

SUPPLEMENTAL MATERIALS

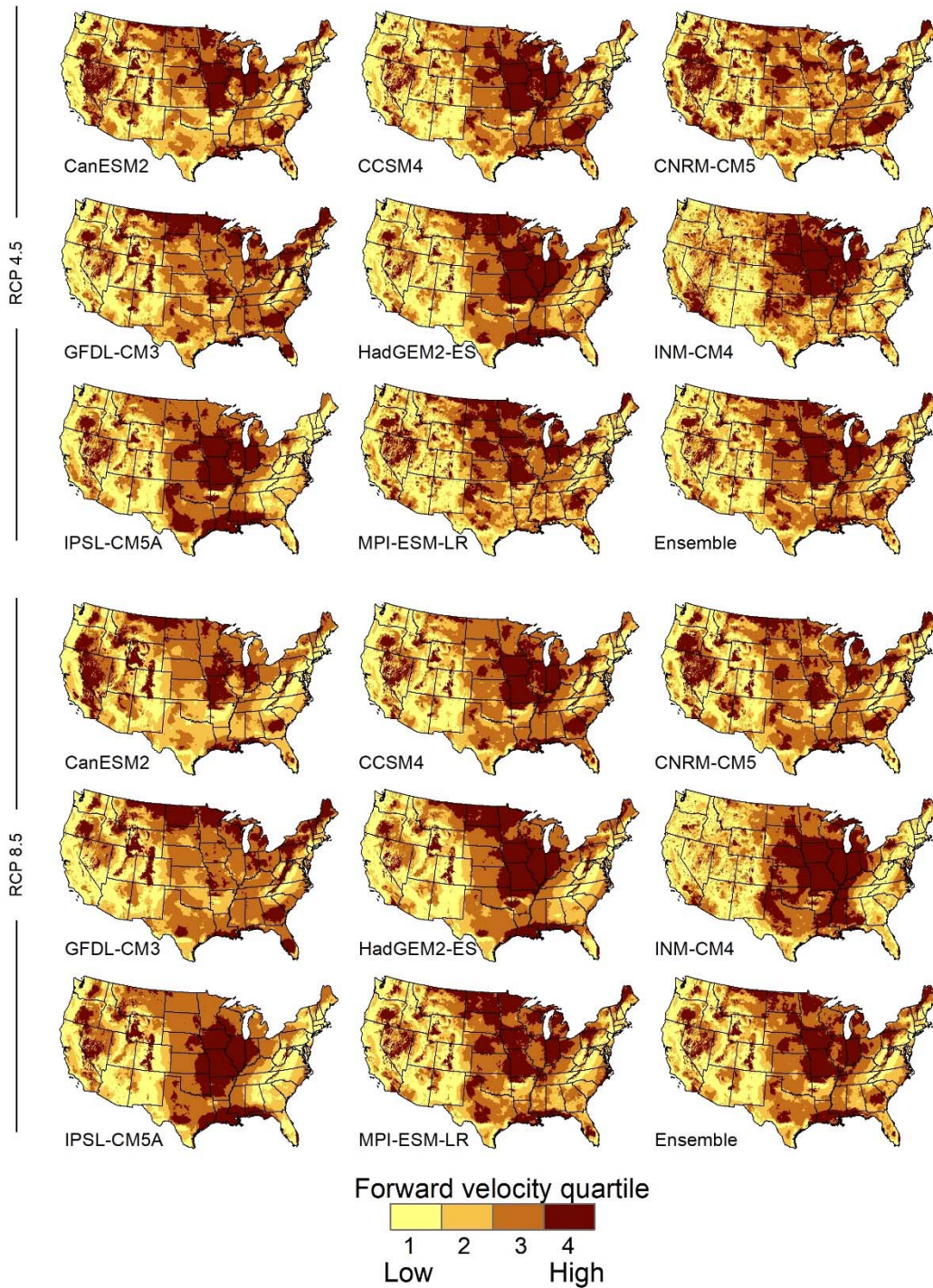
Assessing agreement among alternative climate change projections to inform conservation recommendations in the contiguous United States

R. Travis Belote, Carlos Carroll, Sebastián Martinuzzi, Julia Michalak, John W. Williams,
Matthew A. Williamson, Gregory H. Aplet

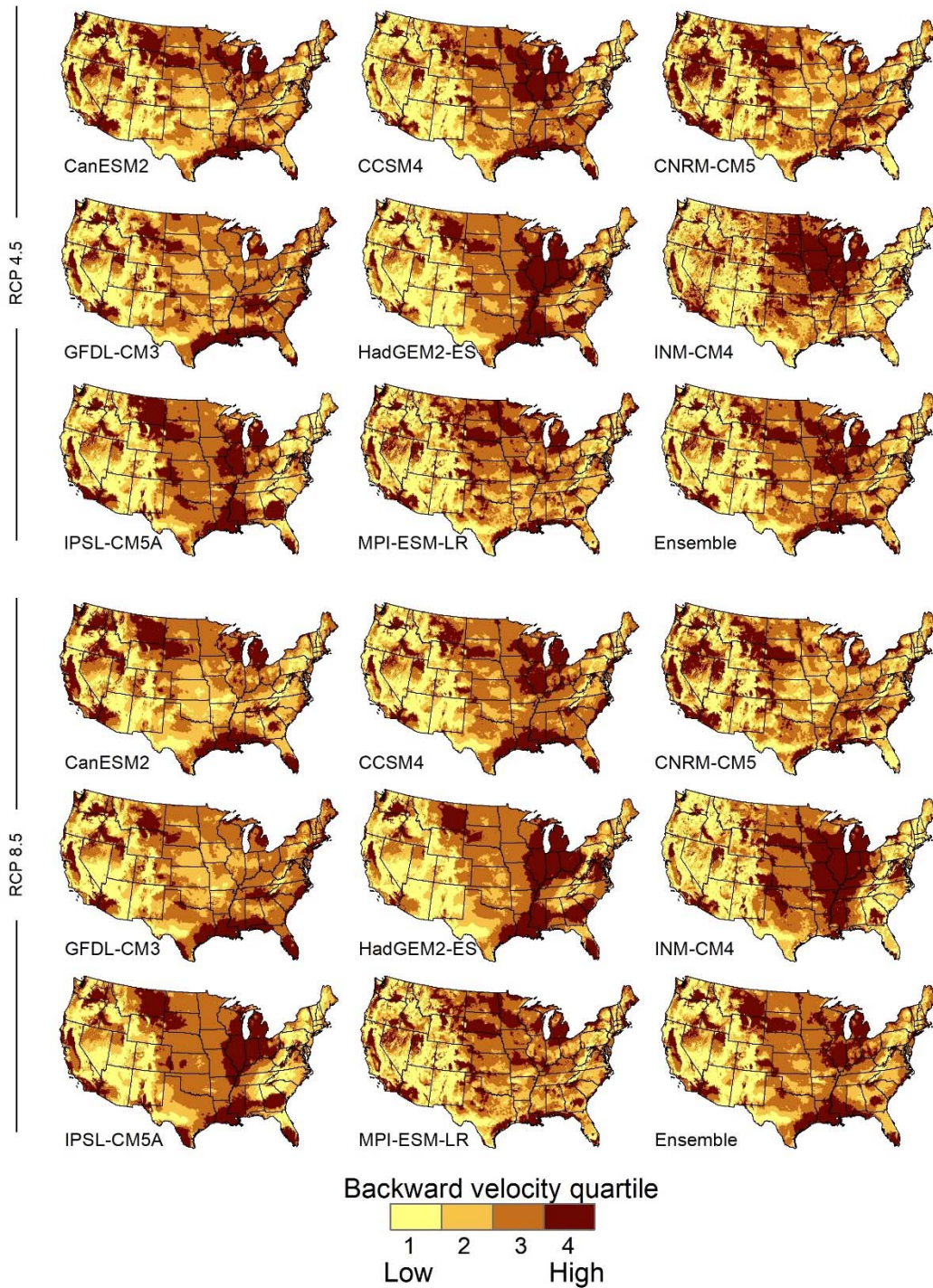
Supplemental Table 1. CMIP5 general circulation models (GCMs) used to evaluate agreement among simulations. The first eight were used as individual simulations with RCP 4.5 and 8.5. In addition to a multi-model ensemble was calculated based on the first eight and the last seven GCMs listed.

Use	GCM	Source
Focal simulations	CanESM2	Canadian Centre for Climate, Canada
	CCSM4	National Center for Atmospheric Research, USA
	CNRM-CM5	Centre National de Recherches Meteorologiques, France
	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA
	HadGEM2-ES	Met Office Hadley Centre, UK
	INM-CM4	Institute for Numerical Mathematics, Russia
	IPSL-CM5A-MR	Institute Pierre-Simon Laplace, France
	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany
For Ensemble only	ACCESS1.0	Commonwealth Scientific and Industrial Research Organization, Australia
	MIROC5	Atmosphere and Ocean Research Institute, Japan
	CSIROMk3.6	Commonwealth Scientific and Industrial Research, Australia
	MRI-CGCM3	Meteorological Research Institute, Japan
	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Japan
	CESM1-CAM5	National Center for Atmospheric Research, USA
	GISS-E2R	NASA Goddard Institute for Space Studies, USA

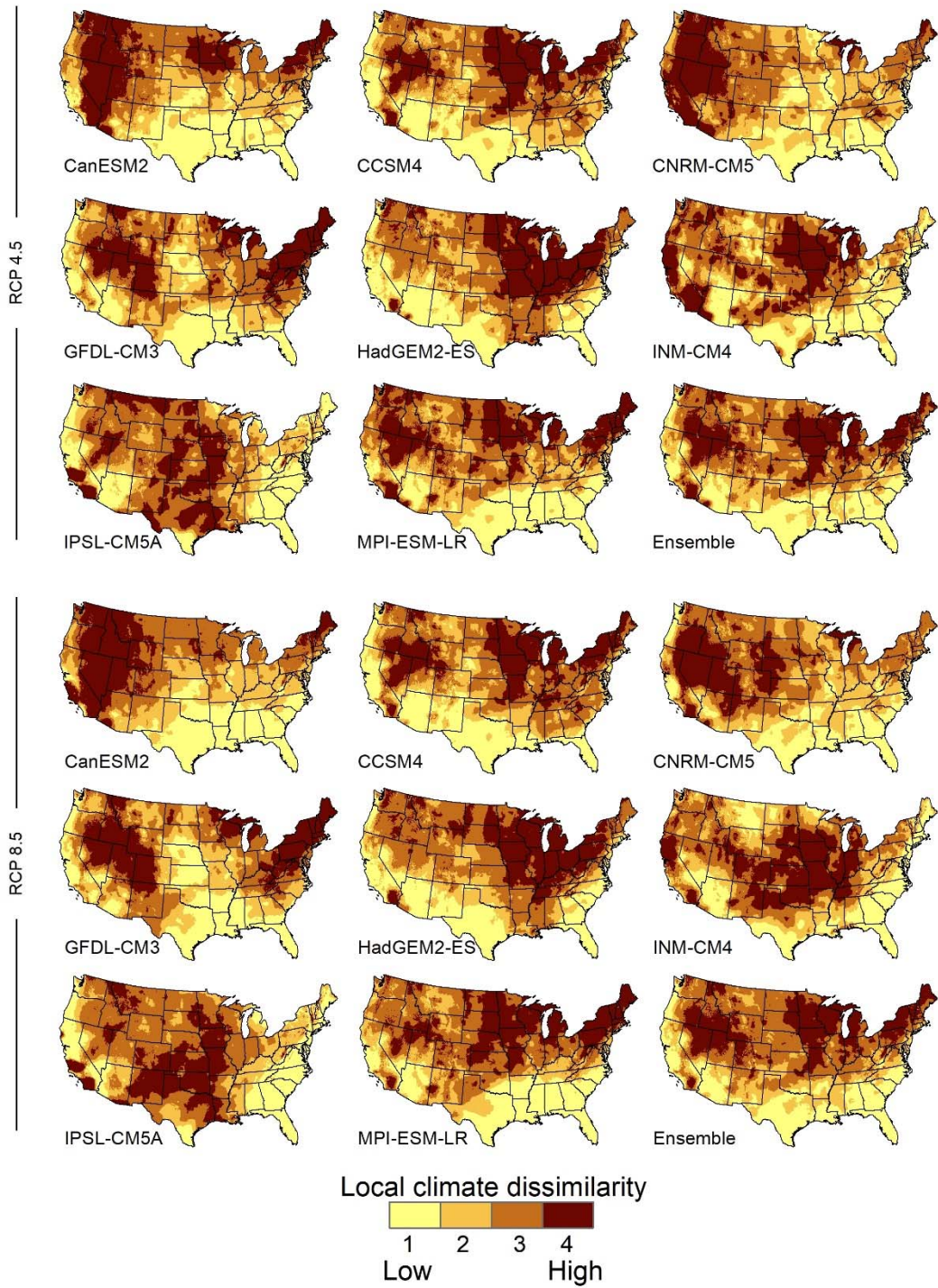
Supplemental Figure 1. Quartiles of all 18 alternative climate projections and scenario outputs for the forward climate velocity. Top nine map panels represent RCP 4.5; bottom 9 maps represent RCP 8.5.



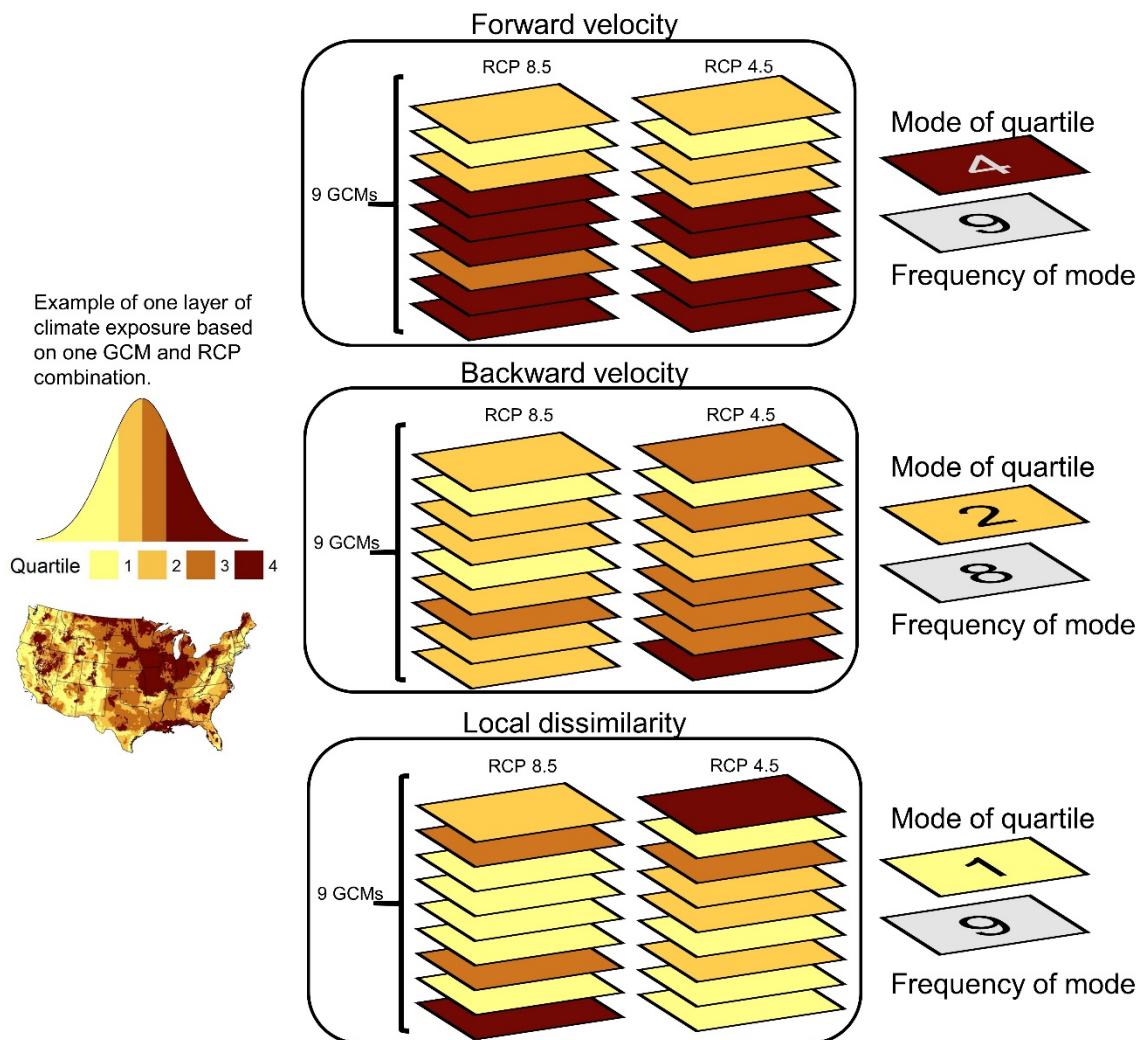
Supplemental Figure 2. Quartiles of all 18 alternative climate projections and scenario outputs for the backward climate velocity. Top nine map panels represent RCP 4.5; bottom 9 maps represent RCP 8.5.



Supplemental Figure 3. Quartiles of all 18 alternative climate projections and scenario outputs for the local climate dissimilarity. Top nine map panels represent RCP 4.5; bottom 9 maps represent RCP 8.5.



Supplemental Figure 4. Simplified depiction of methods used to assess simulation agreement. Each square represents one hypothetical example grid cell location. Three mapped climate metrics for the contiguous U.S. (forward velocity, backwards velocity, local climate dissimilarity) were classified into quartiles and assigned integer values 1 (lower quartile) to 4 (upper quartile). Within each climate exposure metric, classified quartile maps representing estimates from 18 different future climate simulations (9 general circulation models \times 2 representative concentration pathways) were stacked. The mode of quartile and frequency of mode were calculated and used to produce maps of simulation agreement for each climate metric.

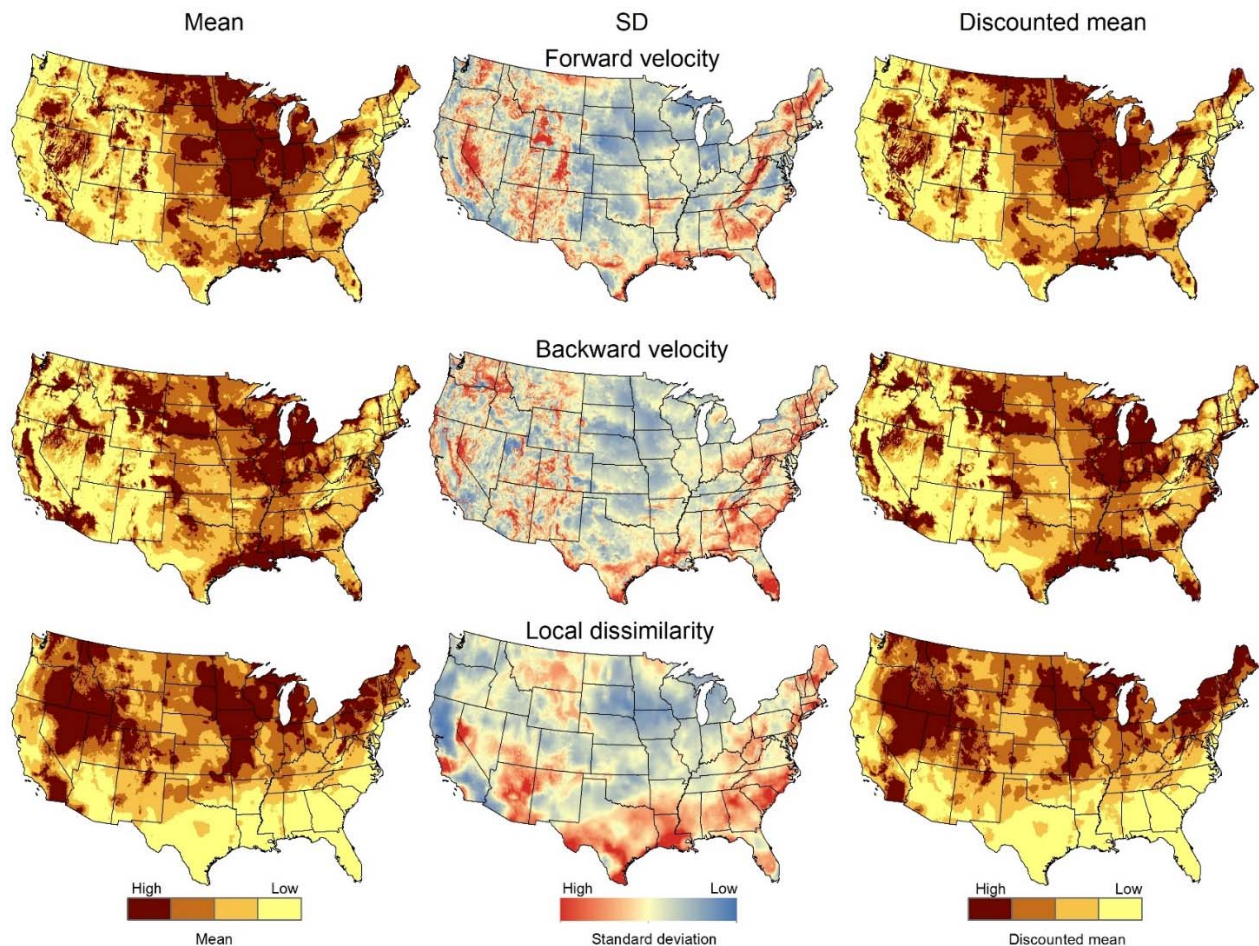


Supplemental Figure 5.

As a complement to the quadrant-based categorization described, we also applied an approach, distribution discounting, that reduces or discounts the estimated exposure of a site based on the level of uncertainty (e.g., the standard deviation between metrics based on alternative future climate projections) shown by metrics measured at that site^{1,2}. Resultant conservation priority areas will then be located preferentially in areas of high agreement between alternative future projections. Because we were interested in assessing uncertainty of the three climate metrics when they were expressed as a conservation target (i.e., with positive values in areas of low climate exposure), we used a refugia index based on -1 times the log transform of the raw metrics³. We followed Carroll et al. (2010)³ in discounting the mean value of the metric across the 18 future projections by one-half of the standard deviation of the metric between future projections. A range of discounting coefficients have been used (e.g., 1.0 rather than 0.5 as used here²), corresponding to differing levels of risk aversion.

Although regional patterns of uncertainty differed between the three metrics (with Pearson's correlations of 0.38-0.46), all metrics showed highest uncertainty in the southeastern US and intermountain West. Standard deviation was moderately correlated with mean values for climate dissimilarity (Pearson's correlation = 0.62) but not for either forward or backward velocity (Pearson's correlation = 0.18 and 0.25, respectively). The standard deviation and frequency of climate modes, two estimates of simulation agreement, were not strongly correlated for any metric (forward velocity: $r = -0.08$; backward velocity: $r = -0.15$; local dissimilarity: $r = -0.13$; although p-values were < 0.0001 for each correlation). Though areas with higher standard deviation among simulations were also characterized by lower frequency of climate modes.

Because the relative uncertainty of environmental dissimilarity values was correlated with mean values, use of distribution discounting spread priorities more broadly as compared to priorities based on undiscounted mean values. Patterns of uncertainty for forward and backward velocity were more complex, but generally lowered priorities in the intermountain West and southeastern US. Discounted means could be used as a substitute for the ensemble or median or mean values in bivariate mapping efforts.



Supplemental Figure 6.

We summarized patterns of predicted climate change through the continuous US by EPA level 3 ecoregions⁵. We calculated the mean value of the three multivariate exposure metrics

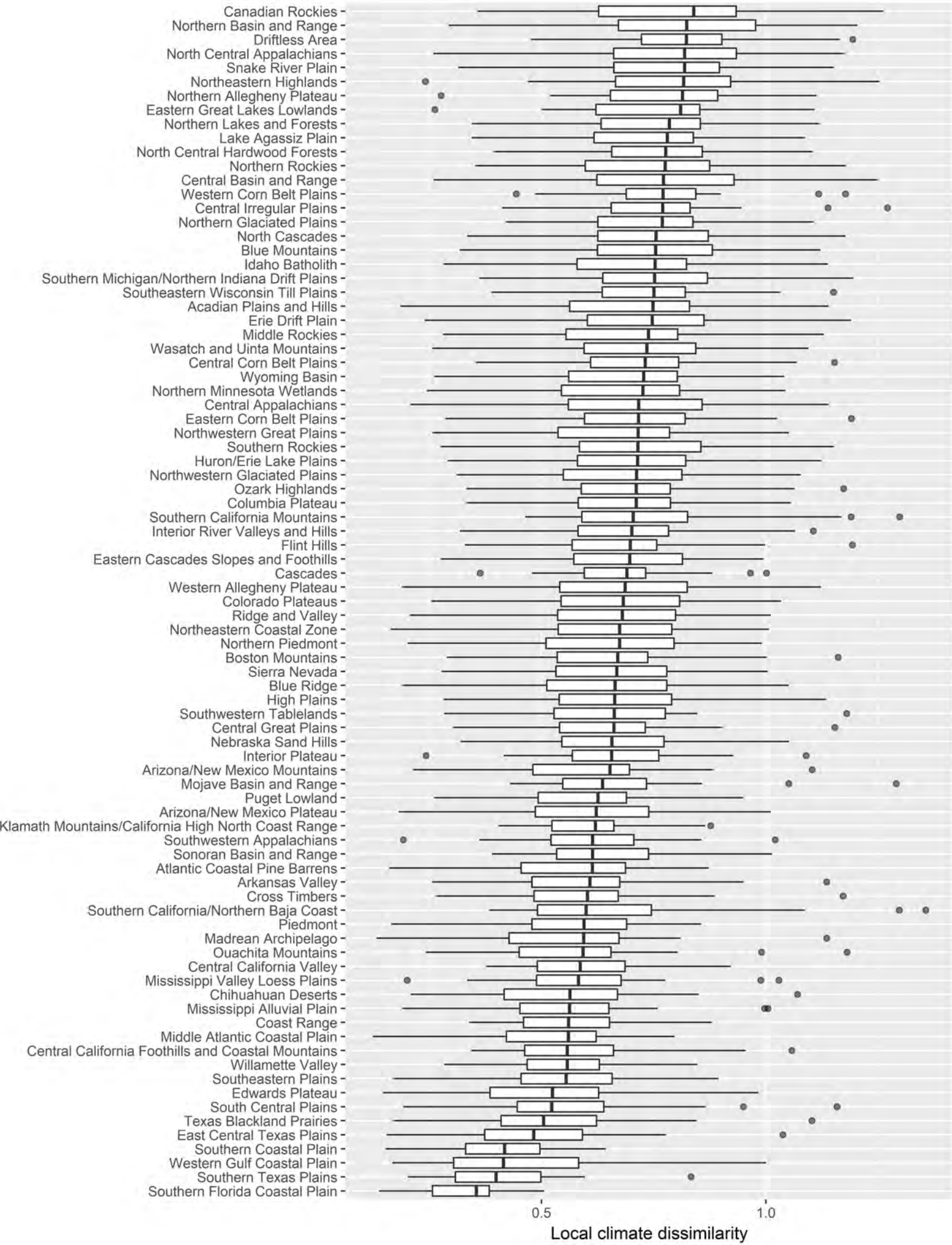
(forward velocity, backward velocity, and local climate dissimilarity) for all 18 climate projections (based on the combinations of GCM and RCP alternatives). We also calculated the predicted degree of change in the 11 climate variables used in the principal components analysis (see list below) that served as the basis for calculating the multivariate exposure metrics. For temperature variables, we calculated the arithmetic difference between future predictions and current observations. For precipitation and number of day variables, we calculated the percent change between current and future values.

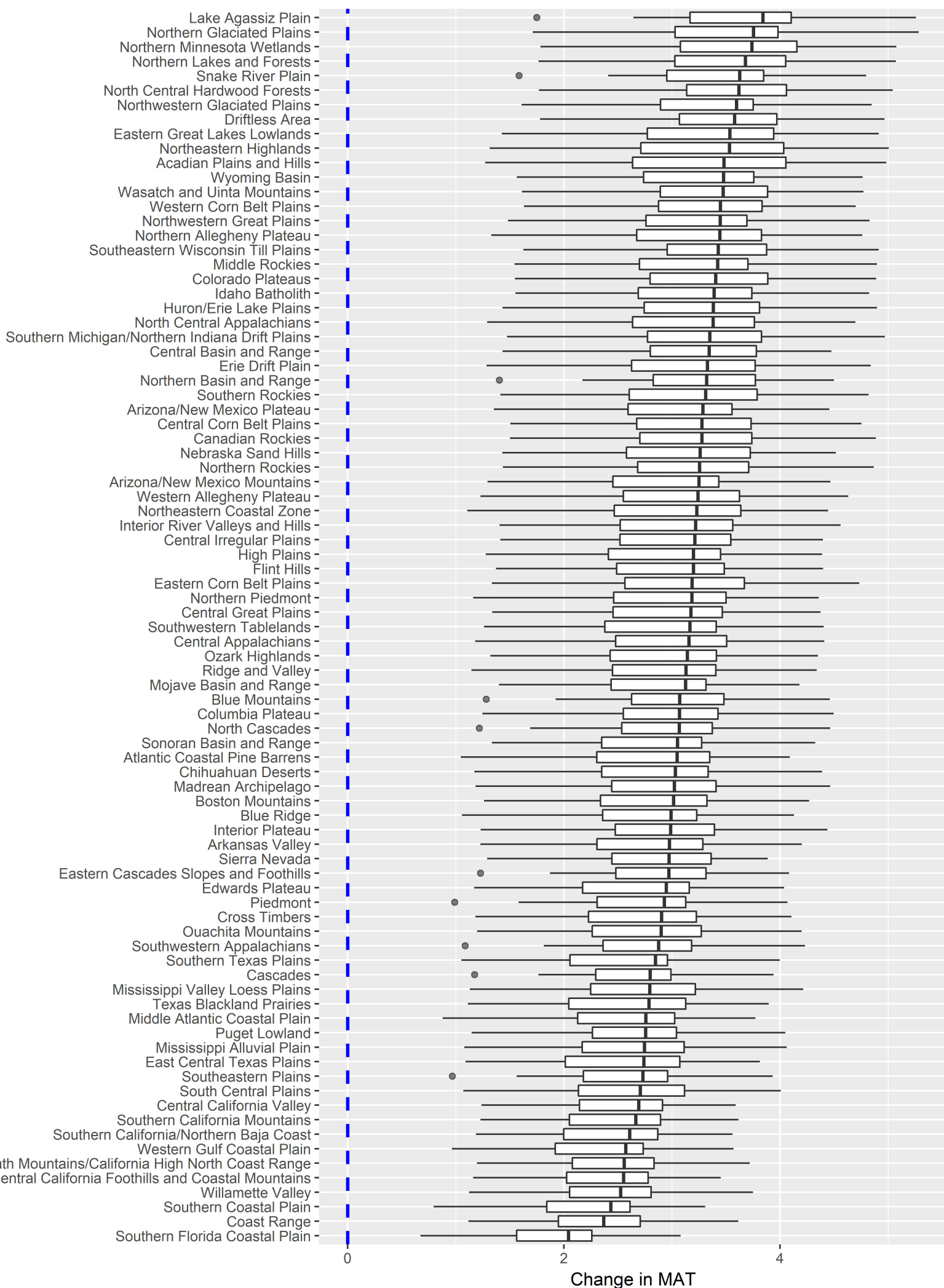
After calculating the mean values for each variable within each ecoregion, we plotted the data using box and whisker plots to summarize variability among ecoregions and alternative climate projections. The variability depicted by the box and whisker plots represent alternative predictions based on the 18 projections. We rank ordered these plots by the median value among the 18 simulation alternatives.

Code	Variable
MAT	mean annual temperature (°C)
MWMT	mean temperature of the warmest month (°C)
MCMT	mean temperature of the coldest month (°C)
TD	difference between MCMT and MWMT, as a measure of continentality (°C)
MAP	mean annual precipitation (mm)
MSP	mean summer (May to Sep) precipitation (mm)
MWP	mean winter (Oct to Apr) precipitation (mm)
DD5	degree-days above 5°C (growing degree days)
NFFD	the number of frost-free days
Eref	Hargreave's reference evaporation
CMD	Hargreave's climatic moisture index.

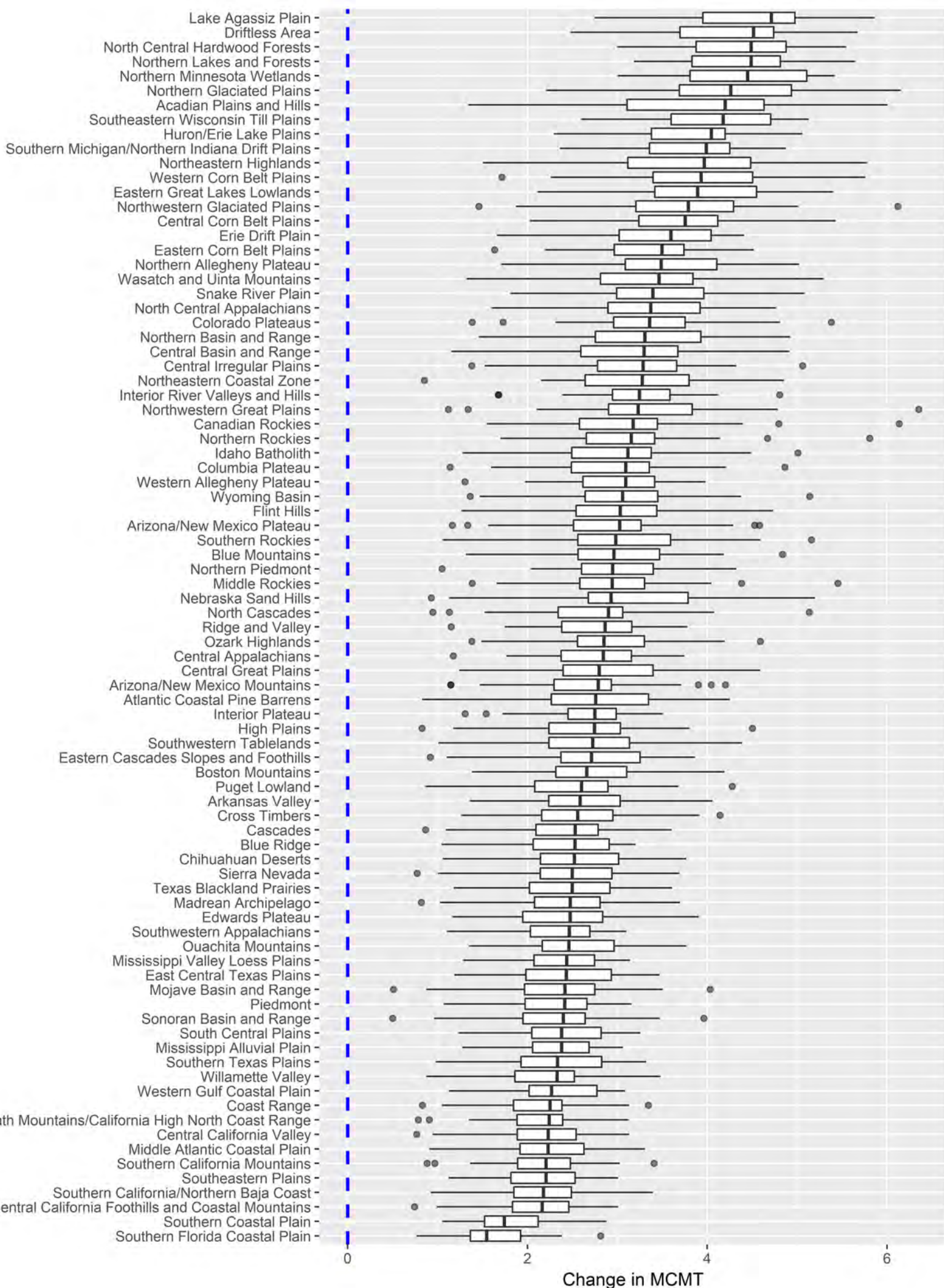


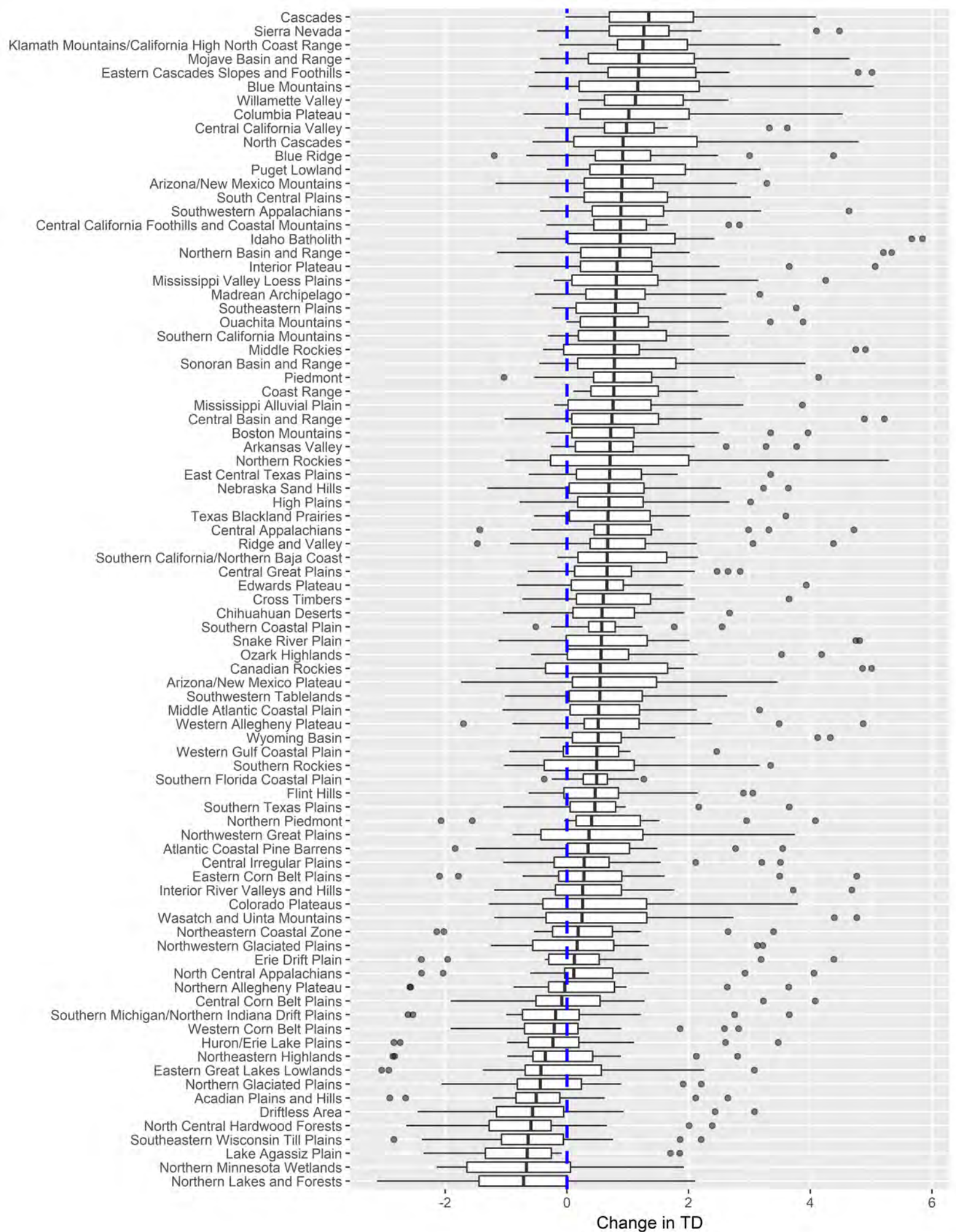


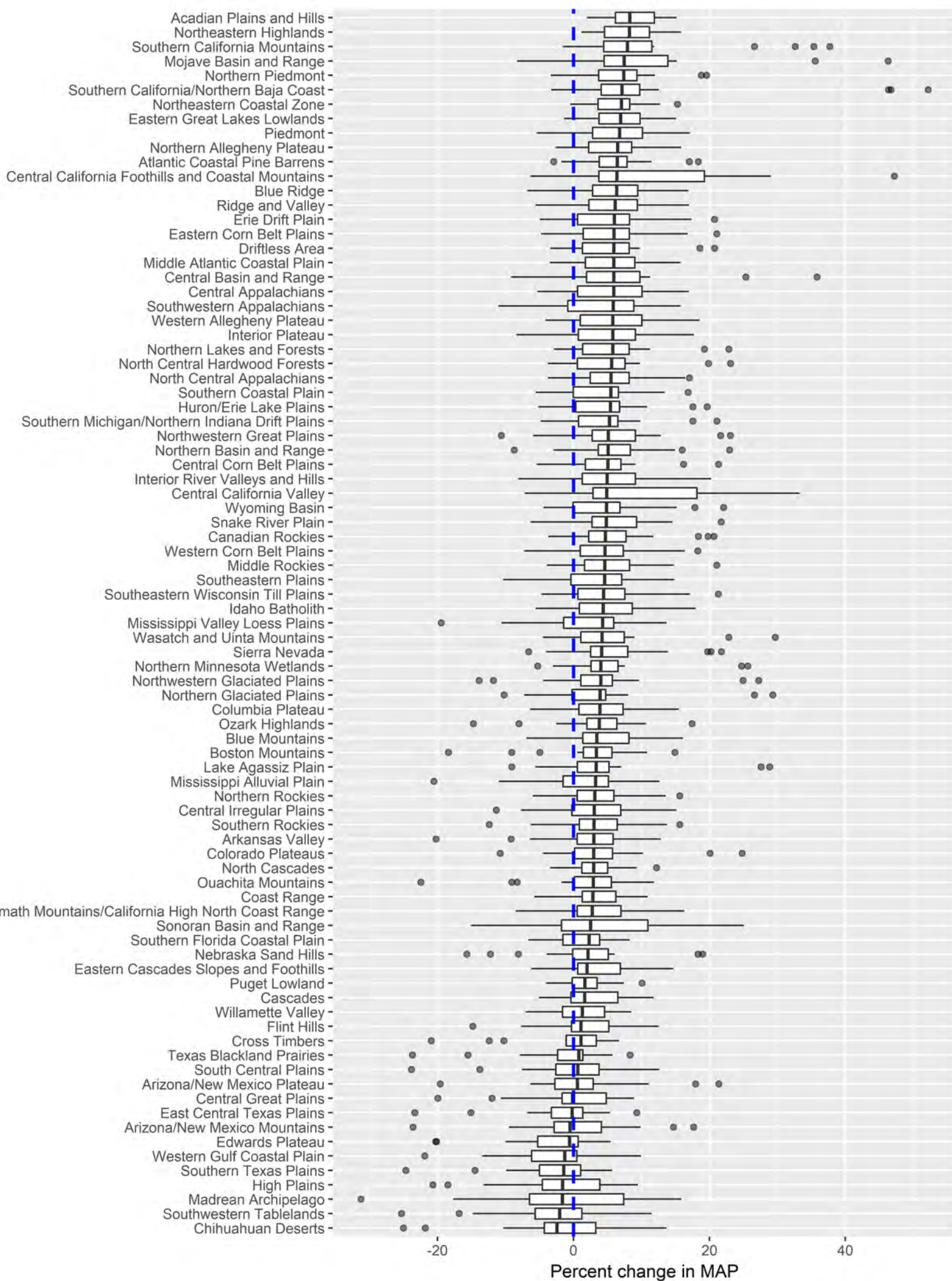


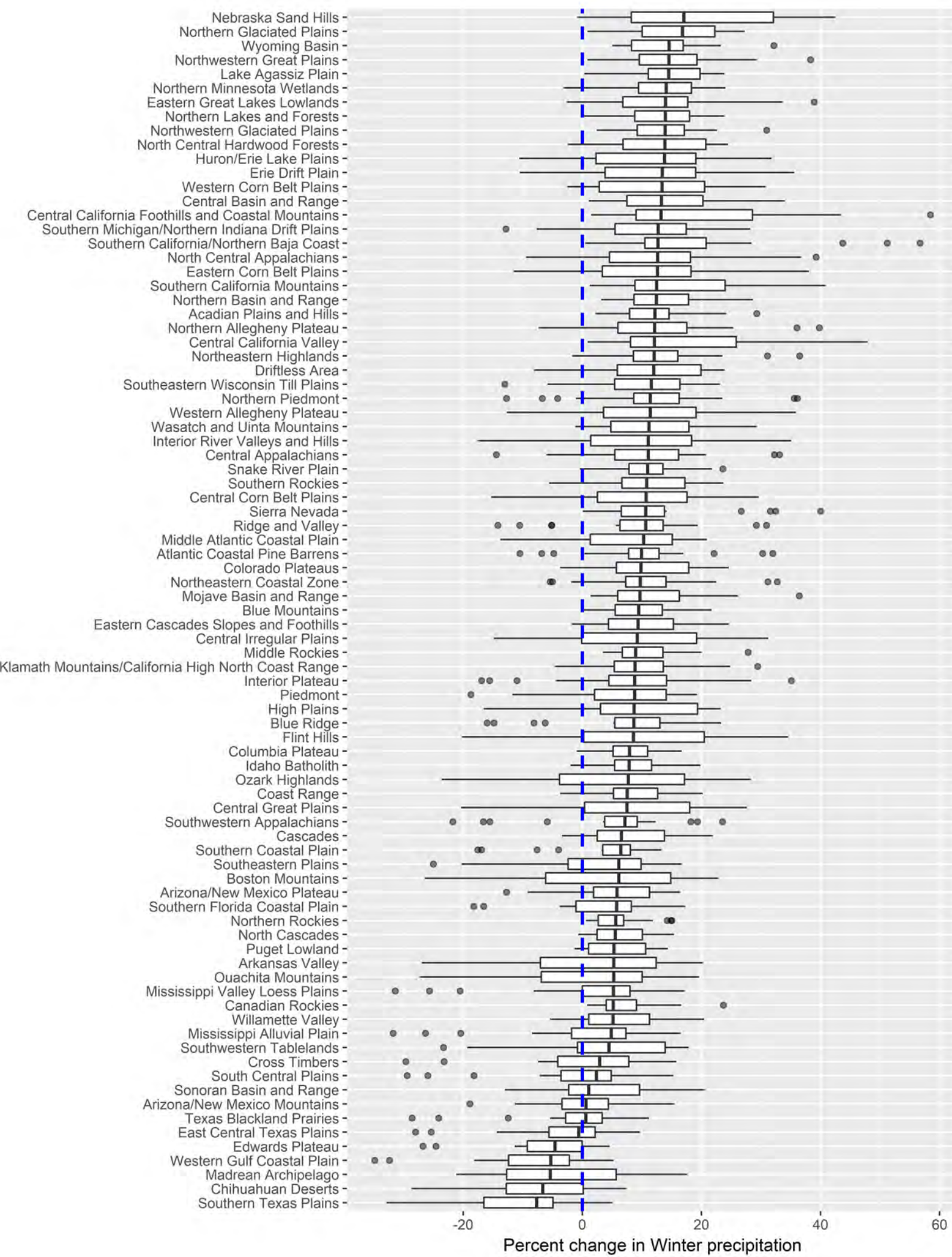


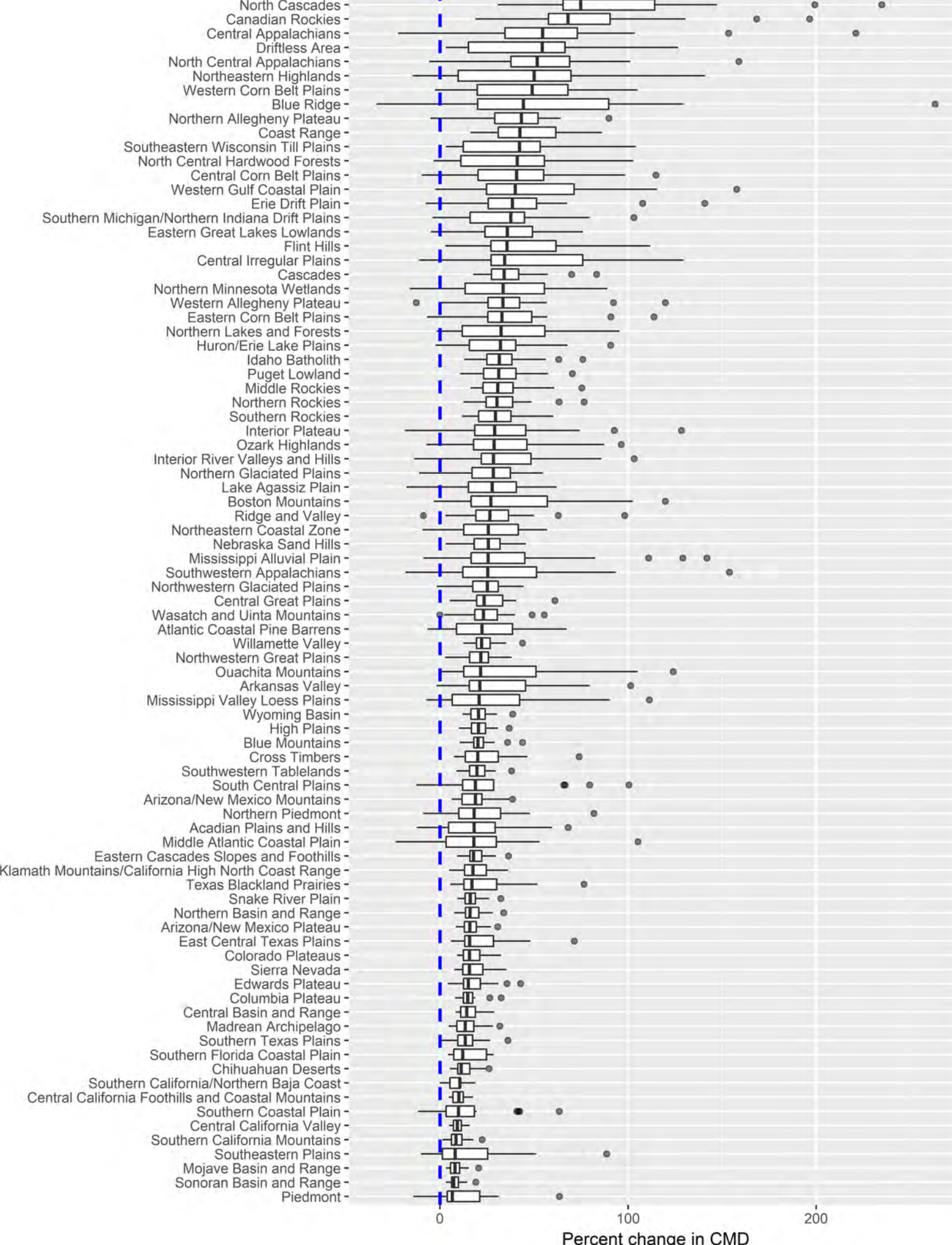


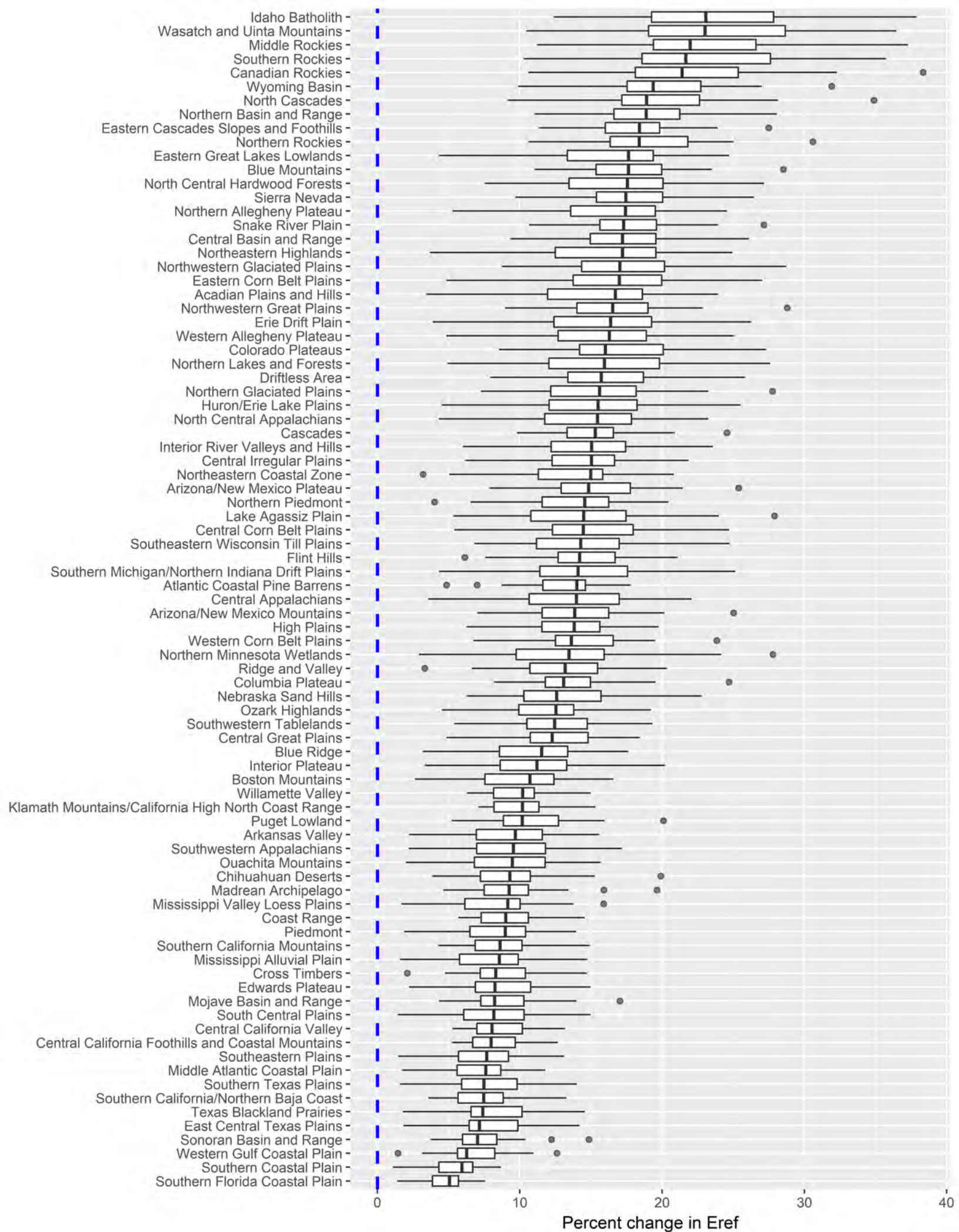


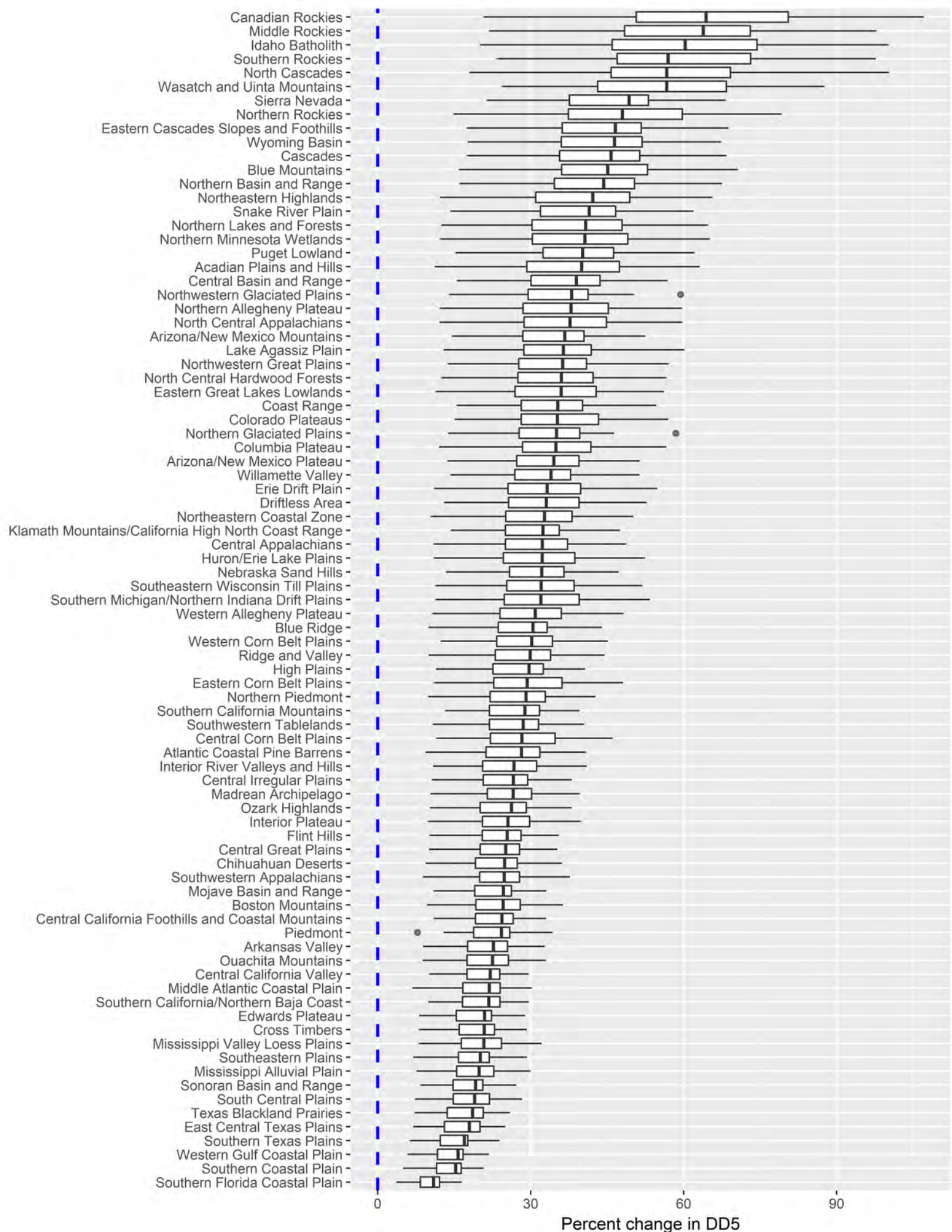


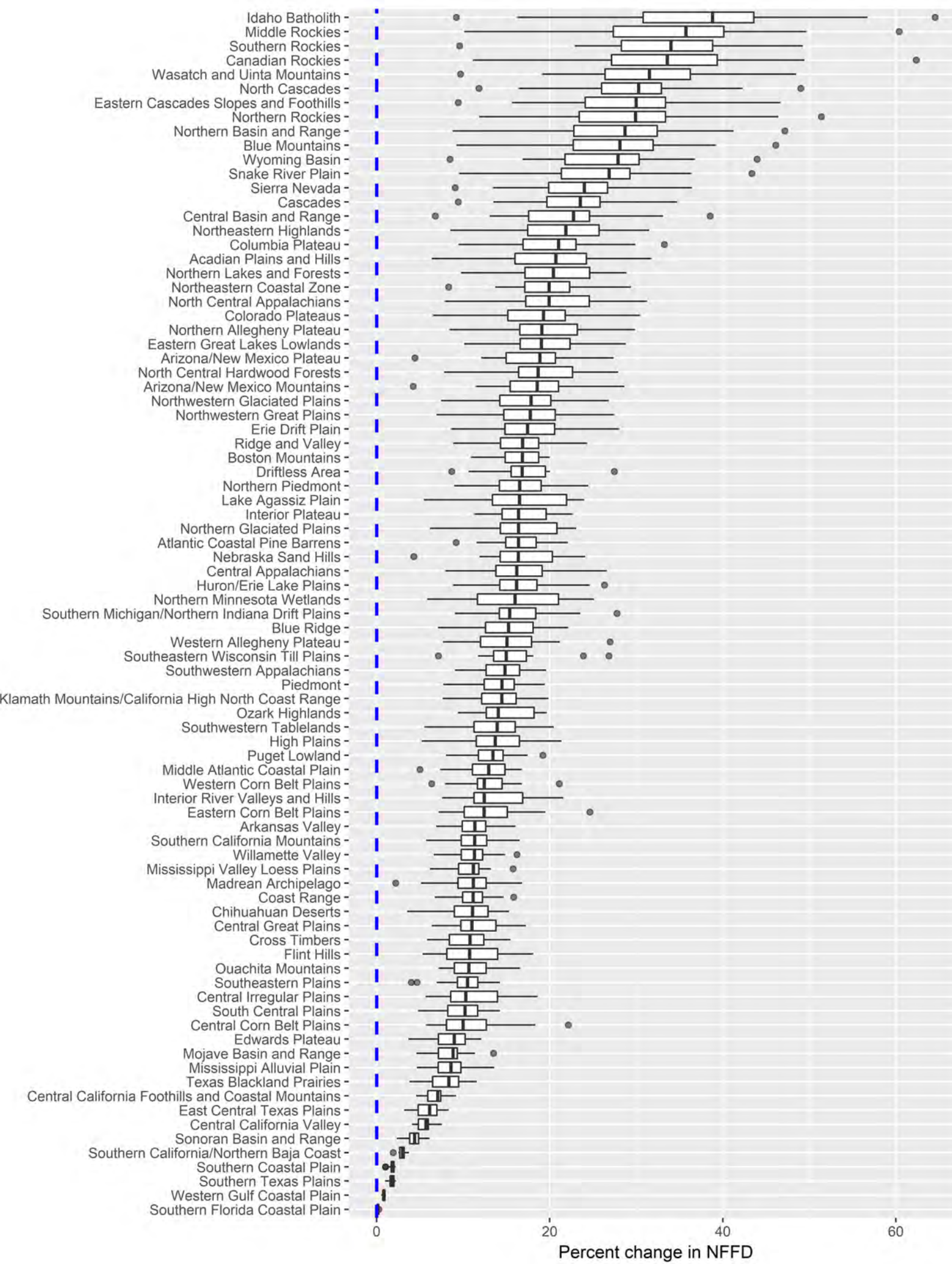












References

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3. Carroll, C. *et al.* Scale-dependent complementarity of climatic velocity and environmental diversity for identifying priority areas for conservation under climate change. *Global Change Biology* (2017). doi:10.1111/gcb.13679
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