SUPPLEMENTARY MATERIAL

Ponderosa pine mortality response to density-drought interactions suggest opportunities to enhance drought resistance of dry forests

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Statistical modeling & model comparison

Survival probability for the 10 years between plot measurements was modeled following Shriver et al. (2021) as

$$s_{i,t+1} \sim Bernoulli(p_{i,t})$$

$$logit(p_{i,t}) = \alpha\, z_{i,t} + \mathbf{X}_{d[i]}\mathbf{b} + \omega_{d[i]}$$

where $p_{i,t}$ is the probability of survival for individual *i* from *t* to *t+1,* $z_{t,i}$ is the diameter of tree *i* in the first census (*t*), α is a regression coefficient for the impact of individual tree size on survival that allows tree size to influence survival rate, $\mathbf{b}$ is a vector of regression coefficients for environmental conditions (temperature and SWA means and anomalies; Table 1) and basal area terms, $\mathbf{X}_{d[i]}$ is a design matrix including all plot-covariates and an intercept for individual *i*, and $\omega_{d[i]}$ is a plot-specific spatial random effect for each individual *i.*

Spatial random effects were fit using a predictive process model (Latimer *et al.* 2009). Predictive process models address the computational challenges of fitting spatial models to large datasets by reducing point locations (i.e. plots) to a lesser number of constituent knots that encapsulate the landscape of spatially autocorrelated processes not explained by covariates. In the case of survival random effects,

$$\boldsymbol{\omega}^{*} \sim MVN(0, \Sigma^{*})$$

$$\Sigma^{*}_{k,k'} = \tau_{(z)} e^{-\phi_{(z)}\delta_{k,k'}}$$

$$\boldsymbol{\omega} = \Sigma_{(\omega,\omega^{*})}\Sigma^{*-1}\boldsymbol{\omega}^{*}$$

$\boldsymbol{\omega}^{*}$ is a K-length multi-variate normally distributed vector of random effects ($\boldsymbol{\omega}^{*}$=$\omega^{*}{}_{1}, \omega^{*}{}_{2}\ldots\omega^{*}{}_{K}$) associated with each knot (*k*). Σ^{*} is a covariance matrix where each element is a correlation among knots weighted by distance, $\delta_{k,k'}$. ϕ is a parameter describing the rate at which correlations decay as a function of distance (km), and τ is an error term. $\boldsymbol{\omega}$ is a Dlength vector of random effects for each plot ($\omega_d = \omega_1, \omega_2 \dots \omega_D$). The underlying knot-based spatial landscape is then linked back to specific plots in $\Sigma_{(\omega,\omega^*)}$, which is a cross-covariance matrix that describes the spatial relationship between plots ($\boldsymbol{\omega}$) and knots ($\boldsymbol{\omega}^*$), where $\delta_{k,k'}$ is the distance (km) between each the fuzzed location of plot (*d*) and knot (*k*) pair. Following Latimer et al. (2009; i.e. 100-400 knots) we used 200 knots whose locations are assigned to maximize coverage of plot locations using the "cover.design" function in the "fields" package (v. 9.6) in R (Nychka *et al.* 2017). We fit models with Hamiltonian Monte Carlo (HMC) using the "rstan" package (Stan Development Team 2020). Models were run with 2 chains and 5000 iterations each, 2500 of which were warmup. Parameter convergence was monitored with convergence statistics (R-hat; Gelman *et al.* 2013).

Model rankings were consistent between deviance information criteria (DIC) and weighted Akaike Information Criterion (wAIC), so model comparison was done with DIC, which is more suited to this Bayesian model fitting approach and is calculated as

$$DIC = D(\bar{\theta}) - 2p_d$$

$$p_d = \overline{D(\theta)} - D(\bar{\theta})$$

Where $D(\bar{\theta})$ is the deviance given the mean parameter set, and $\overline{D(\theta)}$ is the mean deviance across all parameter sets.

Table S1: Results of models utilizing covariates from the forest drought severity index (FDSI). When basal area was not included, the model based on 1-year FDSI (Williams *et al.* 2013) terms was roughly equivalent to our long-term climate model (Table S2: model 0 vs. model F0.1). However, when basal area was included, the models based on FDSI did not perform as well as models based on long-term temperature and SWA. In addition, collinearity between FDSI terms and temperature and soil water availability anomalies (Table S1) would have confounded efforts to formulate models with FDSI terms and those anomalies. FDSI models are compared to models based on long-term mean growing season temperature ($TEMP_{MEAN}$) and soil water availability (SWA_{MEAN}), with and without basal area (BA). FDSI terms include ZlogPPTyrs (the lowest z-score of log(November-March Precipitation) for a single year between measurements), ZPETmeanyrs1 (the highest z-score of May-July and previous August-October PET for a single year between measurements), ZlogPPTyrs8 (the lowest z-score of log(November-March Precipitation) for a consecutive 8-year period between measurements), and ZPETmeanyrs7 (the highest z-score of May-July and previous August-October PET for a 7-year period between measurements).

Model	Hypothesized drivers of tree mortality	SWA_{MEAN}	$TEMP_{MEAN}$	BA	ZlogPPTyrs1	ZPETmeanyrs1	ZlogPPTyrs8	ZPETmeanyrs7	DIC
1	Climate and competition	X	X	X					14109.37
F1.1	Short-term FDSI (single year seasonal PET and PPT) and competition			X	X	X			14112.83
F1.2	Long--term FDSI (multiple year seasonal PET and PPT) and competition			X			X	X	14111.90
0	Climate only	X	X						14309.44
F0.1	Short-term FDSI (single year seasonal PET and PPT) and competition				X	X			14309.68
F0.2	Long--term FDSI (multiple year seasonal PET and PPT)						X	X	14314.89

Table S2: Performance of candidate models for ponderosa pine mortality, sorted by deviance information criteria (DIC). See Figure S3 for covariates distributions associated with each model.

#	Hypothesized drivers of tree mortality	DIC	Δ DIC
5.3	Climate with multiyear hot-dry anomalies, all interacting with competition, and SWA_{3YMAX}	14088.3	
6.4	Climate and SWA_{8YMIN}, all interacting with competition, with $TEMP_{1YMAX}$ and SWA_{3YMAX}	14090.1	1.78
6.5	Climate, SWA_{8YMIN}, and $TEMP_{1YMAX}$, all interacting with competition, and SWA_{3YMAX}	14091.74	3.42
6.1	Climate, interacting with competition, with SWA_{8YMIN}, $TEMP_{1YMAX}$ and SWA_{3YMAX}	14092.1	3.73
5.1	Climate, with SWA_{MEAN} interacting with competition, SWA_{8YMIN} interacting with competition, $TEMP_{7YMAX}$, and SWA_{3YMAX}	14092.3	3.95
5.2	Climate and SWA_{8YMIN}, all interacting with competition, with $TEMP_{7YMAX}$ and SWA_{3YMAX}	14092.5	4.14
6.3	Climate, and $TEMP_{1YMAX}$, all interacting with competition, with SWA_{3YMAX}	14092.60	4.28
4.3	Climate, SWA_{8YMIN}, all interacting with competition, with SWA_{3YMAX}	14093.49	5.17
6.2	Climate and $TEMP_{1YMAX}$, all interacting with competition, with SWA_{8YMIN} and SWA_{3YMAX}	14093.6	5.23
3.8	Climate, competition, & single-year hot-dry anomalies, interacting with competition, moderated by SWA_{3YMAX}	14094.16	5.84
2.8	Climate, competition, & multiyear hot-dry anomalies, interacting with competition, moderated by SWA_{3YMAX}	14094.74	6.42
2.5	Climate, competition, & $TEMP_{7YMAX}$, interacting with competition, moderated by SWA_{3YMAX}	14094.75	6.43
3.5	Climate, competition, & $TEMP_{1YMAX}$, interacting with competition, moderated by SWA_{3YMAX}	14094.82	6.5
6	Climate, with SWA_{MEAN} interacting with competition, SWA_{8YMIN}, $TEMP_{1YMAX}$, and SWA_{3YMAX}	14096.3	7.93
5	Climate, with SWA_{MEAN} interacting with competition, multiyear hot-dry anomalies, and SWA_{3YMAX}	14097.2	8.9
2.2	Climate, competition, & SWA_{8YMIN}, interacting with competition, moderated by SWA_{3YMAX}	14098.07	9.75
4.0	Climate, competition, SWA_{8YMIN}, $TEMP_{1YMAX}$, moderated by SWA_{3YMAX}	14099.4	11.03
2.7	Climate, competition, & multiyear hot-dry anomalies, interacting with competition.	14099.8	11.51
3.2	Climate, competition, & $TEMP_{1YMAX}$, interacting with competition, moderated by SWA_{3YMAX}	14099.93	11.61
4.1	Climate, competition, multiyear hot-dry anomalies, moderated by SWA_{3YMAX}	14100	11.7
2.1	Climate, competition, & SWA_{8YMIN}, interacting with competition.	14102.28	13.96
2	Climate, competition, & SWA_{8YMIN}	14104.37	16.05
1.1	Climate, interacting with competition	14104.76	16.44
3.6	Climate, competition, & single-year hot-dry anomalies	14105.22	16.9
2.6	Climate, competition, & multiyear hot-dry anomalies	14105.64	17.32
2.4	Climate, competition, & $TEMP_{7YMAX}$, interacting with competition.	14105.95	17.63
3.4	Climate, competition, & $TEMP_{1YMAX}$, interacting with competition.	14106.10	17.78
3.3	Climate, competition, & $TEMP_{1YMAX}$	14106.34	18.02
3.7	Climate, competition, & single-year hot-dry anomalies, interacting with competition.	14107.62	19.3
2.3	Climate, competition, & $TEMP_{7YMAX}$	14109.01	20.69
1	Climate and competition	14109.37	21.05
3	Climate, competition, & SWA_{1YMIN}	14109.78	21.46
3.1	Climate, competition, & SWA_{1YMIN}, interacting with competition.	14109.98	21.66
0	Climate	14309.4	221.12

Table S3: Observed values and coefficients for all variables included in the best statistical mortality model. Observations area all at the plot level, except for tree size, which is calculated from the population of individual trees. Variables (except tree size) were normalized to a mean of zero and standard deviation of 1 prior to regression.

		Observations		Coefficients		
Variable	Units	Mean	StDev	Mean	90% CI	
intercept				2.214	1.818	2.620
SWA_{MEAN}	cm	17.1	5.36	0.000438	-0.149	0.148
$TEMP_{MEAN}$	C	13.4	2.13	-0.144	-0.285	-0.001
Basal Area (BA)	m^2ha^{-1}	22.6	14.3	-1.188	-1.636	-0.749
SWA_{8YRMAX}	cm	-0.51	1.43	0.151	0.031	0.277
$TEMP_{7YRMAX}$	C	0.59	0.36	-0.155	-0.274	-0.035
SWA_{3YRMAX}	cm	2.02	1.76	0.122	0.051	0.195
SWA_{MEAN}*BA		389	284	0.352	0.115	0.598
$TEMP_{MEAN}$*BA		306	213	0.368	0.032	0.705
SWA_{8YRMAX}*BA		-12.5	33.1	-0.127	-0.219	-0.033
$TEMP_{7YRMAX}$*BA		14.2	15.5	0.130	-0.001	0.261
Tree DBH	inches	11.3	7.01	0.045	0.039	0.050

Figure S1: Correlations among covariates included in any model. Most pairs of covariates have low correlation, but two pairs display high correlation (SWA_8YR_min with SWA_1YR_MIN, and TEMP_7YR_MAX & TEMP_1YR_MAX) and we did not combine these pairs in any statistical model.

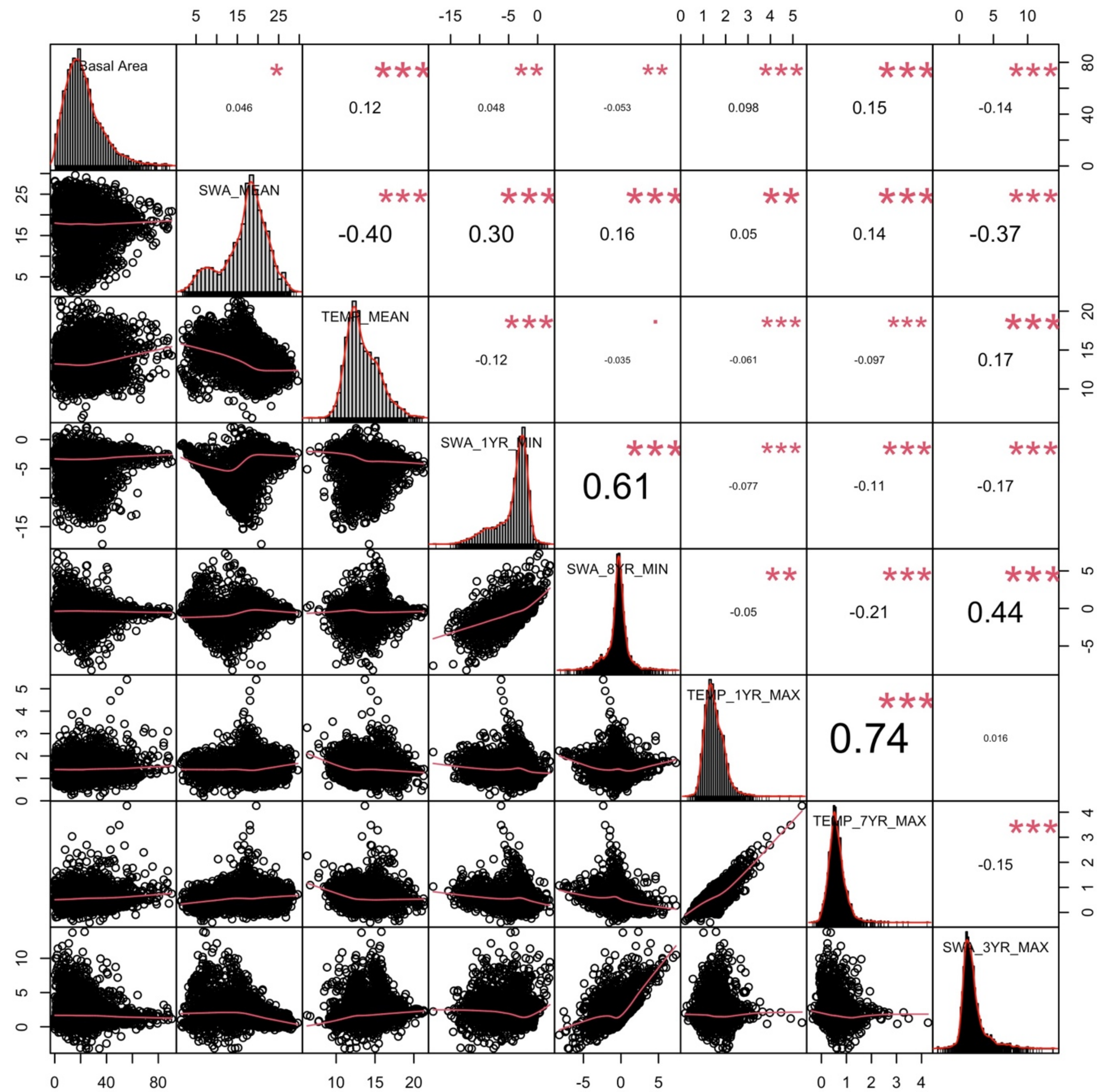


Figure S2: Within-sample posterior predictive checks. (a) Posterior predictive checks indicate good agreement between mean model predictions (black points) and observed data (jittered red points, 1=Alive, 0=Dead). Blue x points indicate the indicate the observed proportion of individuals surviving in 20 equal sized bins across all individuals, which correspond well with model predictions (Black points). Note: 95% CI are omitted and red points are 'jittered' for clarity. (b) Posterior predictive p-values assess model fit by comparing replicated data from the fit model to the real measured data using a test function. P-values <0.05 or >0.95 indicate high probability that model predictions are more extreme than real data, and thus poorer model fit (Gelman et al. 2004). We use a deviance test function for p-values.

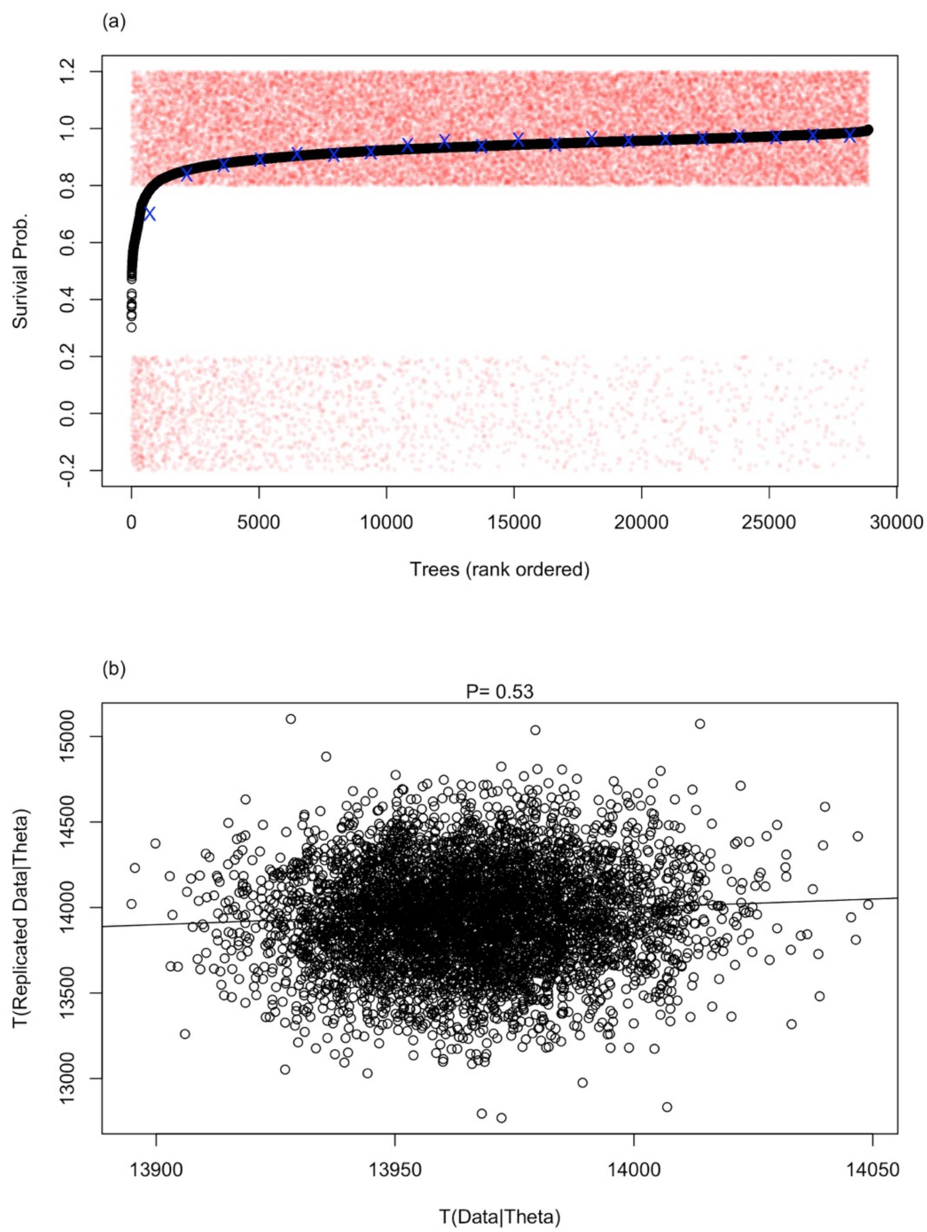


Figure S3: Posterior distributions of coefficient values for all covariates in all candidate statistical models examined. Note that models were fit to observations of 10-year survival, which were converted to annual mortality, so the coefficient signs relate to relationships with survival, and are opposite for mortality.

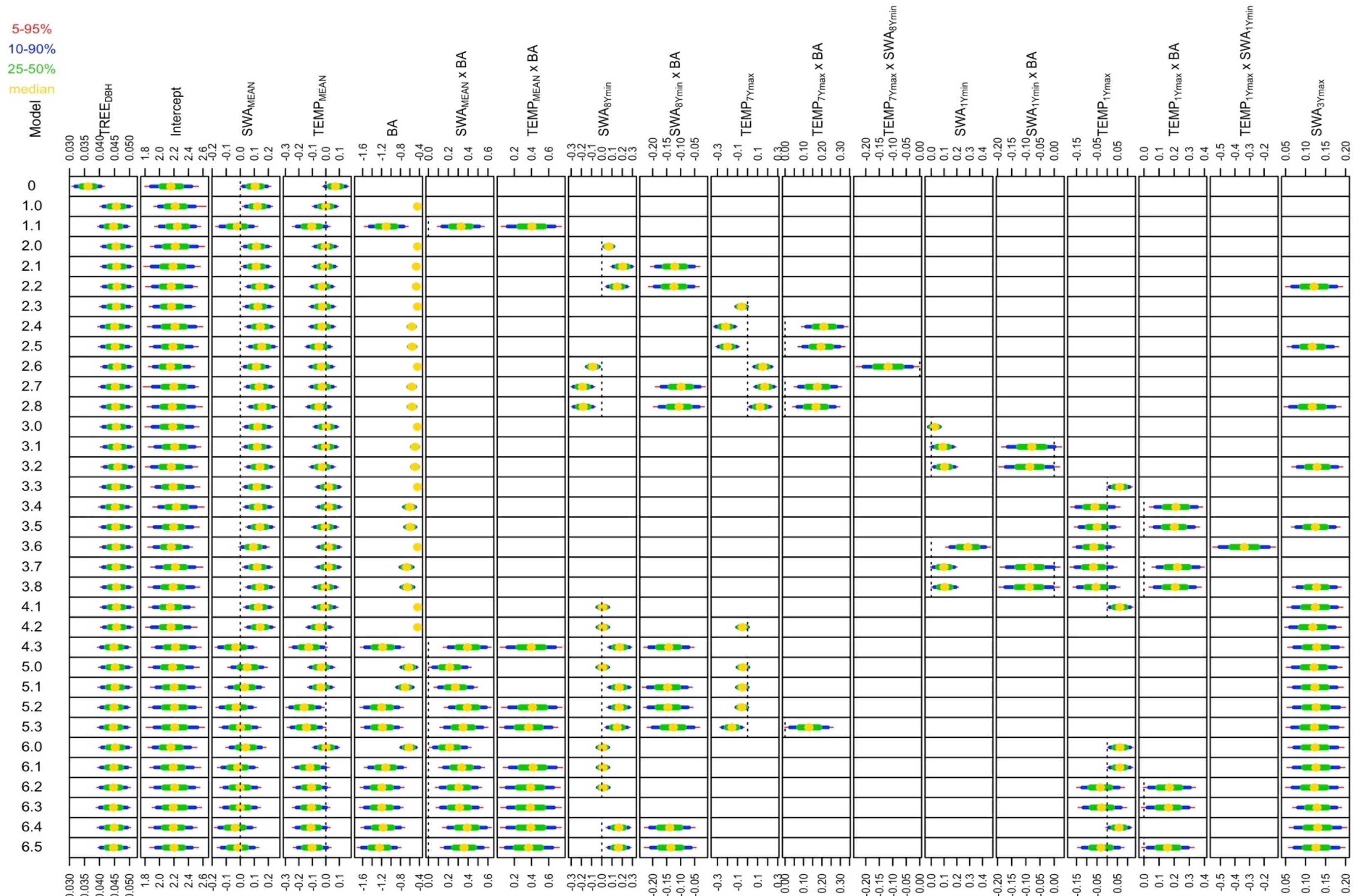
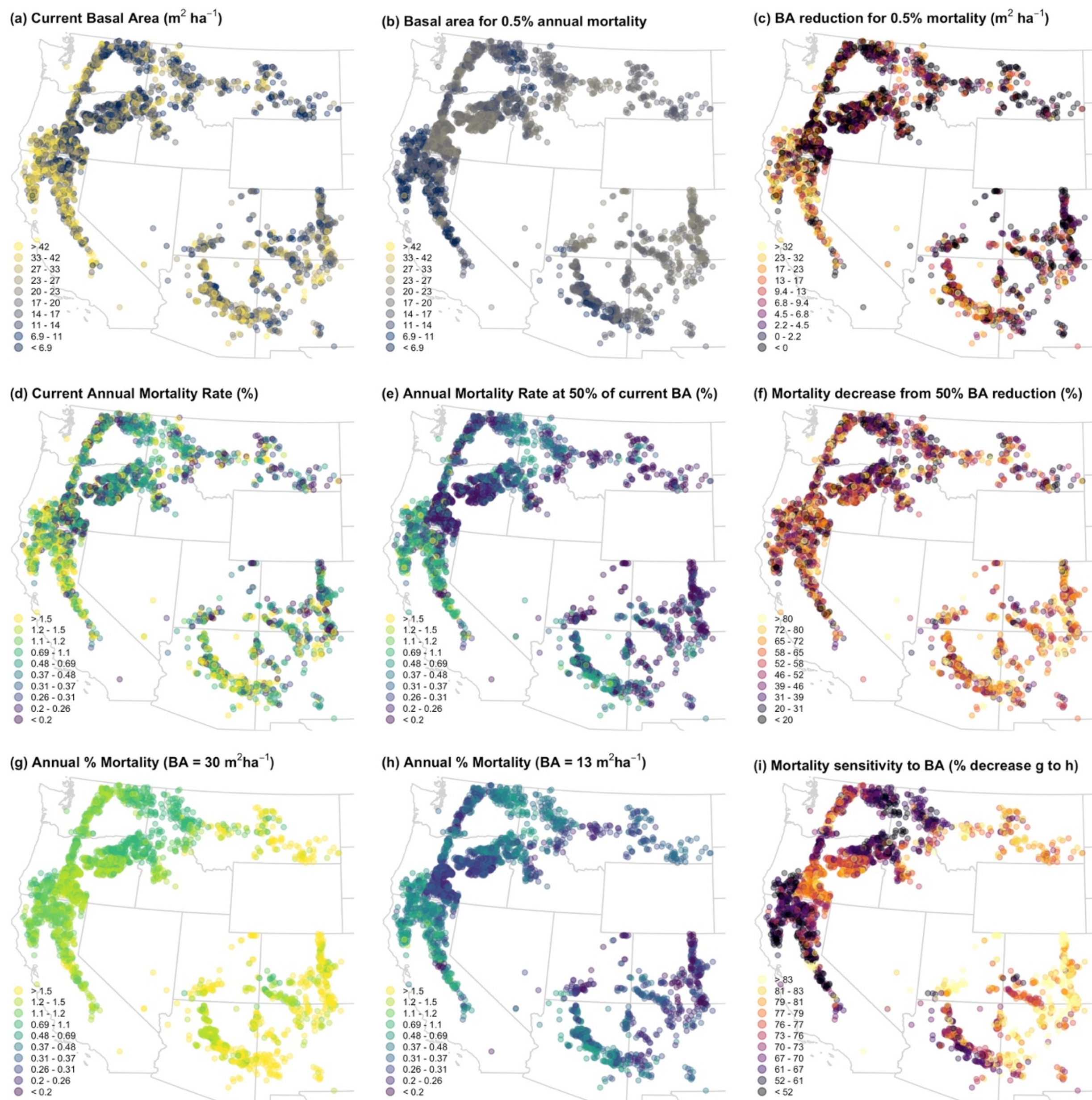


Figure S4: Geographic patterns of basal area, mortality and thinning benefits under various scenarios for ponderosa pine monitoring plots, including (a) current basal area, (b) basal area required to yield 0.5% annual mortality, (c) the reduction in basal area needed to yield an estimated 0.5% annual mortality rate, (d) current estimated annual ponderosa pine mortality, (e) estimated annual mortality rate for a 50% reduction in current basal area, (f) percent decrease in annual mortality rate between current BA and 50% of current BA, (g) estimated annual mortality rate at a fixed high basal area (30 m^2ha^{-1}), (h) estimated annual mortality rate at a fixed low basal area (13 m^2ha^{-1}), and (i) the sensitivity of mortality to differences in basal area, calculated as the % decrease in mortality between g and h. Some panels are repeated from Figure 3 to enable comparisons with values shown here. To enable comparisons among related panels, color scales are consistent between panels a and b, and between panels d, e, g, and h.



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