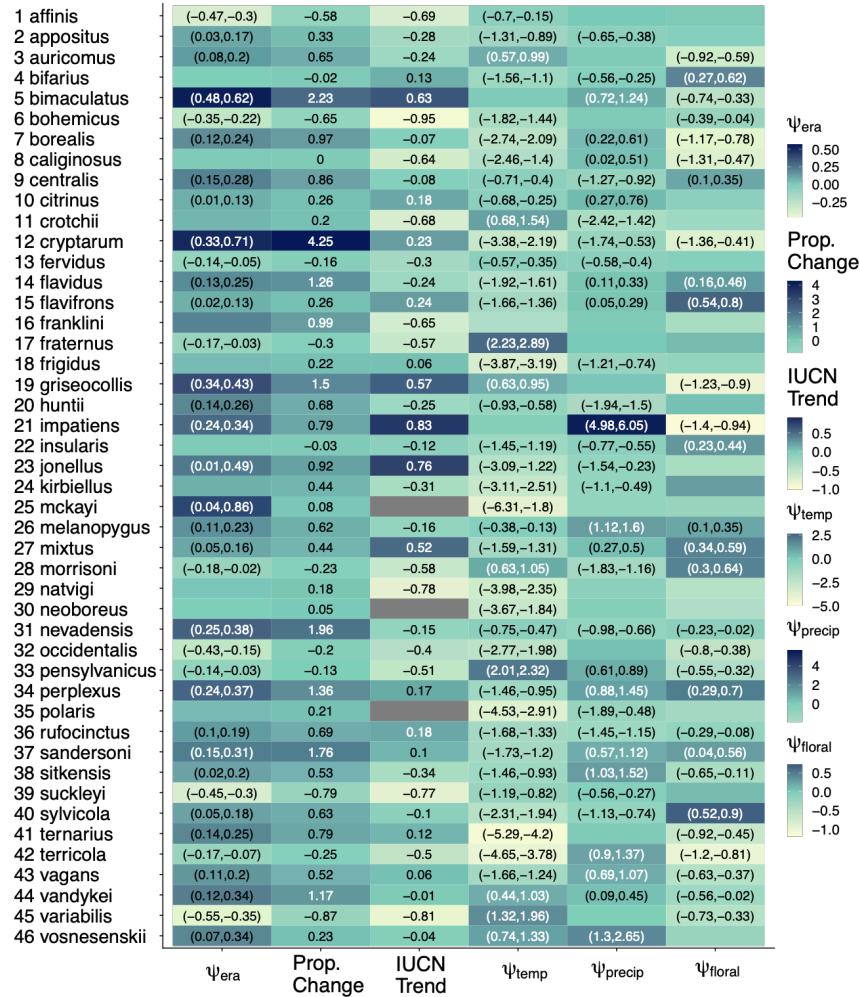


Table S3: Analog of Table 1, but for a site resolution of 50×50 km.

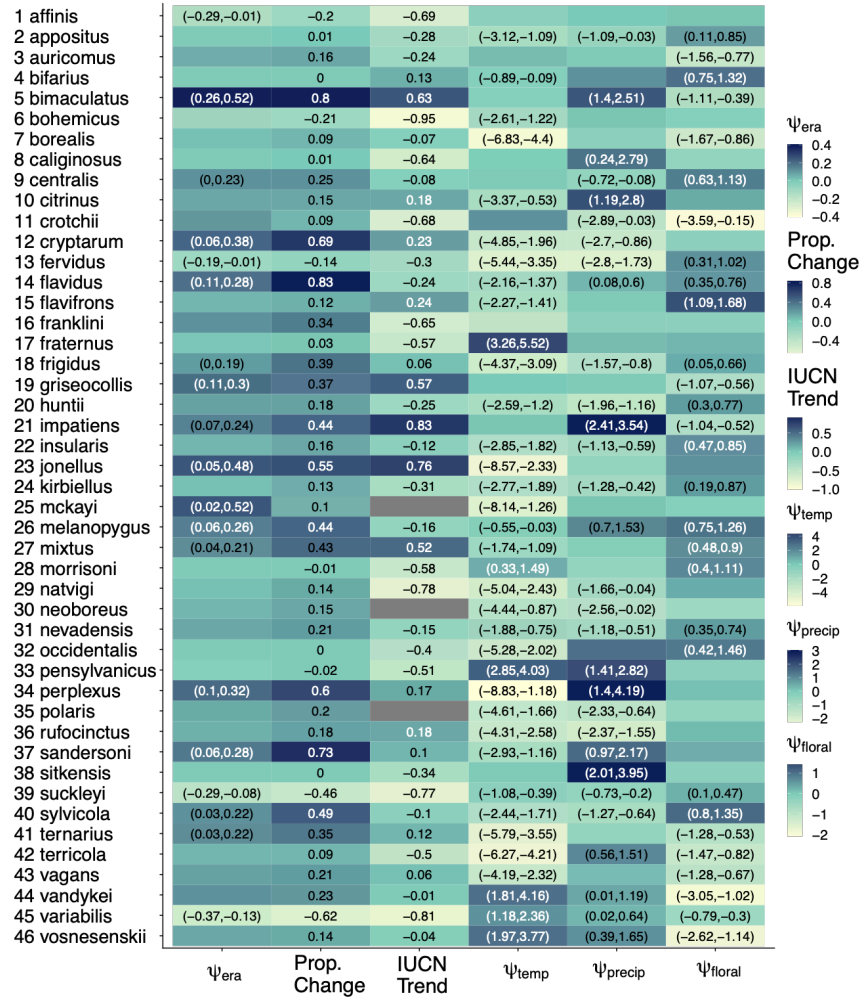


Table S4: Analog of Table 1, but for a site resolution of 250×250 km.

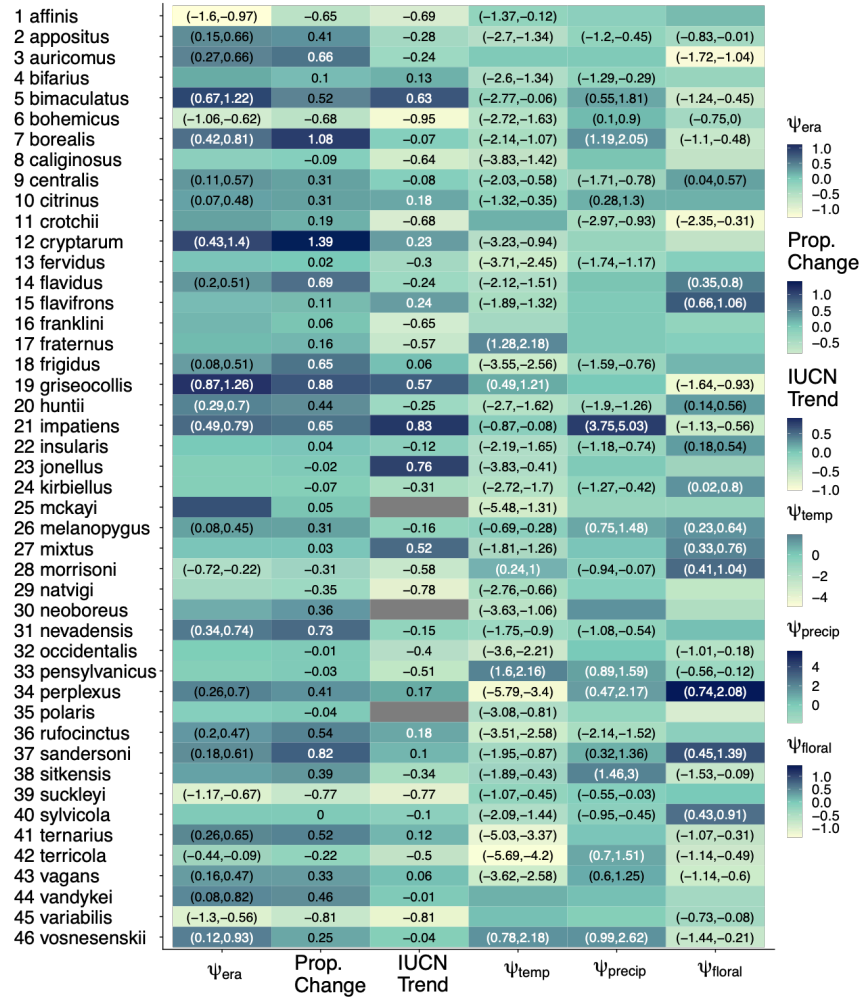


Table S5: Analog of Table 1 but here we only consider records collected from 1960 (instead of 1900). These patterns do not differ qualitatively from those shown in the main text.

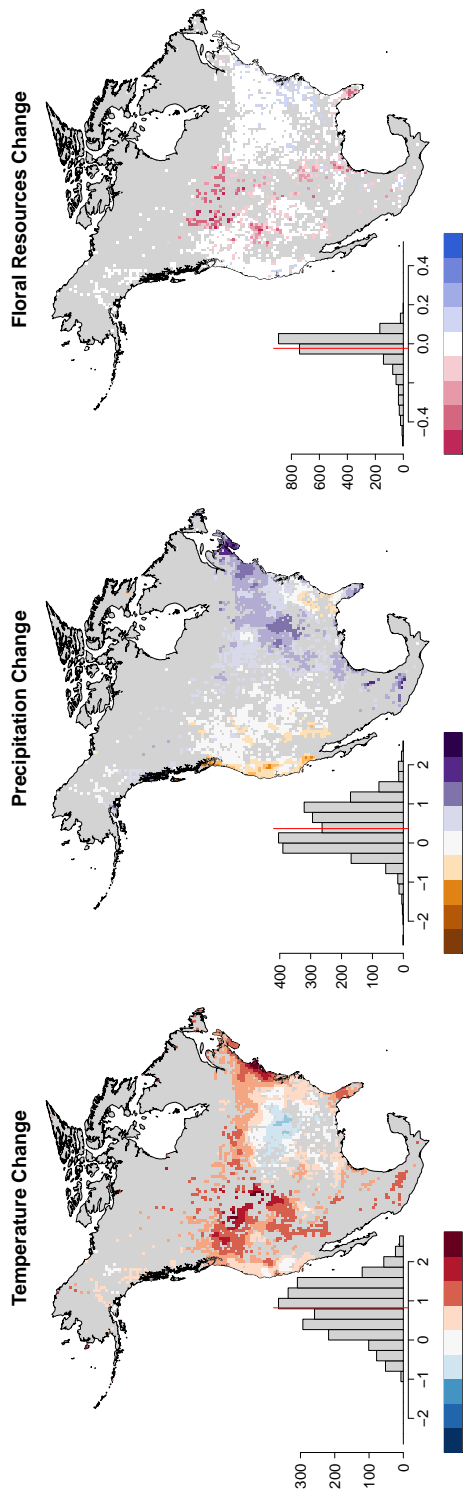


Figure S16: Change in mean temperature, mean precipitation, and mean floral resources, through time at a spatial resolution of 50×50 km.

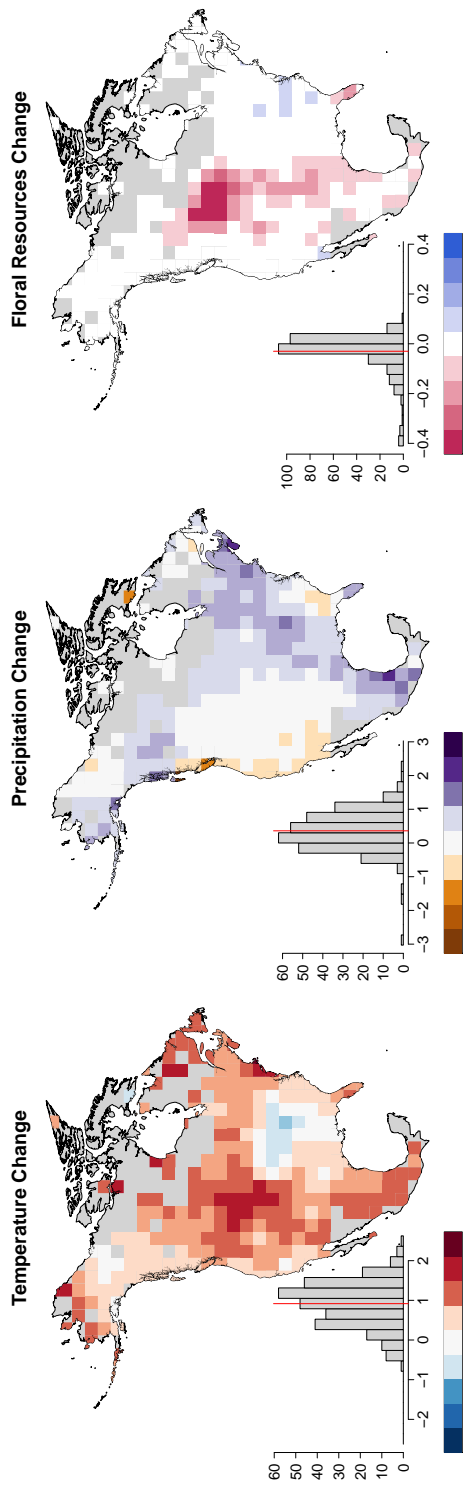


Figure S17: Change in mean temperature, mean precipitation, and mean floral resources, through time at a spatial resolution of 250×250 km.