Supplementary Information for

Recent responses to climate change reveal the drivers of species extinction and survival

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www.pnas.org/cgi/doi/10.1073/pnas.1913007117

Text S1. Extended Methods

Text S1.1. Selection of studies

We used studies summarized by Wiens (1), which was based 27 studies testing for climate-related range shifts, which were found based on a systematic review. That study focused on studies that included surveys of the "warm edge" of the species ranges on each transect (lowest elevations or latitudes). However, the species included in that study (1) were not necessarily biased to show extinctions related to climate change, since they focused on range shifts, which need not include local extinctions at all (i.e. range shifts might involve only expansion at higher elevations without extinctions at lower elevations). We specifically focused on those papers looking at elevational distributions over time in terrestrial environments, given that fewer studies focused on latitudinal gradients or aquatic species. These papers surveyed local sites over at least two time periods (at least 10 years apart) and documented whether each species persisted at each locality over time. We excluded studies that did not provide data on the occurrence of individual species at individual localities at specific time points (see below).

We included data from 10 studies that focused on elevational distributions of terrestrial plants and animals. From the remaining 17 studies included by Wiens (1), six focused on freshwater or marine organisms, and the remaining 11 did not provide sufficiently detailed information on the location of sampling sites and/or species occurrences at those sites.

Text S1.2. Locality data

We were able to obtain all the necessary information directly from three studies (2–4). In other cases, the authors provided detailed locality data but did not provide georeferenced coordinates (and declined to make these available when asked). For example, many studies only presented a map of localities along an elevational transect, and provided the elevation of each locality but not GPS coordinates. In these cases, we used Google Earth to estimate the coordinates of localities corresponding to these elevations. We acknowledge that these estimates might not match exactly the locations of the surveyed sites. However, the main driver of climate among nearby localities along an elevational transect should be elevation (e.g. general linear models fit between elevation vs. annual mean temperatures within each of the 10 transects yield r^2=0.988–0.989, all P<0.001). Therefore, the broad-scale climatic data obtained here should generally correspond to those of the actual sites, especially at such fine geographic scales. Additionally, we ensured that these locations were on the same slope (i.e. north facing vs. south facing) as in the original study, since slope could also impact local climate.

Below, we give a detailed description of how we obtained georeferenced locality data for studies that did not provide site coordinates. Brusca *et al*. (5): because surveys were conducted along a single road (Catalina Highway, Tucson, Arizona, USA) we used Google Earth to geocode each sampled based on their elevation. Chen *et al*. (6): We used Figure 1 of that paper and the elevational data provided therein to estimate coordinates at each sampling site using Google Earth. Felde *et al*. (7): in their paper, their *SI Appendix,* Table A1 provides details on both the lowest and highest elevational occurrences of each species. Because surveys were conducted in a U-shaped valley, the same elevation can be estimated for different localities. We therefore randomly sampled a single locality among all the possible sites at a given elevational band. We used the 1’ altitude raster for Norway (see http://www.viewfinderpanoramas.org/dem3.html) cropped to the study area (longitude=8.85–9.13ºE; latitude=61.45–61.52ºN). Forero-Medina *et al*. (8): we georeferenced the five sampling sites in their study based on their Figure 1 and using Google Earth. Freeman and Freeman (9): for both transects (Mt. Karimu, Karkar Island), we randomly selected a single site among all locations at the same elevational band detailed in their supplement. Menendez *et al*. (10): sampling sites and species ranges were obtained directly from the paper. For several species at Sierra Nevada, some minimum and maximum elevations did not match those of the surveyed sites. We therefore used the closest surveyed location to correct the position for these records. Ploquin *et al*. (11): these authors kindly provided us with their dataset of georeferenced localities. Coordinates were transformed from UTM coordinates (29N and 30N zones) to WGS84.

Text S1.3. Climatic data

We obtained climatic data from georeferenced localities using the CRU TS 3.22 dataset (12). We analyzed CRU NetCDF files for daily mean temperature (CRU code: tmp), monthly average daily minimum temperature (CRU code: tmn), monthly average daily maximum temperature (CRU code: tmx), and precipitation (CRU code: pre). Climatic variables were downscaled to 1 km at each surveyed site using the R package Tusk based on WorldClim raster files (13–18). The resulting dataset provided data on climatic variables for each year between 1901 and 2013 (CRU dataset) at a high resolution (~1 km at the equator). The historical survey date for one study (7) falls outside of the available climatic coverage in our dataset (*SI Appendix,* Table S1), but by only one year. In this case, we assumed analyzed climatic data for the closest date in the dataset (i.e. 1901 instead of 1900; *SI Appendix,* Table S1). This should have no impact, given the one-year difference and given that this time period is well before the major global warming caused by anthropogenic activities. Other potentially relevant datasets either lacked climatic data for exact dates (e.g. WorldClim), or had such a coarse resolution that it was difficult to distinguish climatic conditions at different sites within the same transect [e.g. 2.5º resolution for NCEP/NCAR reanalysis (19)].

For each site, we fit the Empirical Mode Decomposition (EMD) model using the R package EMD (20) based on the entire CRU temporal window [i.e. oldest and modern survey dates (22)]. We used default parameters in the function emd, which are optimized for detrending noise from climatic time series [see below (20,21)]. When sampling was conducted over multiple years for either the historical survey or modern resurveys, we selected the oldest year for the historical survey, and the most recent date for the resurvey (see below for justification).

EMD reduces the effect of year-to-year stochasticity on the estimated value of each climatic variable for each year (21). Many other methods are currently available to extract long-term trends from climatic data [e.g. regression (22,23), moving mean (24,25), Fourier-based filtering (26)]. However, EMD has shown to be especially accurate for extracting signal from nonlinear and nonstationary datasets, such as climate (21,27,28). EMD does not use a fixed set of "windows" to extract climatic trends. Instead, the number (frequency) and duration (amplitude) of temporal windows depend on the analyzed dataset (21,28). EMD has been shown to be a reliable method for removing stochastic noise from climatic data (21,27–31). Moreover, this approach has been widely used for climatic data. For example, the first paper using the EMD approach for climate-change research (21) has been cited 650 times already, as of November 2019.

Nevertheless, we performed additional analyses based on datasets that summarize mean climatic values for each variable during a 5-year window preceding each survey, and a 10-year window. Results based on these analyses are summarized and compared to those from EMD in

SI Appendix, Text S3.3. These results were generally similar to those based on EMD, especially those using the 10-year window

After use of EMD, we then followed the variable definitions in O'Donnell and Ignizio (32) to calculate 19 climatic layers (Bioclim variables Bio1–Bio19; see *SI Appendix*, Table S2). Thus, we focused on climatic variables that have been previously hypothesized to represent important drivers of species geographic distributions (33).

Text S1.4. Data analysis

We generated four datasets to describe the climate at each locality over time, for each of the 19 Bioclim variables (*SI Appendix*, Table S2): (i) historic (for the year of the initial survey of the site); (ii) modern (the year of the resurvey); (iii) absolute change over time (difference between the historic and modern values); and (iv) rate of change (absolute change between surveys divided by the time interval between surveys, which is the date of the resurvey minus the date of the original survey).

In four of the 10 analyzed studies, the initial surveys for each site were conducted over the course of two years (*SI Appendix*, Table S1). For these studies, we selected the earlier date for analyses (e.g. 1981 for surveys conducted over 1981–1982; *SI Appendix,* Table S1). One study (10) had initial surveys conducted over two decades (1980s, 1990s), but each site was sampled in a specific two-year period, and so we used the appropriate set of dates for each site. One resurvey spanned two consecutive years (10)' and here we selected the later date (i.e. 2007 for 2006–2007). Overall, this strategy spanned the maximum range of dates. However, our choice of years should have very little impact on the results, given the relatively long time periods between surveys, and that we used EMD to reduce the stochastic effects of year-to-year climate on long-term trends.

We used two approaches to estimate the potential importance of each climatic variable for local extinctions. For the first approach, we focused on whether there was any local extinction among any of the species surveyed at a local site, and which climatic variables predicted which sites experienced these local extinctions. For the second approach, we tested for relationships between climatic variables and the frequency of local extinction among all the species surveyed at each site. Although this second approach might initially seem more appropriate, local extinctions were entirely absent at the majority of sites (75%). Therefore, our analyses in the main text focused on predicting which sites had any local extinctions at all, rather than on the frequency of local extinction among sites.

Text S1.4.1. Occurrence of local extinction

We used a binary coding to analyze which climatic variables were associated with local extinctions among sites. Specifically, sites were coded based on whether or not at least one species experienced local extinction at that locality. We then used Discriminant Analysis of Principal Components (DAPC) to determine the variables that best differentiated between sites with and without local extinction. DAPC finds the linear combination of variables that maximizes the difference between groups and minimizes within-group variances. The two groups here are sites with and without local extinctions. DAPC were fit independently for three climatic datasets (i.e. historical, absolute change, and rate of change) using the R package adegenet (34), after scaling each variable, and retaining the number of principal components associated with the optimal alpha score [using the optim.a.score function in the same package;

(35)]. The estimated importance of each climatic variable in differentiating between sites with and without local extinction within each dataset is summarized as a DAPC loading (*SI Appendix*, Table S3). Variables with larger DAPC loadings are better at discriminating between sites with and without local extinction. We focused primarily on the variables with loadings in the top 95th percentile in each dataset. The top predictors of local extinction were generally similar across the three datasets (*SI Appendix*, Figure S1).

No *P*-values are associated with DAPC analyses. Therefore, we used univariate logistic regression models to test for significant effects of each climatic variable on the occurrence of local extinction across sites. We fit univariate generalized lineal models in R version 3.4.2 (15). We summarized the estimated odds ratio for every climatic variable. In this case, odds ratios smaller than one indicated an inverse association between the predictor variables and local extinction across sites. Conversely, odds ratios larger than one indicated that increases in the predictor values are associated with a higher likelihood of local extinction.

Text S1.4.2. Frequency of local extinctions

For our second approach, we summarized the frequency of local extinctions at each site and then tested which climatic variables were most strongly related to these extinction frequencies. To estimate the frequency of local extinction at each site, we divided the total number of species that were locally extinct at that site (based on the resurvey) by the total number of species that were historically present (based on the original survey). We then used two methods to infer relationships between extinction frequencies and climatic variables among sites.

First, we used a multivariate approach to estimate the relative importance of each climatic variable. This approach accounted for the correlated structure of the predictors in our dataset (i.e.

the 19 climatic variables). Specifically, we assessed variable importance using the Lindeman, Merenda, and Gold (LMG) index, estimated from alternative multiple linear regression models (36–39). The LMG index is calculated as the difference in r^2 from adding the analyzed predictor to a model containing a subset of the other variables. Next, the LMG is computed for the analyzed predictor by computing the average difference in r^2 over all possible model subsets (36–39). Better predictors have larger values for the LMG index. The LMG index was calculated using the calc.relimp function in the R package relaimpo (36–39). LMG estimates for each variable are summarized in Dataset S4.

Second, we fit univariate linear regression models for the relationship between the frequency of local extinction at each site and each of the climatic variables (independently for each climatic variable). Univariate regression models were fit using the lm function in R version 3.4.2 (15). These models were not used to estimate the relative importance of each climatic variable in predicting extinction frequencies (given potential correlations among variables). Instead they were used to test relationships between climate and extinction for variables identified from the LMG analysis. For those variables found to be most important using LMG (top 95th LMG index within each climatic dataset; Dataset S4), we also report the univariate regression results (i.e. slope, r^2, P).

Overall, results based on extinction frequencies were similar to those based on the presence/absence of local extinction among sites. Based on the variables with the highest LMG, sites with higher frequencies of local extinction were warmer during the initial historical survey of each site, relative to sites with lower extinction frequencies (historical mean annual temperature, Bio1: LMG=8.15%, slope=0.015, r^2=0.169, P<0.001; historical maximum annual temperature, Bio5: LMG=6.37%, slope=0.019, r^2=0.134, P<0.001; historical minimum annual temperature, Bio6: LMG=11.66%, slope=0.013, r^2=0.190, P<0.001; Dataset S4).

When analyzing changes in climate between surveys (both the absolute change and rate of change), we found that the change in annual temperature range (Bio7) was the best predictor of extinction frequencies across sites (absolute change in Bio7, LMG=17.39%, slope=0.142, r^2=0.194, P<0.001; rate of change in Bio7, LMG=20.82%, slope=3.577, r^2=0.129, P<0.001). However, because this variable is defined as the difference between annual maximum (Bio5) and minimum temperatures (Bio6; *SI Appendix*, Table S2), we examined whether increases in Bio7 were primarily driven by increases in Bio5 (maximum temperature) or decreases in Bio6 (minimum temperature). We found that the increase in maximum annual temperature (Bio5) was the main driver of the change in Bio7 (Dataset S4). For the absolute change in climate, we found that the second best predictor of the frequency of local extinctions was maximum temperature (LMG for absolute change in Bio5=9.14%, for absolute change in Bio6=4.81%). Linear regression models fit between extinction frequency and climatic variables also indicated that sites with higher extinction frequencies had smaller changes in minimum temperatures between surveys (absolute change in Bio6, slope=-0.720, r^2=0.091, P<0.001) but larger changes in maximum temperatures (absolute change in Bio5, slope=0.359, r^2=0.114, P<0.001).

We also found similar results based on the rate of change in climate, which also indicated that Bio5 was the main driver of change in Bio7. First, the rate of change in Bio5 is a better predictor of local extinctions relative to rate of change in Bio6 (LMG for rate of change in Bio5=17.21%, Bio6=5.26%). Second, sites with higher frequencies of local extinction experienced slower changes in Bio6 (rate of change in Bio6: slope=-3.934, r^2=0.053, P<0.001), but faster changes in Bio5 (rate of change in Bio5: slope=6.385, r^2=0.111, P<0.001).

Finally, although mean annual temperature (Bio1) was not a top variable picked by the LMG index, we found that sites with higher extinction frequencies had significantly less change in mean annual temperature between surveys (absolute change in Bio1 slope=-0.198, r^2=0.176, P<0.001; Dataset S4). This result is congruent with those based on the occurrence of local extinction across sites (see main text; Fig. 1; *SI Appendix*, Fig. S1).

Text S1.5. Projected climate change and extinction

We explored the potential effects of projected climate change on overall extinction within transects for the year 2070, based on patterns of extinction and dispersal in the recent past. Climatic conditions for 2070 were estimated by averaging projected maximum temperatures between 2061 and 2080. Note that here and throughout this section, when we refer to species distribution and extinction, we are specifically referring to their distribution and extinction within the elevational transect in which they were studied.

Predicted climatic conditions at each sampled site for 2070 were obtained using the WorldClim raster files at a 0.5’ resolution [~1 km at the equator (13)]. We analyzed projected climate change scenarios (14) based on the combination of up to 19 General Circulation Models (GCMs) and four different Representative Concentration Pathways (RCPs). Results presented in the main text are based on an intermediate scenario of predicted climate change (RCP4.5), and a second scenario that assumes minimal or no mitigation of climate change during the next few decades, and thus much more extensive climate warming (RCP8.5). For each of these scenarios, we followed standard practice (40,41) and estimated extinction for each RCP based on the mean of estimates derived from all available GCMs (*SI Appendix*, Tables S4, S7–S9). The RCP4.5 scenario of predicted climate change has been widely used for predicting the impacts of future climate change on species distributions (42–44). This scenario is congruent with the currently implemented policies related to greenhouse emissions (45). The RCP8.5 scenario assumes an overall increase in greenhouse gas emissions during the next several decades. Unfortunately, this scenario has recently been indicated as being highly likely given trends in greenhouse gas emissions over the past two decades (46,47).

We generated results for all four available RCPs, but we did not focus our main results on RCP2.6 or RCP6.0. The RCP2.6 scenario assumes a significant decrease in carbon emissions and is therefore currently considered to be unrealistic (46–48). Achieving the goals that are assumed by the RCP2.6 scenario would require participation of all countries in global policies directed toward mitigating climate change effects, a reduction in greenhouse gas emissions by 70% (relative to the early 2000s), and major changes in energy use (49). Additionally, 21% of GCMs (4 of 19 GCMs) are not available under this scenario (RCP2.6). Results for the RCP6.0 scenario are represented in the range provided by RCP4.5 and RCP8.5. Furthermore, 37% of GCMs (7 of 19) are lacking for RCP6.0 (37,49). In contrast, at least 90% of GCMs are available for both RCP4.5 (19 of 19 GCMs) and RCP8.5 (17 of 19 GCMs).

Based on the different future climate projections (12–19 GCMs and four RCPs), we analyzed four different aspects of species responses to projected climate change. First, we estimated the minimum change in maximum annual temperatures that species will likely experience in a given time period (given our result that maximum annual temperature is generally the most important predictor of local extinctions; see main text). For this, we estimated the difference between the predicted and current maximum annual temperatures across the species' current geographical range (see details below). Second, we analyzed the role of dispersal in potentially allowing species to avoid extinction within transects by moving upwards in elevation and tracking their current climatic niche. Third, we examined the change in maximum annual temperatures that local populations have tolerated in the past without going extinct (niche shifts). Fourth, we examined the combined effects of dispersal and niche shifts in reducing the likelihood that a species will go extinct within their transect.

Text S1.5.1. Minimum increase in maximum annual temperatures

For each species, we evaluated whether the maximum annual temperatures that are present across their current elevational range (at the time of the resurvey) will still be present within their current elevational range in the future. Here and throughout, "current" refers to the time of the relevant resurvey for each species and site. For each species, we first estimated the current maximum annual temperatures at each site across their current distribution. Next, we used the predicted maximum annual temperatures for 2070 to estimate future annual maximum temperatures at each site across their current distribution. If no overlap was found between the future and current maximum annual temperatures across the species current distribution, we considered the species to be exposed to unsuitable conditions across their current range (within the transect).

Next, for those species predicted to be exposed to unsuitable maximum annual temperatures throughout their current distribution on the transect, we estimated the minimum difference between current and future maximum annual temperatures across their current distribution. Specifically, the minimum difference was estimated by subtracting the current value of the maximum annual temperature at the species' current warmest site in their geographic range on the transect (i.e. based on the time of the resurvey) from the projected maximum annual temperature (for 2070) at the coldest site in their current range.

We assumed that species are potentially able to survive the minimum shift in maximum annual temperatures in their current range by either dispersing to higher elevations, tolerating higher temperatures (niche shift), or by doing both simultaneously. The analyses described below explore each of these three possibilities.

Text S1.5.2. Dispersal

We assessed whether species are likely to be able to disperse fast enough to avoid extinction within their transects by 2070. First, we estimated the absolute change in the upper limit of the elevational range for each species that expanded its upper elevational range between surveys. To do this, we subtracted the historical maximum elevation of the species' distribution on the transect (i.e. from the time of the initial survey) from the current maximum record (i.e. from the time of the resurvey). Then, the rate of upward dispersal was estimated by dividing the absolute change in maximum elevation between surveys by the time between surveys. Again, when surveys were conducted over multiple dates (*SI Appendix*, Table S1), the time between surveys was calculated based on the earliest date of the historical survey, and the latest date of the modern resurvey (see Data Analysis section above for details).

Next, we estimated the amount of cooling that can potentially be gained through upward dispersal in the future (2070) using the following equation (units are indicated in parentheses; time is in years):

$$\mathit{Potential\ cooling}\ (\mathrm{sp_i}, \mathrm{t}) = \mathit{upra}_{\mathrm{sp_i}} \left(\mathrm{m}/_{\mathrm{year}}\right) * \Delta\mathrm{Bio5}_{\mathrm{transect(spi)}}\ (^{\circ}\mathrm{C/m}) * (\mathrm{t} - \mathrm{mod_i})$$

Specifically, for each species (sp_i) that was recorded as dispersing upward in the past (between surveys), we multiplied the upward dispersal rate ($upra_i$) by the mean change in maximum annual temperatures (Bio5) with elevation across the species' elevational transect ($\Delta Bio5_{transect(spi)}$; see regressions for each transect in *SI Appendix,* Table S6), and by the number of years between the year of the modern survey (mod_i) and the future date (t=2070). The final units for potential dispersal-related cooling are in ºC.

For each of the upward-dispersing species, we evaluated whether this potential cooling gained through upward dispersal could be as large as the change in maximum annual temperatures over time. We focused on two alternative scenarios. First, an unconstrained scenario in which species disperse upwards with no spatial constraints. Second, a scenario where the height of each mountain range (on which the elevational survey was performed) constrained the amount of cooling that can be gained through upward dispersal. The latter scenario is clearly more realistic (50).

Unconstrained scenario: For each upward-dispersing species, we evaluated whether the cooling gained through recent dispersal (between surveys) was larger than the predicted minimum change in maximum annual temperatures for 2070. If the cooling gained through upward dispersal was larger than the predicted minimum change, we considered dispersal to potentially be fast enough for the species to remain within their current niche for maximum annual temperatures.

Constrained scenario: We evaluated if the mountaintop-constrained cooling gained through upward dispersal was larger than the minimum change in maximum annual temperatures predicted by 2070. For each species, the maximum cooling gained through dispersal was constrained to be equal to the difference between the current maximum annual temperature at the upper limit of their current range and the predicted maximum annual temperature at the mountaintop by 2070. To obtain the maximum annual temperatures at the mountaintop by 2070, we used Google Earth to estimate the latitude and longitude for this site (see Dataset S1 and *SI Appendix*, Table S6), and then obtained climatic data for this site using the WorldClim projections for maximum annual temperature for 2070. Again, we assumed that if the niche-cooling gained through dispersal was larger than the predicted minimum shift in maximum annual temperatures over time, then species could remain within their current niche for maximum annual temperature in 2070.

Finally, we analyzed the potential effects of dispersal in allowing species to persist within their current climatic niches based on all species in the dataset (*n*=538; *SI Appendix*, Table S8), and not only upward-dispersing species. We analyzed three scenarios to address species that did not disperse upwards between surveys. First, we assumed that species that did not previously disperse upwards (at their upper elevational range limits) between surveys would not disperse upwards in the future. Second, we assumed that these previously non-dispersing species would instead move upwards at the mean upward rate across all species that dispersed (including downward dispersal as negative values when calculating the mean). Specifically, for downward-dispersing species, we calculated the change between surveys in their maximum elevation, just as we did for upward dispersing species, but these downward changes yield negative values. Note that “downward dispersal” most likely occurred through range contractions at the upper elevational range edge, but this pattern is clearly inconsistent with upward dispersal. Third, we assumed that these previously non-dispersing species would instead move upwards at the mean upward rate across all species (counting non-dispersing species as zero when calculating the mean, counting species that dispersed downwards at the cool edge as negative, and counting species that dispersed upwards as positive). We performed the same set of analyses described above for each of these three scenarios, evaluating whether the niche-cooling gained through dispersal was larger than the predicted minimum shift in maximum annual temperatures by 2070, thus allowing species to remain in their current climatic niche for maximum temperatures. Extinction frequencies under each of these scenarios were also calculated under a constrained and unconstrained scenarios based on species current distances to the top of the mountain range on which the surveys were performed.

We acknowledge that a species might not be able to survive very long as a single population on a small mountaintop, and so projecting long-term species survival based on this scenario might seem unrealistic. However, our results suggest that most species are not likely to avoid extinction under the constrained dispersal scenario anyways, especially after including the many species that did not disperse upwards between surveys. Furthermore, most species that are projected to be limited in their upward dispersal by mountaintop height are projected to go extinct (see *SI Appendix*, Text S2 below). Therefore, the question of whether long-term species survival on a small mountaintop is realistic or not may be largely moot.

Text S1.5.3. Niche shift

We estimated how much change in maximum annual temperature (Bio5) has typically caused local extinction at the warmest edges of species ranges, and then we used this value to evaluate whether populations will be exposed to similar levels of warming throughout their ranges by 2070. Note that a change in temperature that a species experiences without going extinct can be considered a niche shift. In other words, the set of macroclimatic conditions that the species can tolerate has expanded to encompass these new conditions, either through evolutionary or plastic change (the latter might occur if the new conditions are actually within the species' fundamental climatic niche, even if those conditions were not within the current realized niche).

For each species, we first estimated the absolute change between surveys in maximum annual temperature at the warmest site in their range where they occurred in the initial survey. Note that for species in which local extinctions occurred, these extinctions generally occurred at the warmest site in the species range (191 of 239), with extinctions at additional sites (usually adjacent ones) in some cases. We then fit a logistic regression model between the occurrence of local extinction and the absolute change in maximum annual temperature at the warmest site in the species historical range (i.e. at the time of the initial survey). This model (odds=3.517; $P<0.001$) was then used to estimate the temperature associated with a given probability of local extinction occurrence, by calibrating a binomial assay in the dose.p function from the R package MASS (51). Our main analyses were based on the temperature change associated with a probability of local extinction of 0.95. We assumed that species would not be able tolerate changes exceeding this value. However, it is possible that there could be more widespread extinctions associated with a smaller temperature change. Therefore, we also estimated the change in maximum annual temperature associated with a 0.5 probability of local extinction (but assuming only 50% of species would go extinct with this level of change). Results for both thresholds are presented in the supplemental files (*SI Appendix*, Tables S7, S9; Datasets S7–S10). All analyses included all 538 species, regardless of whether or not they experienced local extinction at their warmest site.

Finally, for each species we evaluated whether they are likely to be able to tolerate the minimum change in maximum annual temperatures across their range by 2070. We assumed that species will be able to tolerate shifts in maximum annual temperatures (Bio5) across their range that are below the estimated threshold that generally caused local extinctions (0.95; see above). Specifically, we compared this threshold to the minimum change in maximum annual temperatures each species is projected to experience in their range on the transect. We considered species to be likely to persist in their transect if the minimum change in maximum temperatures was below the estimated threshold generally leading to local extinction. We also performed analyses using a threshold associated with a 0.50 probability of local extinction. For these analyses, we assumed that only 50% of the species would go extinct in their transect based on this level of temperature change. Therefore, we divided the initial estimated frequency of extinction under each scenario (Datasets S8–S10) by two. The corrected frequencies of extinction are summarized in *SI Appendix*, Table S10 for each climatic scenario. Note that we do not present estimates of extinction for each species separately using the 50% threshold. Instead, we present overall frequencies across all the species that are projected to be unable to disperse quickly enough to remain within their current niche for maximum annual temperature.

Text S1.5.4. Simultaneous effects of dispersal and niche shifts

We analyzed the extent to which the combined effects of dispersal and niche shifts can potentially reduce species extinctions within transects. Above, we estimated the minimum shift in maximum annual temperatures that each species will likely experience, the potential decrease in maximum temperature caused by upward dispersal (based on their past rates of upward dispersal), and the change in maximum annual temperatures at local sites that is likely to cause local extinction (using two different probability thresholds for local extinction, 0.50 and 0.95). For the final set of analyses, we evaluated whether the minimum change in maximum temperatures that species will experience will be below the threshold for local extinction, after incorporating the potential cooling caused by upward dispersal.

We performed three sets of analyses, corresponding to different ways of dealing with the large number of species (*n*=252) that failed to disperse between surveys in the past (see above). In the first set, we assumed that species that did not disperse upwards previously will not disperse upwards in the future. Second, we assumed that these non-dispersing species will instead move upwards at the mean upward rate across all species that dispersed between surveys in the past (including downward dispersal at the cool edge as negative values when calculating the mean). Third, we assumed that these previously non-dispersing species would move upwards at the mean upward rate estimated across all species (counting non-dispersing species as zero when calculating the mean, counting species that dispersed downwards at the cool edge as negative, and counting species that dispersed upwards as positive).

Finally, for each of these three scenarios, we considered dispersal to be constrained by the maximum height of the mountains on which surveys were performed. For this constrained scenario, we assumed that maximum cooling for upward-dispersing species is restricted by the predicted temperatures at the maximum elevation on the mountain range by 2070.

Text S2. General Methodological Issues

Below, we discuss several methodological issues that are potential sources of bias in our study. First, our dataset may include false extinction events. These would occur if a species was not found during the resurvey at a given site, even though it was actually present. We suggest that these false extinctions did not dominate our results. Most local extinctions were inferred based on the absence of a species at the warmest edge (i.e. lowest elevation) of its original elevational range on the transect. This is where extinctions are expected under global warming, given that these sites may have (or be close to) the hottest climates that each species can tolerate, prior to major climate change. We found that 84.5% of the species that were inferred to have one or more local extinctions between surveys had local extinctions at the warmest site in their original range on the transect (202 of 239 species; Datasets S1–S2). In contrast, false extinctions due to failure to detect a species at a given site could occur anywhere on the transect, and are not expected to be concentrated at the warm edge of the species range. Furthermore, if false extinctions dominated our data, then one would not expect particular climatic variables to be significantly associated with local extinctions. Instead, we found significant associations between increases in certain temperature variables and local extinctions.

In a similar vein, we assume that these local extinction events are actually caused by changes in climate. It is possible that some local extinction events were related to habitat modification or other factors. However, this possibility was generally addressed in the 10 original studies that our analyses are based on. In short, these authors concluded that range shifts were related to climate and not other factors, and these authors surveyed these locations themselves. Moreover, these surveys were generally conducted in reserves and other protected and/or undeveloped areas. Two studies conducted in Europe included sites with human impacts such as grazing and selective logging (7,11). However, in the study by Felde *et al*. (7), the authors specifically addressed the idea that changes in grazing at some sites might have impacted their results, and they provided evidence against this idea. Furthermore, in that study, only a tiny fraction of the sites had any local extinctions at all (2.8%) and few species experienced local extinctions (8.6%). Thus, the overall pattern in that study was of species' robustness to climate change, rather than widespread local extinctions that were possibly caused by human impacts. In the study by Ploquin *et al*. (11), many species did experience local extinction, but the authors specifically addressed whether these were caused by major changes in habitat over the relatively brief time between surveys (~20 years), and they suggested that habitat loss and/or fragmentation did not explain their results. Overall, the idea that habitat modification in these two studies explains our main conclusions seems very unlikely. Nevertheless, in a dedicated section below (*SI Appendix*, Text S4), we specifically tested the impact of excluding the sites with local extinction from these two studies (*SI Appendix*, Text S4). The results show that the exclusion of these sites has little impact on our overall conclusions. Finally, as described above, if non-climatic factors generally explained these local extinctions, it is unclear why these extinctions would be concentrated at the warm edge of species ranges and would be significantly related to climatic variables.

We also acknowledge that our study does not address the specific mechanisms by which changes in climate caused local extinctions, even though we identified the climatic variables that seem to best predict these extinctions. Climate may lead to local extinction through a variety of proximate causes (52), including temperatures that exceed the physiological tolerances of individuals and climate-related changes in species interactions (e.g. disease, reductions in prey or host species). We also note that there may be different demographic causes of local extinction, including the death of adult individuals, failure to successfully reproduce, or failure to successfully recruit the next generation. Importantly, we acknowledge that behavioral habitat selection is a potential explanation for local extinction for some organisms (like birds), but not for others (like plants). That is, a given animal species may no longer occur at a site simply because individuals choose to occur elsewhere, not because they are unable to tolerate climatic conditions there. Nevertheless, it is unclear why species would abandon sites where they can still survive and maintain viable populations. Furthermore, habitat selection to avoid warming habitats could presumably lead to massive reductions in the species range and population size, even if species could actually tolerate many of the sites that they chose to avoid. Overall, it clearly would be beneficial to know the detailed causes and mechanisms of local extinctions for the hundreds of species included here. Yet, we think it is still possible to make inferences about which climatic factors are most strongly related to local extinction (and how future climates may impact species survival) without these details.

We also note that we have focused on identifying which climatic variables seem to be the most generally important in predicting local extinctions. However, we acknowledge that a combination of climatic factors might be important in driving extinction in many cases.

There could also be substantial variation in the climatic drivers of local extinction among species and among sites. An alternative approach to analyzing the data would therefore be to conduct analyses only within a given study (i.e. one transect, one group of organisms). This approach would have some advantages, but it would be difficult to incorporate studies with fewer sites (*SI Appendix,* Table S1), given limited statistical power (see also below). Furthermore, synthesizing results across the different sites would not be straightforward.

We acknowledge that our results could be influenced by different climatic drivers in different regions or among taxonomic groups. Specifically, our dataset was dominated by tropical species but temperate sites. Species on transects in tropical/subtropical locations (<35º absolute latitude) with local extinction represented 82% of the species with local extinction in our dataset (198 of 240 species with local extinction), whereas temperate sites (>35º absolute latitude) comprised 75% of the sites with local extinction (111 of 148 sites with local extinction). Similarly, animals represented 75% of the sampled species (406 animal species of 538 total species), and 90% of species with local extinctions (216 of 240 species with local extinction). Plants were sampled at 323 sites whereas animals were sampled at 258. Preliminary analyses showed broadly similar patterns in terms of climatic drivers of extinctions in animals versus plants and tropical versus temperate sites. However, formal statistical analyses of each climatic region and group separately would currently be somewhat problematic given the limited numbers of tropical sites and of plants with local extinction. Both multivariate (e.g. DAPC) and univariate analyses (e.g. logistic regressions) generally require 4–5 more observations than variables (53,54) or at least 100 observations per category (55,56). In our case here, observations would be sites, or sites with local extinction. Nevertheless, we did confirm that changes in maximum annual temperature were significantly associated with local extinctions in both tropical and temperate regions when sites from these regions were analyzed separately, whereas increases in annual mean temperatures were not associated with local extinction in either climatic zone (see main text).

An important assumption in our projections of future species survival on transects is that species will disperse upwards along elevational gradients in the future at the same rate that they dispersed in the past. Instead, it is possible that species will disperse more quickly in the future, especially if there is natural selection favoring individuals that disperse faster. If this is true, then more species may survive on these transects than suggested by our projections. However, almost half of the species included in our study (66%; 353 of 538) failed to disperse upwards at all between surveys, even though every species experienced climate change across their elevational range in these transects. Furthermore, many species actually contracted their ranges at their upper elevational limits (19%; 101 of 538). Thus, the majority of species did not disperse upwards over time. This suggests that it would be problematic to assume that most species will necessarily undertake more rapid upward dispersal at their cool edge in response to future climate change. We also note that in many cases the ability of species to shift their upper elevational ranges to reach cooler temperatures will be constrained by the limited heights of the mountains on which they occur. Thus, no matter how quickly they can move upwards, their ability to reach cooler temperatures will ultimately depend on there being cooler habitats that they can disperse to. Indeed, our analyses suggest that the limited availability of suitable climatic conditions on elevational transects might be important in driving projected extinctions by 2070, if species dispersed faster and reached mountaintops more quickly. Specifically, we compared the number of species predicted to persist when dispersal is not constrained by mountaintop height to the number projected to face extinction if dispersal is constrained (*SI Appendix*, Table S4; Dataset S6). Among the 45 upward-dispersing species projected to reach the highest elevation in their mountain range by 2070, we estimated that 90–99% will likely face extinction within their transect as consequence of limited mountaintop height (range based on RCP4.5 and RCP8.5, not assuming niche shifts; see *SI Appendix*, Table S4).

We also recognize that projected extinction of species on these elevational transects might not reflect the extinction of these species across their entire geographic range. On the one hand, many species ranges might consist of similar elevational distributions across one or more additional mountain slopes, with similar properties to the slopes that were surveyed. In these cases, our projections might offer a reasonable proxy for the likelihood of global extinctions. On the other hand, various factors might increase the chances of species surviving in other parts of their geographic range (i.e. apart from the surveyed transect). These factors might include taller mountain ranges (allowing species to reach cooler habitats), steeper slopes (potentially allowing some species to disperse upwards more quickly), or distributions in other regions where extinction may be less likely (higher latitudes). Our estimates of extinction frequencies may still be conservative (i.e. underestimating extinction) because we do not include the potential effects of dramatically lower population sizes on long-term species survival (57).

Finally, we recognize that our study includes only terrestrial species on elevational gradients. Nevertheless, far more animal species are terrestrial than aquatic (58), even when including the large estimated numbers of undescribed marine species (59). Most plant species are also terrestrial (59). Moreover, many biodiversity hotspots are in montane regions, including the most diverse ones [i.e. the Tropical Andes (60)]. Freshwater species appear to be more sensitive to climate change than terrestrial or marine species, based on patterns of local extinction (1). Dispersal on latitudinal gradients may be slower than on elevational gradients (given that the absolute distances needed to reach lower temperatures may be greater), and may be more likely to be impeded by human habitat modification at low elevations. We have also included only some groups of organisms, with most sampled species being plants, insects, and birds (*SI Appendix,* Table S1; Dataset S1). These groups may not represent all species. However, most species depend on plants, either directly or indirectly. Furthermore, insects and birds may have particularly high rates of dispersal (given that many or most have the ability to fly). Thus, other groups may be even less likely to avoid extinction by dispersal.

Text S3. Alternative methods for summarizing climate at sites

Text S3.1. Overview

The main results of our paper are based on the downscaled and EMD-transformed climatic data from CRU. For each site, an EMD model was fitted on the entire temporal range of CRU data coverage (1901–2013). Consequently, the extraction of climatic trends at each site under EMD accounts not only for climatic variation between surveys but also outside of these two dates. We acknowledge that other methods are currently available to extract temporal trends from climatic data (22–26). However, EMD has shown to be especially accurate for this purpose (21,27,28). In the sections below, we examine if our main conclusions are still supported when a window-based approach is used to summarize climate and climate change over time.

Text S3.2. Methods used to construct alternative climatic datasets

For each site, we estimated mean climatic conditions during the 5-year window and 10-year window preceding the date of each historical survey and recent resurvey. Based on the mean climatic values within these windows for each variable, we then estimated the change in climate between surveys and the rate of change in climate at each site between surveys. However, we used the actual times between surveys when estimating rates of change in climate (not the dates of the 5-year or 10-year windows). We acknowledge that the choice of 5 and 10 years for window sizes is arbitrary. However, we wanted to use time windows that spanned multiple years, in order to reduce stochastic differences in climate from year to year (therefore a window of 4 years or less seemed too small). Using a larger window than 10 years also seemed problematic, given that this would approach the time between the historical and modern surveys (at least in some cases; see below).

The CRU temporal coverage starts in 1901. Therefore, it would be difficult to estimate 5- and 10-year windows for historical surveys close to this date. This was not problematic for most studies, in which the initial surveys were after 1911 (*SI Appendix,* Table S1). However, the initial survey in Felde et al. (7) was conducted in 1901. Given the limitations of the CRU dataset, we did not estimate 5- and 10-year windows for Felde et al. (7) and instead simply used the EMD-based estimates for 1901 (the oldest climatic record in our dataset).

Similarly, it would be problematic to calculate a 10-year window if the historical survey and modern resurvey were 10 or fewer years apart. This was not problematic for most studies, except for Raxworthy et al. (2), in which the surveys were only 10 years apart. For Raxworthy et al. (2), we described mean climate during the resurvey using a 5-year window only.

Mean climatic values for each site based on the 5-year and 10-year windows are compiled in Datasets S11 and S12, respectively. EMD-transformed climate data are summarized in Dataset S3. We compared climatic conditions between sites with and without local extinctions based on these three datasets (5-year window, 10-year window, and EMD). Specifically, we examined whether the three datasets agreed on the four main conclusions based on the resurvey data (not the conclusions based on future projections). These four main conclusions were as follows. (i) Based on Discriminant Analysis of Principal Components (DAPC), the most important climatic variable that distinguishes sites with and without local extinction is the change in maximum annual temperatures (Bio5). (ii) On average, mean annual temperatures at sites with local extinction changed less relative to sites without local extinctions. (iii) On average, maximum annual temperatures increased more and increased faster at sites with local extinction relative to those without. (iv) On average, annual precipitation and decreased more and decreased faster between surveys at sites with local extinction. We compare these conclusions based on EMD to those based on 5-year and 10-year windows below.

Text S3.3. Comparing main conclusions from climate data from EMD and window-based data

Overall, results based on the three different climatic datasets (5-year window [Dataset S13], 10-year window [Dataset S14], and EMD [*SI Appendix,* Table S3]) generally agreed with each regarding the main conclusions. The only exception was the variable selection for the 5-year window. Variable selection based on DAPC was consistent between the EMD and 10-year window datasets. These two datasets suggested that change in maximum annual temperatures was the main driver of local extinctions between surveys (DAPC for the EMD dataset: *SI Appendix,* Table S3; DAPC for the 10-year dataset: Dataset S14). Using a 5-year window, sites with and without local extinction differed most strongly in the absolute change between surveys in minimum annual temperatures (Bio6; Dataset S13). Specifically, minimum temperatures at sites with local extinction increased less between surveys relative to other sites (mean absolute change in Bio6, sites with local extinction=0.378ºC vs sites without=2.264ºC; Dataset S13). However, these changes seem highly unlikely to explain local extinction at these sites (i.e. if increases in this variable were important in driving local extinctions, then changes should be larger at sites with local extinction, not those without). When analyzing rates of change, the 5-year window dataset indicated that the most important variable was mean temperature during the warmest quarter (Bio10; Dataset S13). Sites with local extinctions experienced faster increases in mean warmest quarter temperatures (mean rate of change Bio10 for sites with local extinction=0.008ºC yr^{-1} vs without=0.002ºC yr^{-1}; Dataset S13). This finding is more consistent with those from EMD and the 10-year window, showing the importance of temperatures during the hottest part of the year, and is inconsistent with the selection of minimum temperatures (Bio6) for this same time 5-year time window. Overall, the differences in variable selection between the 5-year window versus the 10-year window and EMD datasets suggest that the 5-year window is more sensitive to stochastic variation in climate from year-to-year, consistent with the smaller time window considered.

The three other main conclusions were all consistent between the data from EMD, the 10-year window, and the 5-year window. Sites where local extinctions occurred tended to experience smaller changes in mean annual temperatures (average change in mean annual temperature, Bio1; EMD: sites with local extinction=0.413ºC vs sites without=1.174ºC, logistic regressions between the change in Bio1 between surveys and the occurrence of local extinction: $P<0.001$; 10-year window: sites with local extinction=0.579ºC vs sites without=0.801ºC, $P=0.043$; 5-year window: sites with local extinction=0.552ºC vs sites without=0.945ºC, $P=0.027$).

Similarly, for all three datasets, sites with local extinction experienced larger increases in maximum annual temperatures between surveys (mean absolute change in maximum annual temperature, Bio5; EMD dataset: sites with local extinction=0.413ºC vs sites without=0.147ºC, $P<0.001$; 10-year window: sites with local extinction=0.400ºC vs sites without=-1.515ºC, $P=0.043$; 5-year window: local extinction=0.464ºC vs sites without=-0.840ºC, $P=0.048$). Sites with local extinction also experienced faster increases in maximum annual temperatures (mean rate of change in maximum annual temperature, Bio5; EMD dataset: sites with local extinction=0.018ºC yr^{-1} vs sites without=0.005ºC yr^{-1}, $P<0.001$; 10-year window: sites with local extinction=0.008ºC yr^{-1} vs sites without=-0.033ºC yr^{-1}, *P*<0.001; 5-year window: sites with local extinction=0.008ºC yr^{-1} vs sites without=-0.018ºC yr^{-1}, *P*<0.001).

Based on all three datasets, sites with local extinction became drier between surveys relative to sites without (mean absolute change in annual precipitation, Bio12: EMD dataset: sites with local extinction=-29.029 mm vs sites without=80.008 mm, *P*<0.001; 10-year window: sites with local extinction=7.587 mm vs sites without=117.597 mm, *P*=0.006; 5-year window: sites with local extinction=-40.263 mm vs sites without=102.242 mm, *P*=0.003). Sites with local extinction also had faster rates of decrease in annual precipitation (mean rate of change in annual precipitation, Bio12: EMD dataset: sites with local extinction=-1.130 mm yr^{-1} vs sites without=0.614 mm yr^{-1}, *P*<0.001; 10-year window: sites with local extinction=-0.242mm yr^{-1} vs sites without=2.437 mm yr^{-1}, *P*<0.001; 5-year window: sites with local extinction=-0.973mm yr^{-1} vs sites without=1.673 mm yr^{-1}, *P*<0.001).

Text S4. Addressing the possible impacts of land-use change

Changes in land use by humans over time might cause local extinctions that mimic the impacts of climate change. Some sites in the studies by Ploquin et al. (11) and Felde et al. (7) may have been impacted by land-use changes between the historical and modern surveys. However, this possibility was explicitly addressed in these papers, and therefore seems very unlikely (see Text S2). Nevertheless, we examined the impacts of excluding potentially affected sites in those two studies. We assumed that land-use change could cause sites to have local extinctions that were unrelated to climate change. Therefore, we excluded those sites with local extinctions in these two datasets. Specifically, we excluded the 9 sites with local extinction from Felde et al. (7) and 76 sites with local extinction from Ploquin et al. (11). Thus, we excluded 85 sites from the full EMD dataset (sites in the original dataset=581; sites in the reduced dataset=496). Next, we compared climatic characteristics of sites with local extinction (sites with local extinction in the original dataset=148; sites with local extinction in the reduced dataset=63) and without local extinction (sites without local extinction in both the original and reduced datasets=433) in the reduced dataset (i.e. all sites except those with local extinction in Ploquin et al. [11] and Felde et al. [7]).

We found that the exclusion of these 85 sites had no effect on our main conclusions (Dataset S15). In line with our main conclusions, DAPC analyses based on the reduced dataset suggested that the absolute amount of change in maximum annual temperatures (and the rate of change in maximum annual temperatures) was the main driver of local extinctions across sites (Dataset S15). We also compared the climatic characteristics of sites with and without local extinction based on the reduced dataset. There were significantly larger changes in maximum annual temperatures between surveys at sites with local extinction relative to those without (mean absolute change in Bio5, sites with local extinction=0.421ºC vs sites without=0.146ºC, *P*<0.001, all based on logistic regression). The mean rate of change in maximum annual temperature was also faster at sites with local extinction (mean rate of change in Bio5, sites with local extinction=0.017ºC yr^{-1} vs sites without=0.004ºC yr^{-1}, *P*<0.001). Sites with local extinction had smaller changes in mean annual temperature between surveys than those without local extinction (mean absolute change in mean Bio1, sites with local extinction=0.425ºC vs sites without=1.173ºC, *P*<0.001). Finally, annual precipitation decreased more at sites with local extinctions (mean absolute change in Bio12, sites with local extinction=-56.853 mm vs sites without 80.008 mm, *P*<0.001). Annual precipitation also decreased more rapidly at sites with local extinction (mean rate of change in Bio12, sites with local extinction=-1.571 mm yr^{-1} vs sites without=0.614 mm yr^{-1}, *P*<0.001).

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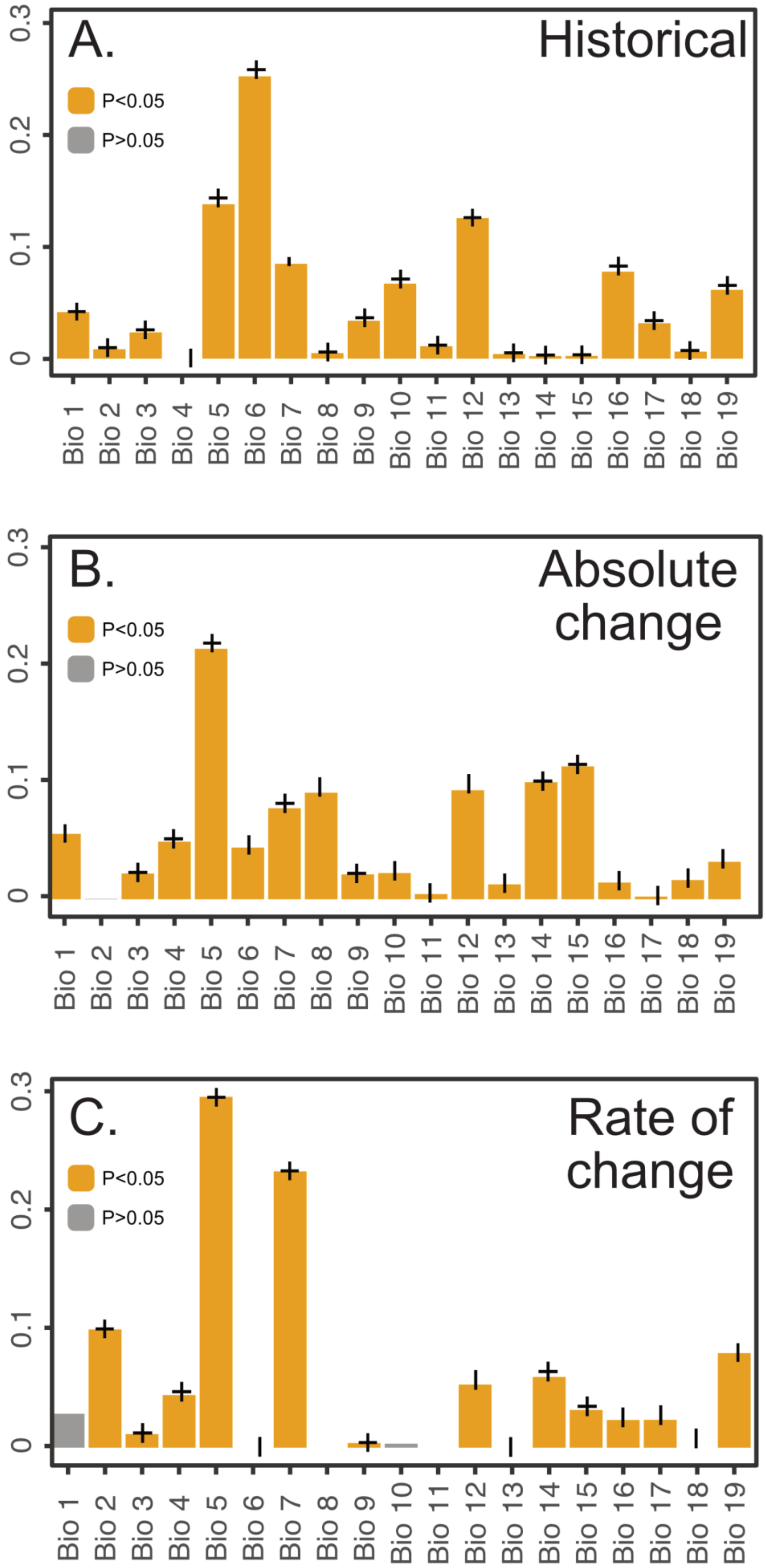

Fig. S1. Contributions of different variables to climatic differences between sites with and without local extinction. We present results for the (**A**) historical climate, and both the (**B**) absolute change, and (**C**) rate of change in climatic variables between surveys. DAPC loadings (Y axis) are shown for each Bioclim variable during the initial survey. Results for (A) address how climatic variation among sites at the same time period (before major warming) predicted which sites showed local extinctions in the subsequent resurvey. Historically warmer sites (i.e. higher values of minimum annual temperatures, Bio6) were more likely to contain species that underwent local extinction between surveys (A). Sites in which local extinctions occurred were most distinct from those without in having greater increases in maximum annual temperatures (Bio5) between surveys (B) and a faster rate of change in this variable (C). We also show odds ratios and *P*-values for univariate logistic regressions between climatic descriptors and occurrence of local extinction across sites. Odds ratios larger than 1 (indicated with "**+**") suggest that increases in predictor variables are associated with a higher likelihood of local extinction. Conversely, if odds rations are smaller than 1 (indicated with a vertical line "**|**"), the likelihood of local extinction is inversely related to increases in predictor variables. Definitions of Bioclim variables are given in *SI Appendix,* Table S2.

Supplementary Tables

Table S1. Summary information for the analyzed datasets. Columns are labeled as follows. Study: original paper from which the data were obtained. Sites: number of specific locations surveyed and resurveyed on each transect. Species: total number of species found on the transect. Local extinction (species): proportion of the total sampled species that had local extinctions at one or more sites on the transect. Local extinction (sites): proportion of the total sampled sites where at least one species had a local extinction between surveys. Survey date: year when the initial survey was conducted. Resurvey date: year when the resurvey of the transect was conducted. Taxonomic group: higher taxon to which the sampled species belong. Continent: general location of the transect. Lists of species for each transect (and the sites at which they were found in the survey and resurvey) are given in Dataset S1. Geographic coordinates used for each site are given in Dataset S2.

Study	Sites	Species	Local extinction (species)	Local extinction (sites)	Survey date	Resurvey date	Taxonomic group	Continent
Brusca *et al*. (5)	8	27	0.5556	1.0000	1963	2011	Plants	North America
Chen *et al*. (6)	10	208	0.5577	1.0000	1965	2007	Insects	Asia
Felde *et al*. (7)	315	105	0.0857	0.0285	1900	2008	Plants	Europe
Forero-Medina *et al*. (8)	5	55	0.2909	0.8000	1969	2010	Birds	South America

Freeman and Freeman (9)	37	54	0.7407	0.6216	1965	2012	Birds	Oceania
Menendez *et al*. (10)	40	39	0.5385	0.4250	1981–1982; 1992–1993	2006–2007	Insects	Europe
Ploquin et al. (11)	119	16	0.6875	0.6386	1988–1989	2009	Insects	Europe
Raxworthy *et al*. (2)	3	30	0.3667	0.3333	1993	2003	Frogs/Lizards	Madagascar
Sheldon (3)	31	2	0.0000	0.0000	1977–1978	2006	Insects	North America
Warren and Chick (4)	13	2	0.0000	0.0000	1973–1974	2012	Insects	North America

Table S2. Definitions for Bioclim variables (32).

Code	Description
Bio1	Annual mean temperature
Bio2	Mean diurnal range (mean of monthly (max temp - min temp))
Bio3	Isothermality (100*Bio2/Bio7)
Bio4	Temperature seasonality
Bio5	Maximum temperature of warmest month
Bio6	Minimum temperature of coldest month
Bio7	Temperature annual range (Bio5-Bio6)
Bio8	Mean temperature of wettest quarter
Bio9	Mean temperature of driest quarter
Bio10	Mean temperature of warmest quarter
Bio11	Mean temperature of coldest quarter
Bio12	Annual precipitation
Bio13	Precipitation of wettest month
Bio14	Precipitation of driest month
Bio15	Precipitation seasonality (coefficient of variation)
Bio16	Precipitation of wettest quarter
Bio17	Precipitation of driest quarter
Bio18	Precipitation of warmest quarter
Bio19	Precipitation of coldest quarter

Table S3. Summary of statistical results comparing climatic variables at sites with and without local extinction. For each climatic variable, we present both the mean and standard deviation for sites with and without local extinction (sites are considered as having local extinction if any of the species surveyed had a local extinction at that site, as indicated by failure to find that species at that site during the resurvey). Next, we show results for univariate logistic regressions between each climatic variable and the occurrence of local extinction. We then summarize odds and *P*-values for each of the models. We also performed DAPC analyses between the occurrence of local extinction across sites and all climatic variables. These analyses were fit independently for variables for historical climate (i.e. climate for the year of the initial survey), absolute change in climate (historical – modern values), and rate of change in climate (absolute change/time between surveys). We refer to each climatic variable with the prefix "historical", "absolute.change" and "rate.change" and we present the results for these three sets of variables in that order. We show DAPC loadings (LD1 loading) for each of these variables within each of the three analyzed datasets. Bioclim variables are defined in *SI Appendix,* Table S2. Given that some odds were very large, we summarize odds greater than nine as ">9".

Variable	Descriptive statistics				Univariate logistic regression		DAPC
	No local extinction		Local extinction		Odds	*P*	LD1
	Mean	SD	Mean	SD			loading
historical.Bio1	1.530	6.080	11.600	5.410	1.250	<0.001	0.039
historical.Bio2	8.770	1.900	9.710	1.830	1.260	<0.001	0.009
historical.Bio3	30.800	11.500	48.500	19.700	1.070	<0.001	0.023
historical.Bio4	7.110	1.490	4.310	2.300	0.508	<0.001	0.000
historical.Bio5	17.800	5.050	23.900	3.860	1.250	<0.001	0.129
historical.Bio6	-12.700	7.130	1.330	7.680	1.210	<0.001	0.275
historical.Bio7	30.100	4.240	22.500	7.000	0.804	<0.001	0.091
historical.Bio8	6.090	3.640	11.000	5.560	1.250	<0.001	0.006
historical.Bio9	0.271	7.960	13.500	5.620	1.230	<0.001	0.035
historical.Bio10	10.500	4.920	17.100	3.680	1.280	<0.001	0.069
historical.Bio11	-6.630	7.180	6.680	7.570	1.210	<0.001	0.011
historical.Bio12	929.000	526.000	1350.000	941.000	1.000	<0.001	0.128
historical.Bio13	159.000	69.200	225.000	115.000	1.010	<0.001	0.005
historical.Bio14	29.300	21.200	36.100	41.900	1.010	0.012	0.003
historical.Bio15	53.400	8.550	59.100	16.200	1.050	<0.001	0.003
historical.Bio16	339.000	175.000	506.000	292.000	1.000	<0.001	0.077
historical.Bio17	139.000	98.900	186.000	182.000	1.000	<0.001	0.035
historical.Bio18	259.000	141.000	301.000	279.000	1.000	0.018	0.006
historical.Bio19	214.000	126.000	333.000	190.000	1.010	<0.001	0.060
absolute.change.Bio1	1.170	0.516	0.413	0.367	0.060	<0.001	0.057
absolute.change.Bio2	0.061	0.348	0.056	0.214	0.951	0.864	0.001
absolute.change.Bio3	-0.003	0.749	0.428	1.380	1.550	<0.001	0.023
absolute.change.Bio4	-0.065	0.070	0.011	0.106	>9	<0.001	0.050

Variable	Descriptive statistics				Univariate logistic regression		DAPC
	No local extinction		Local extinction		Odds	*P*	LD1
	Mean	SD	Mean	SD			loading
absolute.change.Bio5	0.147	0.205	0.413	0.299	>9	<0.001	0.216
absolute.change.Bio6	1.210	1.210	0.231	0.505	0.111	<0.001	0.045
absolute.change.Bio7	-0.763	0.729	0.264	0.709	5.240	<0.001	0.079
absolute.change.Bio8	1.040	1.800	0.311	0.866	0.757	<0.001	0.092
absolute.change.Bio9	-0.563	1.560	0.190	1.040	1.420	<0.001	0.022
absolute.change.Bio10	1.050	0.420	0.445	0.456	0.071	<0.001	0.023
absolute.change.Bio11	0.373	0.294	0.205	0.199	0.050	<0.001	0.005
absolute.change.Bio12	80.000	83.000	-29.000	102.000	0.988	<0.001	0.094
absolute.change.Bio13	-2.290	10.900	-8.880	20.700	0.966	<0.001	0.013
absolute.change.Bio14	6.520	11.900	13.000	30.300	1.020	0.001	0.101
absolute.change.Bio15	-7.780	4.560	-0.845	4.600	1.320	<0.001	0.115
absolute.change.Bio16	16.100	25.200	1.260	40.100	0.980	<0.001	0.015
absolute.change.Bio17	7.440	19.000	-1.180	27.600	0.981	<0.001	0.003
absolute.change.Bio18	28.500	26.400	9.870	53.600	0.984	<0.001	0.017
absolute.change.Bio19	8.980	22.700	-10.900	34.300	0.970	<0.001	0.033
rate.change.Bio1	0.015	0.005	0.013	0.009	0.000	0.077	0.029
rate.change.Bio2	-0.001	0.011	0.003	0.007	>9	<0.001	0.100
rate.change.Bio3	0.003	0.020	0.015	0.042	>9	<0.001	0.012
rate.change.Bio4	-0.001	0.002	0.001	0.004	>9	<0.001	0.045
rate.change.Bio5	0.005	0.012	0.018	0.017	>9	<0.001	0.297
rate.change.Bio6	0.015	0.017	0.006	0.011	0.000	<0.001	0.000
rate.change.Bio7	-0.008	0.025	0.017	0.028	>9	<0.001	0.234
rate.change.Bio8	0.015	0.029	0.014	0.029	0.565	0.861	0.000
rate.change.Bio9	0.003	0.037	0.013	0.039	>9	0.008	0.004
rate.change.Bio10	0.014	0.007	0.015	0.011	>9	0.105	0.004
rate.change.Bio11	0.007	0.008	0.007	0.007	>9	0.747	0.000
rate.change.Bio12	0.614	1.830	-1.130	2.500	0.695	<0.001	0.054
rate.change.Bio13	-0.100	0.333	-0.415	0.640	0.214	<0.001	0.000
rate.change.Bio14	0.088	0.259	0.295	0.643	2.990	<0.001	0.060
rate.change.Bio15	-0.082	0.070	-0.018	0.131	>9	<0.001	0.032
rate.change.Bio16	0.102	0.503	-0.142	1.130	0.608	<0.001	0.024
rate.change.Bio17	-0.043	0.461	-0.150	0.658	0.669	0.032	0.024
rate.change.Bio18	0.238	0.692	-0.031	1.300	0.703	0.002	0.000
rate.change.Bio19	0.003	0.890	-0.588	1.080	0.518	<0.001	0.080

Table S4. Summary of the proportion of species vulnerable to extinction from climate change (without dispersal or niche shifts). For each combination of RCP and available GCM, we estimate the number of species projected to have their current distributions (on their transect) outside of their current range of values for maximum annual temperature by 2070. These species are vulnerable to extinction from climate change, unless they undergo dispersal or niche shifts. The number of these species is then divided by the total number of species in our dataset (*n*=538) to estimate the proportion of species vulnerable to extinction (without dispersal or niche shifts). We also summarize the distance to the current thermal niche (for maximum annual temperature) as the mean across all species for each combination of RCP and GCM. This distance is the difference between the projected value for maximum annual temperature in 2070 at the coolest site in the species' current range (usually the highest elevation site) and the current maximum value of maximum annual temperature within the species current range (at the time of the resurvey). The species-level data on which this summary is based are presented in Dataset S5.

RCP	GCM	Proportion species outside current niche	Distance to current niche
2.6	BC	0.703	0.536
2.6	CC	0.704	0.529
2.6	CN	0.695	0.545
2.6	GD	0.539	0.550
2.6	GF	0.829	2.243
2.6	GS	0.604	0.473
2.6	HD	0.511	0.941

2.6	HE	0.770	1.032
2.6	IP	0.708	1.198
2.6	MC	0.742	1.041
2.6	MG	0.636	0.498
2.6	MI	0.855	1.440
2.6	MP	0.641	0.821
2.6	MR	0.807	1.760
2.6	NO	0.727	0.593
4.5	AC	0.745	1.765
4.5	BC	0.710	1.032
4.5	CC	0.734	1.217
4.5	CE	0.875	2.820
4.5	CN	0.779	1.082
4.5	GD	0.714	1.095
4.5	GF	0.890	2.995
4.5	GS	0.714	1.022
4.5	HD	0.799	1.959
4.5	HE	0.842	1.761
4.5	HG	0.792	1.606
4.5	IN	0.667	0.437
4.5	IP	0.779	1.932
4.5	MC	0.822	1.574

4.5	MG	0.664	0.999
4.5	MI	0.922	2.018
4.5	MP	0.697	1.561
4.5	MR	0.901	2.074
4.5	NO	0.762	1.251
6	BC	0.732	1.248
6	CC	0.738	1.319
6	GD	0.730	1.205
6	GS	0.725	1.136
6	HD	0.801	1.522
6	HE	0.879	1.880
6	IP	0.781	1.962
6	MC	0.768	1.639
6	MG	0.680	1.253
6	MI	0.929	2.266
6	MR	0.870	2.108
6	NO	0.749	1.215
8.5	AC	0.868	2.688
8.5	BC	0.762	2.064
8.5	CC	0.835	2.250
8.5	CN	0.851	1.777

8.5	GF	0.948	4.325
8.5	GS	0.805	1.710
8.5	HD	0.928	2.601
8.5	HE	0.941	3.151
8.5	HG	0.931	2.987
8.5	IN	0.684	1.374
8.5	IP	0.894	3.223
8.5	MC	0.892	2.342
8.5	MG	0.770	2.092
8.5	MI	0.950	3.529
8.5	MP	0.777	2.852
8.5	MR	0.950	3.621
8.5	NO	0.866	2.033

Table S5. Mean distances and rates of elevational dispersal at species' upper elevational range limits. Many species moved upwards in elevation between surveys (*n*=185), and for these species we calculated the absolute amount (in meters above sea level) that their upper elevational limit increased between surveys. A large number of species (*n*=101) moved downwards at their upper elevational ranges over time instead (presumably due to local extinctions at upper sites). For these species, we calculated the decrease in the elevation of their upper ranges as the amount of dispersal, and this value divided by the time between surveys yields the downward dispersal rate (although this presumably reflects local extinction rather than movement of individuals). Note that 47% of the analyzed species (*n*=252) did not disperse between surveys at their upper elevational range limits. Species-level data are provided in Dataset S6.

Species	*n*	Dispersal amount	Dispersal rate
Upward dispersing	185	312.872 m (SD=246.242)	9.899 m/year (SD=10.868)
Downward dispersing	101	-241.810 m (SD=413.607)	-3.965 m/year (SD=20.035)

Table S6. Summary statistics for univariate regressions testing the relationship between maximum annual temperatures (Bio5) and elevation across sites. We fit separate regression models for each transect. We also summarize here the elevation at the highest sampled site on the transect, and the highest elevation on the mountain on which the transect is located.

Study	Maximum elevation along the transect	Mountain summit	r^2	P	Slope
Brusca *et al*. (5)	2743	2791	0.992	1.66E-07	-7.18E-03
Chen *et al*. (6)	3675	4021	0.948	2.07E-06	-4.38E-03
Felde *et al*. (7)	1610	2292	0.841	5.72E-127	-6.24E-03
Forero-Medina *et al*. (8)	2220	2274	0.989	4.92E-04	-2.92E-03
Freeman and Freeman (9)	2382	2423	0.763	1.76E-12	-4.10E-03
Menendez *et al*. (10)	2518	3322	0.198	4.05E-03	-4.40E-03
Ploquin *et al*. (11)	2306	2549	0.724	1.66E-34	-2.18E-03
Raxworthy *et al*. (2)	2500	2774	0.982	8.54E-02	-5.18E-03
Sheldon (3)	1113	1929	0.967	3.95E-23	-6.58E-03
Warren and Chick (4)	1052	1565	0.958	6.14E-09	-5.24E-03

Table S7. Estimated level of extinction assuming that upward-dispersing species respond to climate change only by dispersing. We include only species that dispersed upwards (at their upper elevational range limits) between surveys (*n*=185). We show estimates for the proportion of these 185 species that are projected to go extinct by 2070, for two alternative dispersal scenarios. The unconstrained scenario assumes that upward dispersal is not restricted by the height of the mountain range on which the survey was undertaken. The constrained scenario assumes that species can only disperse until they reach the highest elevation possible on the mountain range containing their elevational transect (i.e. the top of the mountain range). Results are shown for multiple climatic scenarios based on the 12–19 available GCMs for each of the four RCPs. We present results for two different RCPs in the main text: RCP4.5 and RCP8.5. For each of these two RCPs, we simply averaged the extinction frequencies across all nested GCMs. Not all combinations of GCMs and RCPs are available. The species-level data are presented in Dataset S6, along with model abbreviations.

RCP	GCM	Extinction frequency (Unconstrained)	Extinction frequency (Constrained)
2.6	BC	0.135	0.168
2.6	CC	0.130	0.157
2.6	CN	0.151	0.178
2.6	GD	0.092	0.124
2.6	GF	0.330	0.384
2.6	GS	0.097	0.135
2.6	HD	0.168	0.205

2.6	HE	0.222	0.308
2.6	IP	0.232	0.314
2.6	MC	0.184	0.222
2.6	MG	0.119	0.146
2.6	MI	0.314	0.324
2.6	MP	0.162	0.189
2.6	MR	0.308	0.330
2.6	NO	0.119	0.157
4.5	AC	0.324	0.411
4.5	BC	0.200	0.238
4.5	CC	0.232	0.319
4.5	CE	0.643	0.735
4.5	CN	0.238	0.276
4.5	GD	0.211	0.292
4.5	GF	0.578	0.681
4.5	GS	0.200	0.238
4.5	HD	0.357	0.443
4.5	HE	0.368	0.459
4.5	HG	0.319	0.400
4.5	IN	0.092	0.135
4.5	IP	0.357	0.443
4.5	MC	0.286	0.378

4.5	MG	0.211	0.286
4.5	MI	0.416	0.481
4.5	MP	0.292	0.368
4.5	MR	0.411	0.486
4.5	NO	0.243	0.303
6	BC	0.254	0.292
6	CC	0.254	0.335
6	GD	0.216	0.254
6	GS	0.243	0.335
6	HD	0.341	0.432
6	HE	0.400	0.476
6	IP	0.368	0.449
6	MC	0.308	0.400
6	MG	0.222	0.303
6	MI	0.443	0.503
6	MR	0.416	0.470
6	NO	0.249	0.276
8.5	AC	0.578	0.676
8.5	BC	0.341	0.427
8.5	CC	0.416	0.514
8.5	CN	0.373	0.449

8.5	GF	0.768	0.859
8.5	GS	0.346	0.411
8.5	HD	0.524	0.611
8.5	HE	0.654	0.741
8.5	HG	0.649	0.735
8.5	IN	0.232	0.330
8.5	IP	0.703	0.789
8.5	MC	0.551	0.649
8.5	MG	0.384	0.443
8.5	MI	0.546	0.616
8.5	MP	0.535	0.611
8.5	MR	0.659	0.724
8.5	NO	0.427	0.524

Table S8. Estimated level of extinction assuming that all species respond to climate change only by dispersing. We include species that dispersed upwards between surveys, in addition to species that dispersed downwards or did not disperse between surveys. We show estimates for the proportion of these 538 species projected to go extinct by 2070, for three alternative dispersal scenarios. Scenario 1: we assumed that species that did not previously disperse upwards (at their upper elevational range limits) between surveys would not disperse upwards in the future. Scenario 2: we assumed that these previously non-dispersing species would instead move upwards at the mean upward rate across all species that did disperse upwards (including downward dispersal as negative values when calculating the mean). Scenario 3: we assumed that these previously non-dispersing species would instead move upwards at the mean upward rate across all species (including downward dispersal as negative values when calculating the mean and counting non-dispersing species as zero). For each of these three scenarios, we also estimated the projected proportion of extinctions if species are not restricted by the height of the mountain range on which the survey was undertaken (unconstrained), or if species can only disperse until they reach the highest elevation possible on the mountain range containing their elevational transect (i.e. the top of the mountain range; constrained). Results are shown for multiple climatic scenarios based on the 12–19 available GCMs for each of the four RCPs. We present results for two different RCPs in the main text: RCP4.5 and RCP8.5. For each of these two RCPs, we simply averaged the extinction frequency across all nested GCMs. Not all combinations of GCMs and RCPs are available. The species-level data are presented in Dataset S6, along with model abbreviations.

RCP	GCM	Scenario1_Unconstrained	Scenario1_Constrained	Scenario2_Unconstrained	Scenario2_Constrained	Scenario3_Unconstrained	Scenario3_Constrained
2.6	BC	0.416	0.428	0.416	0.428	0.416	0.428
2.6	CC	0.416	0.426	0.416	0.426	0.416	0.426
2.6	CN	0.420	0.429	0.420	0.429	0.420	0.429
2.6	GD	0.314	0.325	0.314	0.325	0.314	0.325
2.6	GF	0.593	0.612	0.593	0.612	0.593	0.612

2.6	GS	0.362	0.375	0.362	0.375	0.362	0.375
2.6	HD	0.303	0.316	0.303	0.316	0.303	0.316
2.6	HE	0.507	0.537	0.507	0.537	0.507	0.537
2.6	IP	0.468	0.496	0.468	0.496	0.468	0.496
2.6	MC	0.476	0.489	0.476	0.489	0.476	0.489
2.6	MG	0.374	0.383	0.374	0.383	0.374	0.383
2.6	MI	0.604	0.608	0.604	0.608	0.604	0.608
2.6	MP	0.388	0.398	0.388	0.398	0.388	0.398
2.6	MR	0.554	0.561	0.554	0.561	0.554	0.561
2.6	NO	0.442	0.455	0.442	0.455	0.442	0.455
4.5	AC	0.522	0.552	0.522	0.552	0.522	0.552
4.5	BC	0.459	0.472	0.459	0.472	0.459	0.472
4.5	CC	0.485	0.515	0.485	0.515	0.485	0.515
4.5	CE	0.730	0.762	0.730	0.762	0.730	0.762
4.5	CN	0.530	0.543	0.530	0.543	0.530	0.543
4.5	GD	0.463	0.491	0.463	0.491	0.463	0.491
4.5	GF	0.716	0.751	0.716	0.751	0.716	0.751
4.5	GS	0.467	0.480	0.467	0.480	0.467	0.480
4.5	HD	0.569	0.599	0.569	0.599	0.569	0.599
4.5	HE	0.617	0.649	0.617	0.649	0.617	0.649
4.5	HG	0.556	0.584	0.556	0.584	0.556	0.584

4.5	IN	0.375	0.390	0.375	0.390	0.375	0.390
4.5	IP	0.552	0.582	0.552	0.582	0.552	0.582
4.5	MC	0.576	0.608	0.576	0.608	0.576	0.608
4.5	MG	0.422	0.448	0.422	0.448	0.422	0.448
4.5	MI	0.686	0.708	0.686	0.708	0.686	0.708
4.5	MP	0.472	0.498	0.472	0.498	0.472	0.498
4.5	MR	0.665	0.691	0.665	0.691	0.665	0.691
4.5	NO	0.509	0.530	0.509	0.530	0.509	0.530
6	BC	0.489	0.502	0.489	0.502	0.489	0.502
6	CC	0.494	0.522	0.494	0.522	0.494	0.522
6	GD	0.481	0.494	0.481	0.494	0.481	0.494
6	GS	0.487	0.519	0.487	0.519	0.487	0.519
6	HD	0.572	0.604	0.572	0.604	0.572	0.604
6	HE	0.649	0.675	0.649	0.675	0.649	0.675
6	IP	0.554	0.582	0.554	0.582	0.554	0.582
6	MC	0.537	0.569	0.537	0.569	0.537	0.569
6	MG	0.454	0.481	0.454	0.481	0.454	0.481
6	MI	0.704	0.725	0.704	0.725	0.704	0.725
6	MR	0.647	0.665	0.647	0.665	0.647	0.665
6	NO	0.500	0.509	0.500	0.509	0.500	0.509

8.5	AC	0.701	0.734	0.701	0.734	0.701	0.734
8.5	BC	0.532	0.561	0.532	0.561	0.532	0.561
8.5	CC	0.625	0.658	0.625	0.658	0.625	0.658
8.5	CN	0.621	0.647	0.621	0.647	0.621	0.647
8.5	GF	0.820	0.851	0.820	0.851	0.820	0.851
8.5	GS	0.586	0.608	0.586	0.608	0.586	0.608
8.5	HD	0.727	0.757	0.727	0.757	0.727	0.757
8.5	HE	0.781	0.810	0.781	0.810	0.781	0.810
8.5	HG	0.773	0.803	0.773	0.803	0.773	0.803
8.5	IN	0.452	0.485	0.452	0.485	0.452	0.485
8.5	IP	0.760	0.790	0.760	0.790	0.760	0.790
8.5	MC	0.714	0.747	0.714	0.747	0.714	0.747
8.5	MG	0.561	0.582	0.561	0.582	0.561	0.582
8.5	MI	0.749	0.773	0.749	0.773	0.749	0.773
8.5	MP	0.608	0.634	0.608	0.634	0.608	0.634
8.5	MR	0.788	0.810	0.788	0.810	0.788	0.810
8.5	NO	0.651	0.684	0.651	0.684	0.651	0.684

Table S9. Estimated level of extinction assuming that species respond to climate change by shifting their climatic niches. We estimate the proportion of all 538 species that are projected to go extinct (within their transect) by 2070, assuming that these species can respond to climate change only by shifting their climatic niches, not by dispersing. For each species we evaluated whether all sites across their current range will warm above the estimated threshold for maximum annual temperatures that typically leads to local extinction, using two different thresholds. First, we used the increase in maximum annual temperature (Bio5) at which 95% of the species experienced local extinction at their warmest site (2.860ºC). Second, we used the increase in maximum annual temperature at which 50% of the species experienced local extinction at their warmest site (0.519ºC). For the 0.50 threshold, we assumed that only 50% of the species that experienced temperatures above this threshold would go extinct. Results are shown for multiple climatic scenarios based on 12–19 GCMs and all four RCPs. We present results for two different RCPs in the main text: RCP4.5 and RCP8.5. For each of these two RCPs, we averaged the extinction frequency across all nested GCMs. Not all combinations of RCPs and GCMSs are available (especially for RCP 2.6 and 6). Species-level data are presented in Dataset S7, along with model abbreviations.

RCP	GCM	Extinction frequency	
		Niche shift threshold=0.95 (2.860ºC)	Niche shift threshold=0.50 (0.519ºC)
2.6	BC	0.000	0.117
2.6	CC	0.000	0.124
2.6	CN	0.000	0.121
2.6	GD	0.000	0.079

2.6	GF	0.216	0.399
2.6	GS	0.000	0.105
2.6	HD	0.002	0.176
2.6	HE	0.000	0.315
2.6	IP	0.000	0.340
2.6	MC	0.000	0.326
2.6	MG	0.000	0.096
2.6	MI	0.221	0.298
2.6	MP	0.000	0.252
2.6	MR	0.180	0.350
2.6	NO	0.000	0.141
4.5	AC	0.052	0.364
4.5	BC	0.002	0.322
4.5	CC	0.004	0.352
4.5	CE	0.231	0.418
4.5	CN	0.000	0.368
4.5	GD	0.091	0.248
4.5	GF	0.257	0.424
4.5	GS	0.000	0.316
4.5	HD	0.152	0.380
4.5	HE	0.130	0.399
4.5	HG	0.034	0.374

4.5	IN	0.000	0.089
4.5	IP	0.091	0.367
4.5	MC	0.104	0.386
4.5	MG	0.000	0.304
4.5	MI	0.223	0.443
4.5	MP	0.080	0.339
4.5	MR	0.232	0.421
4.5	NO	0.034	0.365
6	BC	0.048	0.356
6	CC	0.004	0.355
6	GD	0.091	0.339
6	GS	0.000	0.349
6	HD	0.041	0.385
6	HE	0.167	0.415
6	IP	0.091	0.366
6	MC	0.011	0.366
6	MG	0.000	0.326
6	MI	0.294	0.459
6	MR	0.245	0.417
6	NO	0.004	0.358
8.5	AC	0.303	0.414

8.5	BC	0.206	0.369
8.5	CC	0.143	0.396
8.5	CN	0.106	0.399
8.5	GF	0.771	0.468
8.5	GS	0.054	0.379
8.5	HD	0.316	0.447
8.5	HE	0.431	0.467
8.5	HG	0.385	0.461
8.5	IN	0.026	0.337
8.5	IP	0.701	0.421
8.5	MC	0.218	0.424
8.5	MG	0.164	0.365
8.5	MI	0.444	0.475
8.5	MP	0.258	0.376
8.5	MR	0.429	0.474
8.5	NO	0.218	0.412

Table S10. Estimated level of extinction assuming that species respond to climate change by both dispersing and shifting their climatic niches. For each of the analyzed species (*n*=538), we estimated if dispersal could decrease the change in maximum annual temperatures that a species experiences to below the estimated threshold for local extinction (i.e. the amount of niche shift possible without extinction). We used two different thresholds. First, the increase in maximum annual temperature at which 95% of the species experienced local extinction at their warmest site (2.860ºC). Second, the increase in maximum annual temperature at which 50% of the species experienced local extinction at their warmest site (0.519ºC). For the 0.50 threshold, we assumed that only 50% of the species that experienced temperatures above this threshold would go extinct. We explored three different dispersal scenarios. Scenario 1: we assumed that species that did not previously disperse upwards (at their upper elevational range limits) between surveys would not disperse upwards in the future. Scenario 2: we assumed that these previously non-dispersing species would instead move upwards at the mean upward rate across all species that dispersed (including downward dispersal as negative values when calculating the mean). Scenario 3: we assumed that these previously non-dispersing species would instead move upwards at the mean upward rate across all species (counting non-dispersing species as zero when calculating the mean and including downward dispersal as negative values). Results are shown for multiple climatic scenarios based on the 12–19 GCMs and all four RCPs. We present results for two different RCPs in the main text: RCP4.5 and RCP8.5. For each of these two RCPs, we simply averaged the extinction frequency across all nested GCMs. Not all combinations are available. The species-level data are presented in Dataset S8 for the first scenario, Dataset S9 for the second, and Dataset S10 for the third. Model abbreviations are explained in Dataset S8.

RCP	GCM	Niche shift threshold=0.95 (2.860ºC)			Niche shift threshold=0.5 (0.519ºC)		
		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
2.6	BC	0.056	0.056	0.056	0.137	0.129	0.130
2.6	CC	0.052	0.052	0.052	0.133	0.118	0.123
2.6	CN	0.052	0.052	0.052	0.144	0.130	0.135
2.6	GD	0.043	0.041	0.041	0.111	0.112	0.112
2.6	GF	0.231	0.238	0.238	0.309	0.305	0.309
2.6	GS	0.054	0.050	0.054	0.113	0.111	0.112
2.6	HD	0.048	0.043	0.043	0.129	0.130	0.133
2.6	HE	0.069	0.067	0.067	0.231	0.225	0.234
2.6	IP	0.097	0.091	0.091	0.239	0.235	0.240
2.6	MC	0.089	0.087	0.087	0.225	0.226	0.227
2.6	MG	0.052	0.052	0.052	0.116	0.107	0.108
2.6	MI	0.199	0.193	0.199	0.257	0.247	0.256
2.6	MP	0.082	0.080	0.080	0.188	0.185	0.188
2.6	MR	0.225	0.212	0.206	0.273	0.260	0.273
2.6	NO	0.060	0.058	0.058	0.139	0.138	0.141
4.5	AC	0.128	0.110	0.110	0.280	0.282	0.283
4.5	BC	0.078	0.071	0.071	0.225	0.218	0.229
4.5	CC	0.089	0.087	0.087	0.249	0.248	0.251
4.5	CE	0.283	0.292	0.290	0.377	0.371	0.374

4.5	CN	0.087	0.086	0.086	0.263	0.256	0.260
4.5	GD	0.128	0.132	0.132	0.198	0.174	0.179
4.5	GF	0.303	0.307	0.305	0.363	0.360	0.362
4.5	GS	0.091	0.069	0.069	0.230	0.221	0.234
4.5	HD	0.197	0.173	0.175	0.302	0.304	0.304
4.5	HE	0.184	0.152	0.152	0.320	0.315	0.319
4.5	HG	0.119	0.100	0.100	0.289	0.286	0.290
4.5	IN	0.050	0.050	0.050	0.105	0.084	0.101
4.5	IP	0.178	0.164	0.162	0.289	0.284	0.289
4.5	MC	0.178	0.152	0.151	0.287	0.284	0.287
4.5	MG	0.082	0.082	0.082	0.221	0.217	0.218
4.5	MI	0.281	0.266	0.264	0.351	0.348	0.351
4.5	MP	0.149	0.132	0.132	0.257	0.258	0.260
4.5	MR	0.284	0.266	0.266	0.325	0.326	0.327
4.5	NO	0.102	0.099	0.099	0.252	0.253	0.255
6	BC	0.125	0.106	0.106	0.248	0.246	0.250
6	CC	0.100	0.093	0.093	0.253	0.254	0.256
6	GD	0.171	0.156	0.154	0.237	0.230	0.232
6	GS	0.113	0.091	0.091	0.248	0.246	0.249
6	HD	0.126	0.108	0.108	0.282	0.278	0.281
6	HE	0.219	0.204	0.203	0.336	0.334	0.337
6	IP	0.180	0.165	0.164	0.289	0.288	0.290

6	MC	0.106	0.099	0.099	0.270	0.265	0.268
6	MG	0.089	0.087	0.087	0.246	0.239	0.244
6	MI	0.314	0.316	0.318	0.365	0.365	0.368
6	MR	0.271	0.279	0.273	0.330	0.324	0.329
6	NO	0.115	0.093	0.093	0.253	0.248	0.253
8.5	AC	0.299	0.296	0.301	0.358	0.353	0.355
8.5	BC	0.214	0.225	0.223	0.285	0.286	0.286
8.5	CC	0.227	0.214	0.214	0.329	0.323	0.328
8.5	CN	0.184	0.167	0.167	0.317	0.313	0.316
8.5	GF	0.548	0.554	0.545	0.444	0.444	0.445
8.5	GS	0.128	0.125	0.125	0.293	0.286	0.289
8.5	HD	0.327	0.340	0.333	0.383	0.382	0.383
8.5	HE	0.420	0.431	0.424	0.410	0.407	0.410
8.5	HG	0.357	0.364	0.364	0.402	0.403	0.403
8.5	IN	0.115	0.097	0.097	0.234	0.236	0.239
8.5	IP	0.476	0.480	0.478	0.390	0.388	0.392
8.5	MC	0.253	0.260	0.262	0.355	0.353	0.354
8.5	MG	0.197	0.201	0.199	0.286	0.285	0.286
8.5	MI	0.457	0.467	0.465	0.407	0.410	0.410
8.5	MP	0.279	0.290	0.286	0.310	0.311	0.311
8.5	MR	0.448	0.455	0.454	0.414	0.415	0.417
8.5	NO	0.231	0.238	0.240	0.329	0.326	0.326