

Visual interpretation and time series modeling of Landsat imagery highlight drought's role in forest canopy declines

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Abstract. Remote sensing studies indicate that slow and subtle degradation of forest canopies, or forest canopy declines, has increased in extent during recent decades, possibly due to hotter and drier droughts. However, it is difficult to collect consistent, high-quality time series of forest canopy decline occurrence observations needed for examining multi-year drought contributions to forest canopy decline at an annual scale. In this research, we leveraged a tool for visual interpretation of annual Landsat satellite imagery (TimeSync) and a hierarchical Bayesian time series modeling approach (stochastic antecedent modeling, SAM) in five forest type groups located in the western United States to assess (1) what seasonal and inter-annual patterns in vapor pressure deficit (VPD) and precipitation preceded forest canopy decline events, (2) how drought effects on forest canopy decline events differed by forest type group, and (3) whether or not drought effects on forest canopy decline events were uniform within forest type groups. We examined observations of forest canopy decline over three decades (1985–2013) at 126 plots where we collected annual TimeSync observations. Stochastic antecedent modeling indicated that January–March VPD and July–September precipitation anomalies for the current year and 1–3 yr in the past contributed to defining drought conditions in relation to forest canopy decline dynamics. The probability of forest canopy decline decreased with summer precipitation for all forest type groups and increased with winter VPD for the warmest and the coldest forest type groups. However, the magnitude and direction of forest canopy decline sensitivity to drought varied substantially within forest type groups. The ubiquitous, but not uniform, effects of drought on forest canopy decline dynamics implied that local biotic (e.g., forest structure and composition, tree genetics) and abiotic (e.g., topography and soils) factors act to mediate effects of drought on forest change. The integration of the TimeSync satellite image interpretation tool with SAM provides a promising approach to link ecological understanding of tree drought responses to forest and landscape responses at regional and continental scales.

Key words: drought; forest canopy decline; Landsat; Special Feature: Emerging Technologies in Ecology; stochastic antecedent modeling; TimeSync; western United States.

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INTRODUCTION

Recently observed tree mortality events indicate a pressing need to understand the climatic conditions contributing to drought-induced forest disturbance (van Mantgem et al. 2009, Allen et al. 2010). As with drought impacts on tree growth in moisture-limited landscapes (Chen et al. 2010, Williams et al. 2013), the seasonality and duration of climatic anomalies representing variation in moisture inputs (e.g., precipitation) and outputs (e.g., evapotranspiration) likely define the consequences of drought on tree mortality. The resulting spatio-temporal complexity of drought and tree mortality can lead to staggering and surprising landscape change events, such as widespread forest tree mortality from 2015 to 2016 in California following 2–4 yr of protracted drought (Young et al. 2017). Such complexity in the consequence of multi-year climatic variation highlights a need to understand length, temporal pattern, and strength of drought-related forest ecological memory (*sensu* Anderegg et al. 2015a, Ogle et al. 2015, Peltier et al. 2016). This paper utilizes multi-decadal time series of disturbance and climate data to examine the temporally complex contribution of drought to the timing and duration of forest canopy decline in forests of the western United States.

Understanding the role of climatic variations, such as drought, on forest change requires repeated measurements through time at relatively fine temporal scales (e.g., annual), not just spatial variation in mean climatic conditions (Ibáñez et al. 2006, Dietze and Moorcroft 2011, Clark et al. 2016). Multi-decadal, satellite remote sensing can provide wall-to-wall time series data appropriate for examining the spatio-temporal complexity inherent in climate-induced forest disturbance events at landscape to global scales (McDowell et al. 2015). Annual Landsat time series (LTS) add to traditional field-based monitoring efforts (e.g., 5- to 10-yr return intervals for many forest inventory systems) through improved temporal sampling (Schroeder et al. 2014). TimeSync is a visual interpretation and data collection tool for LTS observations of vegetation status and change through time (Cohen et al. 2010). TimeSync

enables human interpreters to assign agent, timing, and duration of forest change at a set of sample locations (Fig. 1). In particular, interpretation of LTS provides opportunities to quantify and understand more gradual forms of forest disturbance, such as insect-, disease-, and drought-induced mortality (Vogelmann et al. 2016). For example, TimeSync observations of disturbance incidence and duration across the United States indicated that slow and subtle declines in forest canopy cover and health (hereafter, forest canopy decline) became the dominant disturbance type in the western United States forests coincident with a series of regional droughts, impacting 8% of the forested landscape at its peak in the early 2000s (Cohen et al. 2016). Consequently, annual forest canopy decline data developed by LTS interpretation offers ecologists an opportunity to assess the contribution of climatic variation to forest change not generally possible using traditional field-based forest inventory data.

TimeSync may be particularly valuable for unraveling drought effects on forests due to temporally complex tree responses to climatic conditions. For example, growth in three tree species of the American Southwest varied as a function of current and past year's summer vapor pressure deficit (VPD) and winter precipitation (Williams et al. 2013), though such patterns may vary regionally (Chen et al. 2010) and depend on multi-year climatic variation (Anderegg et al. 2015a). In comparison, tree mortality is a notoriously complex process to understand, often unfolding over the course of multiple years (Franklin et al. 1987), implying that mortality dynamics might be governed by hysteresis that can be characterized by temporal lags that generate varying degrees of ecological memory on individuals or stands of trees. The concept of ecological memory, here defined as the capacity of past states or experiences to influence present and future responses (Padisák 1992), is characterized by the length, temporal pattern, and strength of memory (Ogle et al. 2015) as well as whether the drivers are exogenous (e.g., climate) or endogenous (e.g., density dependence; Peterson 2002, Anand et al. 2010, Johnstone et al. 2016). For example, carbon starvation, embolism, and biotic agents can all contribute to drought-induced mortality

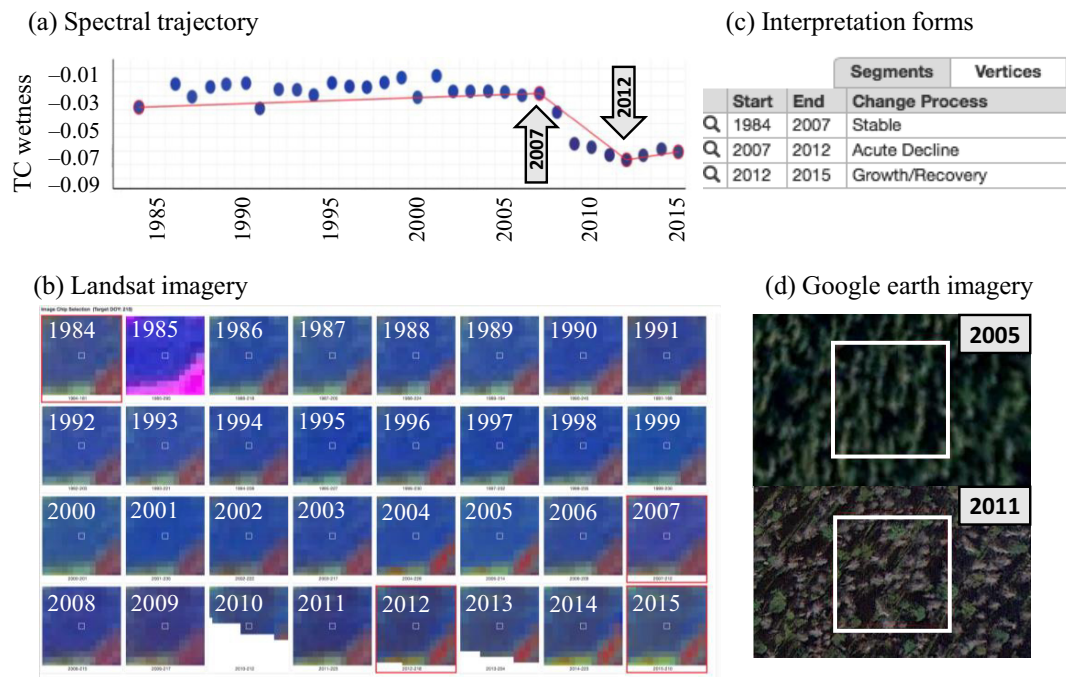


Fig. 1. Example of decline observation in the TimeSync visualization and interpretation tool showing (a, b) Landsat spectral data, (c) data form for interpretations, and (d) Google Earth imagery. TimeSync has three main windows: (a) the spectral trajectory (tasseled cap wetness) observed in selected annual chips (blue dots) and the fitted temporal segmentation from the LandTrendr disturbance algorithm (Kennedy et al. 2010) representing the interpretation (red line segments); (b) the Landsat imagery chip display showing one image subset per year (1984–2015) containing the single 30-m plot (white boxes) and the surrounding plot neighborhood; and (c) the interpretation forms where start and end dates for change processes are entered by the interpreter. The interpreter identified a decline event beginning in 2007 and ending in 2012, as indicated by the five-year trend in reduced tasseled cap wetness, and can be seen in the image chips as a subtle darkening and reddening color in and surrounding the plot during that time period. (d) High-spatial-resolution Google Earth images available prior to and during the forest canopy decline event confirm the decline interpretation: (top) a 2005 image showing nearly closed canopy of healthy green trees and (bottom) a 2011 image showing mortality of over 75% of those trees. This is a typical example of beetle kill, where affected trees are not all killed in the same year, yielding (in this case) a 5-yr decline segment. Note also that not all trees in the plot were killed in this event.

(McDowell et al. 2008), laying the foundation for ecological memory to shape patterns of tree mortality. Therefore, analytical approaches to assessing drought effects on forest canopy decline need to accommodate both spatial variation in forest responses to drought and the cumulative impacts of drought as they develop over several years, as has been demonstrated for tree growth (Anderegg et al. 2015a). As opposed to tree growth, annual observations of forest mortality are less common, but TimeSync observations of forest canopy decline, a surrogate for tree mortality, can be efficiently and accurately collected over

multiple decades (1985–2013) at random locations across a study area.

In this research, we integrated annual TimeSync observations with a flexible time series modeling approach to characterize the timing and duration of forest canopy decline events in the western United States as a function of seasonal variation in drought-related climatological variables. We assessed whether temporal patterns of 127 forest canopy decline events in the western United States measured with TimeSync were preceded by multi-year drought across five forest type groups (Table 1, Fig. 2). Specifically,

Table 1. Summary of forest type group biophysical setting (mean annual precipitation and vapor pressure deficit [VPD]), area within study region, and TimeSync observations.

Forest type group	Precipitation (mm)†	VPD (kPa)†	Area (1000s km ²)	TimeSync observations	Forest canopy decline observations
Subalpine	1175 (603)	0.55 (0.11)	148	91	50
Lodgepole Pine	799 (246)	0.56 (0.08)	66	61	22
Douglas-fir	1183 (742)	0.60 (0.11)	205	61	30
Ponderosa Pine	555 (179)	0.79 (0.12)	122	90	11
Pinyon-Juniper	412 (121)	1.04 (0.21)	216	14	14

Note: Forest type groups are sorted from highest elevations to lowest elevations.
† For precipitation and VPD, means and standard deviations (in parentheses) are presented.

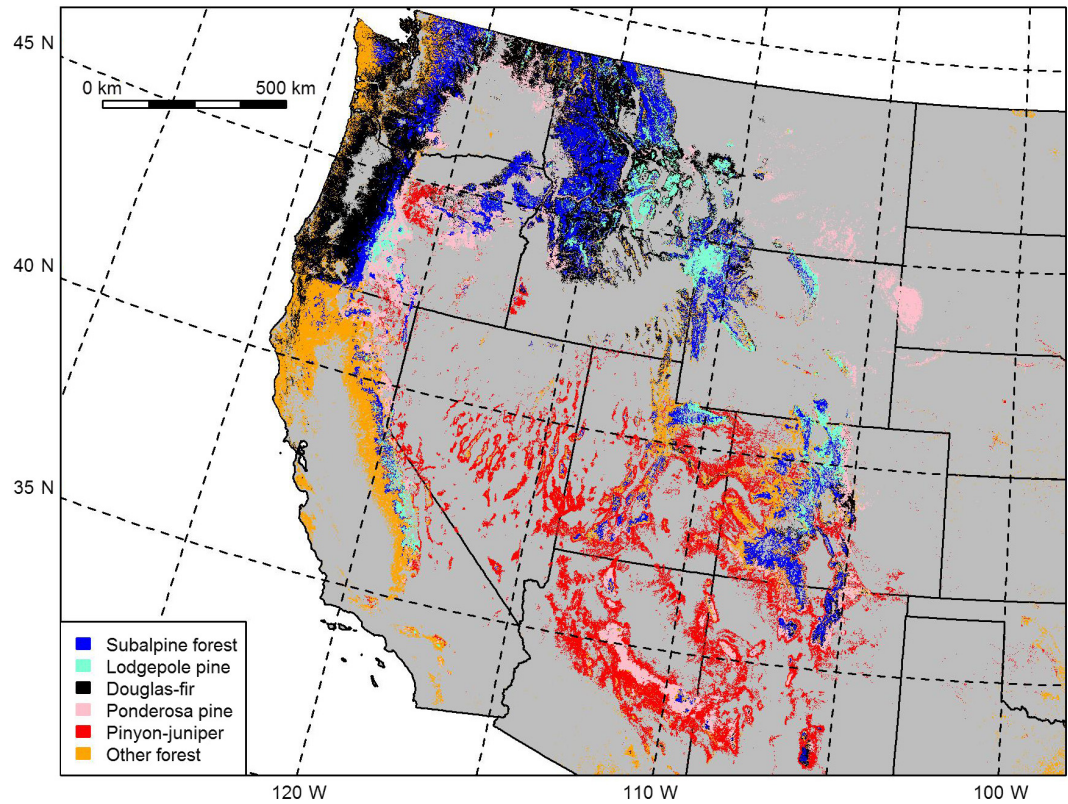


Fig. 2. Map of forest type groups in the western United States derived from MODIS satellite imagery collected during 2002–2003 growing seasons (Ruefenacht et al. 2008). Administrative boundaries between states are indicated by solid lines. Dashed lines are graticules representing parallels of latitude and meridians of longitude.

we asked: (1) What were the seasonal and inter-annual patterns in VPD and precipitation that defined multi-year drought anomalies-related forest canopy decline events? (2) Did drought effects on forest canopy decline events differ by forest type group? and (3) Were drought effects on forest canopy decline events uniform within forest type groups?

METHODS

Study area

We focused on five forest type groups (Ruefenacht et al. 2008) distributed across a wide geographic range of environmental and climatic settings that dominate western United States forest landscapes (85% of forested area; Fig. 2):

subalpine, lodgepole pine, Douglas-fir, ponderosa pine, and pinyon-juniper. Each forest type group (FTG) classification was derived from moderate resolution imagery spectroradiometer (MODIS) composite images from 2002 to 2003 in combination with other geospatial data layers (e.g., slope, aspect). The five FTGs examined in this study represent a gradient in biophysical conditions from relatively cool and wet (subalpine FTG) to warm and dry (pinyon-juniper FTG), with each exhibiting substantial within FTG variability in mean annual climate (Table 1). Three FTGs are dominated by the nominal tree species: lodgepole pine (*Pinus contorta* Douglas ex Loudon), Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco), and ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson). The subalpine FTG is dominated by firs (*Abies* spp.), spruces (*Picea* spp.), and/or mountain hemlock (*Tsuga mertensiana* (Bong.) Carrière). The pinyon-juniper FTG is dominated by junipers (*Juniperus* spp.) and pines (*Pinus* spp.) common to woodland forests of western North America, such as *Juniperus osteosperma* and *Pinus edulis*. Other forest type groups have experienced recent canopy declines in the western United States, such as mixed-conifer forests in California and aspen forests in the Southern Rocky Mountains, but our disturbance dataset (see *Landsat plot and climate data*) did not include sufficient sample sizes for analysis.

Landsat plot and climate data

We used human interpretations of the LTS from the TimeSync tool to provide annual temporal resolution assessment of forest canopy decline events for conterminous United States (detailed description in Cohen et al. 2016). We used a two-stage stratified cluster sampling design to establish 7200 plot locations across the conterminous United States. First, 180 Thiessen Scene Areas (TSAs; Kennedy et al. 2010) were randomly selected from across regional strata, with the probability of a given TSA being selected being proportional to the product of stratum area and forested area within each stratum. Second, a simple random sample was used to select 40 single pixel-sized (900 m²) Landsat plots within each selected TSA. Out of the 7200 Landsat plot locations, initial interpretation indicated that 3861 were forested based on the definition used by the USDA Forest Service Forest

Inventory and Analysis program: planted or natural vegetated land likely to contain at least 10% tree cover that was not an agricultural crop (Bechtold and Patterson 2005).

At each forested Landsat plot, LTS (1984–2013) was visually interpreted and disturbance data were collected using an updated version (Cohen et al. 2016) of the original TimeSync tool (Cohen et al. 2010). TimeSync allows for simultaneous viewing of LTS in and around the plot location, rapid toggling between different spectral reflectance bands, and temporal snapshots of high-resolution imagery from Google Earth (Fig. 1). Such data have been shown to perform well in providing accurate disturbance information, with mortality identified by visual interpretation of LTS producing similar results as USDA Forest Service Forest Inventory and Analysis field observations of canopy dominant and co-dominant tree death (Schroeder et al. 2014). As a result, TimeSync data characterize changes for canopy trees, not understory trees that are not directly observable with satellite imagery or aerial photography. Annual interpretations were made for each Landsat plot, indicating the presence or absence of a forest canopy decline event during the previous year for each year–plot combination between 1985 and 2013. For the purposes of LTS interpretation through TimeSync, forest canopy decline events were defined as a general loss of canopy leaf area density not associated with management, fire, wind, flooding, land-use change, or landslide. These declines are reflected in several components of the multispectral LTS signal, but are most notable when viewing tasseled cap wetness (e.g., Fig. 1a, b), an index predominantly associated with (in a forest) moisture and shadow within a tree canopy (Cohen and Spies 1992). In the western United States forests, forest canopy decline events tended to occur over several years and were relatively subtle, resulting in canopy cover reductions 50% and 66% less severe than fire and harvest, respectively (Cohen et al. 2016).

To understand potential impacts of drought on forest canopy decline, we selected precipitation and VPD as predictor variables because these variables can explain substantial variation in annual tree growth (Williams et al. 2013, Restaino et al. 2016). We extracted monthly total precipitation and mean VPD from 30 arc-sec (approximately

800 m) resolution data from the Parameter-elevation Regressions on Independent Slopes Model dataset (Daly et al. 2008, PRISM Climate Group 2014). Mean monthly temperature was not used in this analysis due to its high correlation with VPD (Pearson's correlation = 0.77). We extracted data for 1980–2013 to ensure that at least five years of climate data preceding each TimeSync disturbance observation (1985–2013) were available. Both precipitation and VPD were standardized to range from 0 to 1 to make the effect sizes of regression parameters comparable.

Stochastic antecedent modeling for forest canopy decline events

In order to understand and characterize the complexity of temporal patterns of remotely sensed forest canopy decline, we examined annual observations of forest canopy decline at TimeSync plots where at least one event was observed (Table 1). Spatial and temporal patterns of slow and subtle forest canopy changes observable with remote sensing have become common in the western United States (Cohen et al. 2016), but not all lands have been impacted. Furthermore, some forests may not be particularly susceptible due to a variety of factors, including the drought tolerance of individual tree species and topographic features buffering forests against climate anomalies. To model multi-year climatic impacts on observed forest canopy decline events, we utilized the stochastic antecedent modeling (SAM) framework described by Ogle et al. (2015). The SAM framework is a flexible analytical approach for evaluating the length, temporal pattern, and strength of ecological memory with respect to antecedent conditions (i.e., weighted past conditions) on current dynamics. Using SAM, we captured both (1) the temporally complex contributions of seasonal climatic anomalies to an antecedent climate anomaly and (2) the response of the system to those anomalies.

In this study, the antecedent anomaly represents the ecological memory of forest canopy decline events to climatological variables associated with water inputs (i.e., precipitation) and exports (i.e., VPD). Precipitation and VPD have been used to explain annual tree growth across the study region (Williams et al. 2013, Restaino et al. 2016), and growth is often taken as a measure of tree vigor and inversely related to

mortality risk (Clark et al. 2011, Vanderwel et al. 2013). Note that VPD is not a direct measure of water export, but rather correlates strongly with stomatal regulation, and thus transpiration (Oren et al. 1999). We assume here that the previous five years (current years to 4 yr in the past) of climatological variation can all contribute to observed responses. We limited our scope of inference to the five years preceding observations (i.e., 5-yr antecedent windows) to avoid overfitting and to mirror drought-related ecological memory in tree growth (Anderegg et al. 2015a). Testing with a longer antecedent window resulted in similar weighting of recent climate anomalies on the antecedent anomaly. The process model for the antecedent variables for precipitation $P_{\text{ant},i}(t)$ and VPD $V_{\text{ant},i}(t)$ for year t and plot i are as follows:

$$P_{\text{ant},i}(t) = \sum_{y=0}^4 \sum_{s=1}^4 P_i(t-y, s) \times w_{P,\text{seas}}(s|y) \times w_{P,\text{year}}(y) \quad (1)$$

$$V_{\text{ant},i}(t) = \sum_{y=0}^4 \sum_{s=1}^4 V_i(t-y, s) \times w_{V,\text{seas}}(s|y) \times w_{V,\text{year}}(y) \quad (2)$$

where y is the year in the past (0 for present, 1 for previous year, etc.), s is the three-month season (January–March, April–June, July–September, and October–December), $P_i(t-y, s)$ and $V_i(t-y, s)$ are the observed seasonal precipitation and VPD anomalies for year $t-y$ and season s at plot i , $w_{P,\text{seas}}(s|y)$ and $w_{V,\text{seas}}(s|y)$ are the seasonal weightings for season s in year y , and $w_{P,\text{year}}(y)$ and $w_{V,\text{year}}(y)$ are the yearly weightings for year y . Seasonal blocks rather than months were used to reduce the number of weight parameters to be estimated. We assumed that the weights for year 0 and October–December equaled zero as these months represent the period of time following the growing season being observed, and thus after our LTS-based forest canopy decline observations. Following Ogle et al. (2015), we used a Dirichlet prior for the weights, such as $w_{P,\text{seas}}(1:4|y)$, $w_{V,\text{seas}}(1:4|y)$, $w_{P,\text{year}}(0:4)$, $w_{V,\text{year}}(0:4) \sim \text{Dirichlet}(\mathbf{1})$, where $\mathbf{1}$ is a vector of ones with length consistent with the corresponding weightings. Weights where the 75% and 95% of the posterior distributions were greater than random

(>0.053) were considered marginal and strong weights, respectively, thus representing an important role in defining antecedent precipitation and VPD anomalies.

Our response variable Y_{it} is the presence ($Y_{it} = 1$) or absence ($Y_{it} = 0$) of a forest canopy decline event during year t at plot i and was modeled as

$$Y_{it} \sim \text{Bernoulli}(x_{it}\beta + x_{it}\gamma_i) \quad (3)$$

where x_{it} is the 1 by 3 vector of covariates [$1 P_{\text{ant},i}(t) V_{\text{ant},i}(t)$], β are the fixed effects, and γ_i are the random effects. Random effects were incorporated to account for differences among sites in the sensitivity of forest canopy decline to precipitation and VPD anomalies, likely representing how local topography, community composition, and forest structure all mediate forest responses to climate. Mean climatic conditions (e.g., wet vs. dry locations) were initially considered, but these effects were rarely different from zero; therefore, we excluded these effects for the purpose of this research. Thus, the sensitivity of the forest canopy decline probability at any given plot to variation in an antecedent variable is the sum of the main and random effects (i.e., plot-level effect). Increasing probability of forest canopy decline with high VPD and low precipitation is indicated by positive and negative effects of VPD and precipitation, respectively. Priors for the fixed effects β were assumed $N(0, \sigma^2)$, and priors for the random effects were assumed to be $N(0, \tau^2)$. Hyperpriors σ^2 and τ^2 were both assumed to be weak and distributed as $\text{gamma}^{-1}(1,1)$. All models were implemented using a modified version of the code for the SAM framework (Ogle et al. 2015) implemented in the R statistical environment version 3.3.2 (R Development Core Team 2016) with JAGS version 4.1 (Plummer 2016) and rjags version 3-13 (Plummer 2014). Models for each FTG were run for 50,000 Gibbs steps, discarding the first 30,000 steps and thinning the chains to every tenth step to avoid autocorrelation.

Model predictions were assessed by examining the differences between the mean predicted probability of forest canopy decline for years with vs. years without observed forest canopy decline at each plot (hereafter, prediction differences). Thus, positive prediction differences indicated greater capacity of the model to differentiate between

decline and non-decline years. The prediction differences were calculated based on both in-sample and out-of-sample validation strategies. For in-sample assessments, all plots and years were incorporated into the SAM modeling and prediction differences were generated for each plot. For out-of-sample assessments, we excluded from SAM modeling the year with the second, fourth, and sixth most observed forest canopy declines and three randomly selected years with no forest canopy declines for each forest type group. We then calculated the prediction differences based on the six years excluded from modeling. We report only those results associated with the subset of plots experiencing three decline and three non-decline years in the six years to ensure that multiple years contribute to the analysis at each plot. We avoided excluding entire plots as this would make estimation of plot-level random effects impossible, reducing the utility of out-of-sample validation.

RESULTS

The SAM models exhibited high predictive performance, as indicated by greater predicted probabilities of decline during observed decline years vs. non-decline years (Fig. 3). With the exception of the lodgepole pine FTG, in-sample assessment indicates that the prediction difference between decline and non-decline years was greater than zero for 91–100% and 82–100% of TimeSync plots based on 68% and 95% credible intervals, respectively. Prediction differences for the lodgepole pine FTG were greater than zero for 86% and 55% of TimeSync plots based on 68% and 95% credible intervals, respectively. Out-of-sample assessments were qualitatively similar, but indicated somewhat less capacity to distinguish decline from non-decline years (68% and 95% credible intervals for the prediction differences were greater than zero for 40–88% and 11–75% of TimeSync plots, respectively). The primary exception to this qualitative agreement was the pinyon-juniper FTG, where in-sample validation indicated the positive prediction differences for all plots (100% of plots with 95% credible interval > 0) and out-of-sample validation indicated a minority of plots exhibiting positive prediction differences (44% and 11% of 68% and 95% credible intervals > 0).

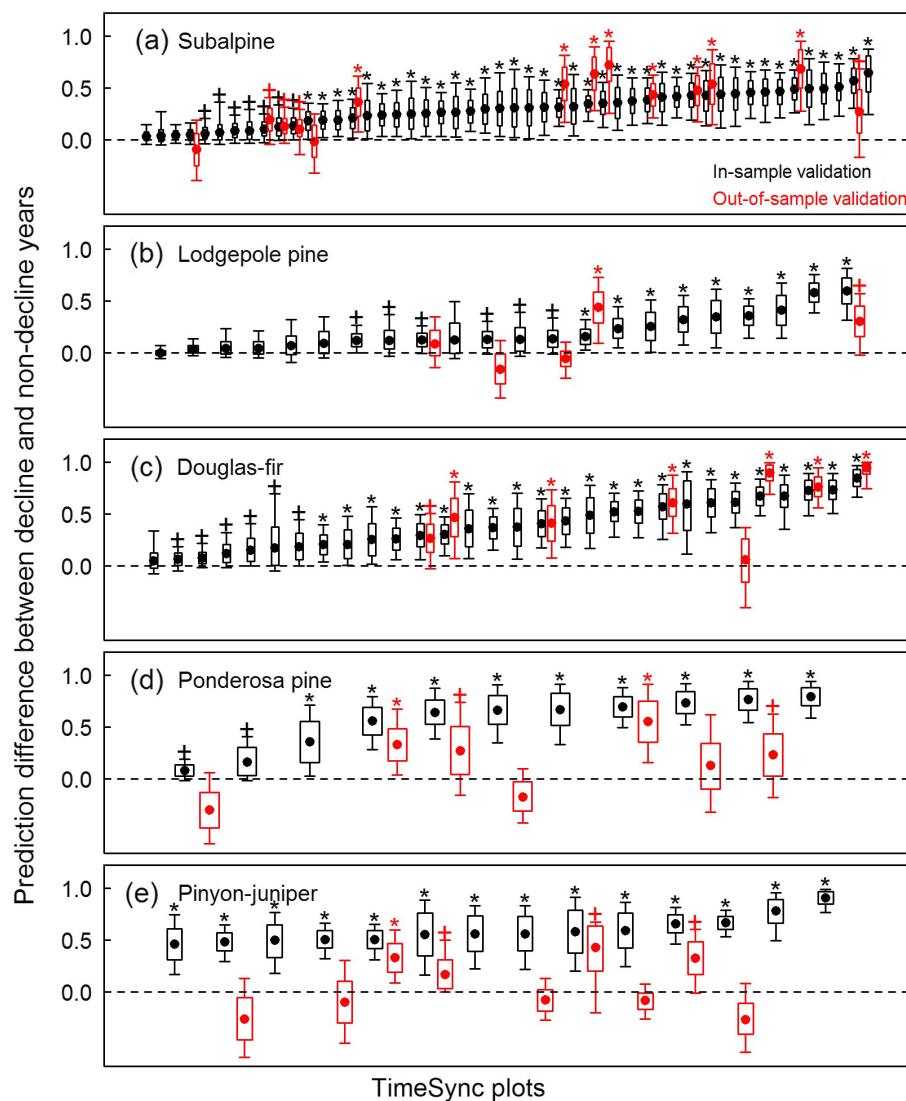


Fig. 3. The difference in predicted probability of forest canopy decline during observed decline vs. non-decline years for each TimeSync plot in each forest type group based on in-sample (black) and out-of-sample validation (red). Five forest type groups are shown: (a) subalpine, (b) lodgepole pine, (c) Douglas-fir, (d) ponderosa pine, and (e) pinyon-juniper. Values with intervals above the zero line indicate that models predicted a greater probability of decline during observed events as opposed to non-decline years. The plot-level mean prediction difference (solid point), 68% credible interval (box), and 95% credible interval (whiskers) are presented. TimeSync plots where 68% and 95% credible intervals do not include zero (dashed line) are indicated by + and *, respectively.

Weightings for the contributions to the antecedent VPD and precipitation anomalies indicated that January to March VPD and July to September precipitation anomalies were dominant across all FTGs, though the weights varied among FTGs and climate variables (Fig. 4). For all FTGs except lodgepole pine, there was strong support for greater than random weighting for

January to March VPD 1–2 yr in the past and marginal support 0–3 yr in the past (Fig. 5a). For the precipitation anomalies, weights greater than random were most often observed for July–September, with subalpine, lodgepole pine, and Douglas-fir FTGs exhibiting strong or marginal support 0–4 yr in the past and ponderosa pine and pinyon-juniper FTGs exhibiting strong or

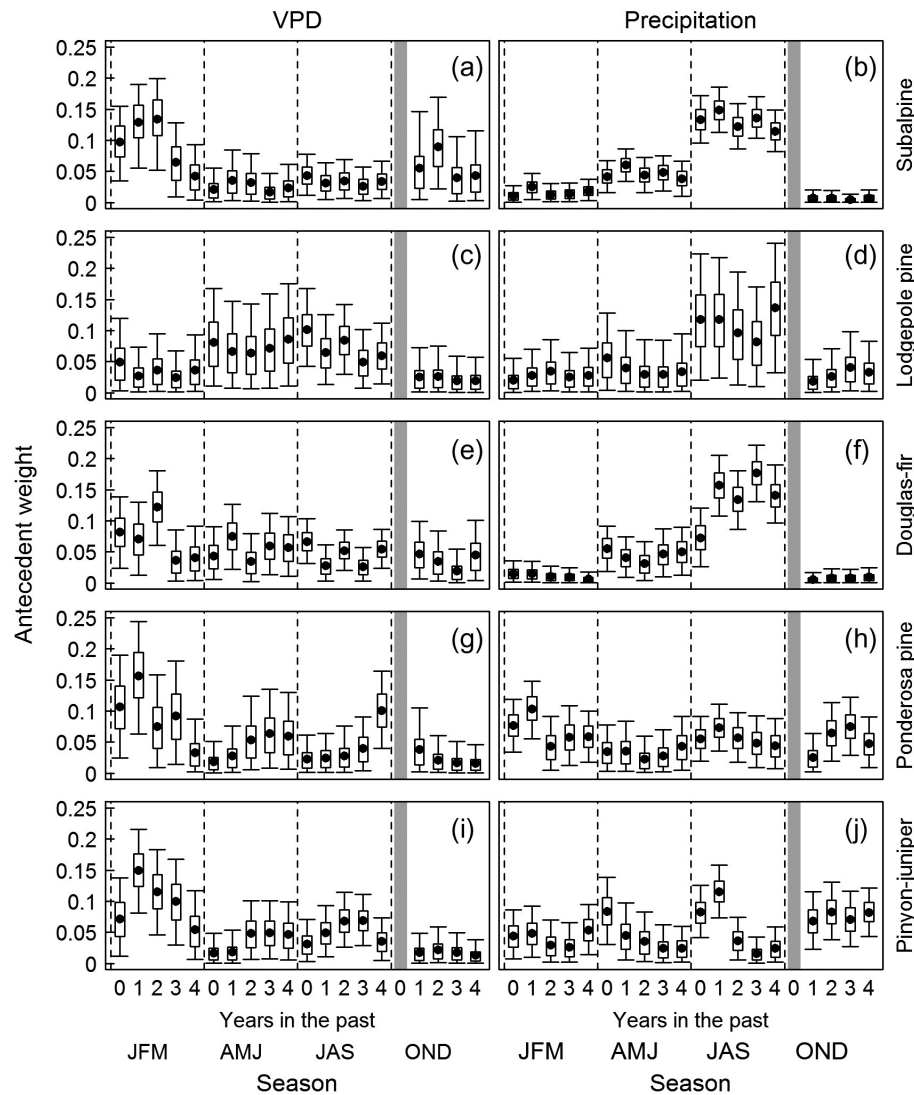


Fig. 4. Mean and 68% and 90% credible intervals for the antecedent weights in the (a, b) subalpine, (c, d) lodgepole pine, (e, f) Douglas-fir, (g, h) ponderosa pine, and (i, j) pinyon-juniper FTGs for (a, c, e, g, i) VPD and (b, d, f, h, j) precipitation. Weights are grouped by season to highlight changing seasonal contributions across years. Climate anomalies during October–December of the current year were not used in our analysis (gray areas; b, d, f, h, j).

marginal support 0–1 yr in the past (Fig. 5g). Ponderosa pine FTG also exhibited strong or marginal support for a contribution of January–March precipitation (Fig. 5e). Other season-by-anomaly weights greater than random were marginally supported, such as October–December precipitation in ponderosa pine and pinyon-juniper FTGs (Fig. 5h) and July–September VPD in all FTGs except subalpine (Fig. 5c).

Forest type group-level effects (β) of the antecedent precipitation and VPD anomalies on the probability of forest canopy decline were consistent with a drought effect. For precipitation anomalies, the 68% credible intervals were less than zero for all FTGs and the 95% credible intervals were less than zero for all FTGs except lodgepole pine (Fig. 6a). For VPD anomalies, the 68% credible intervals were greater than zero for all

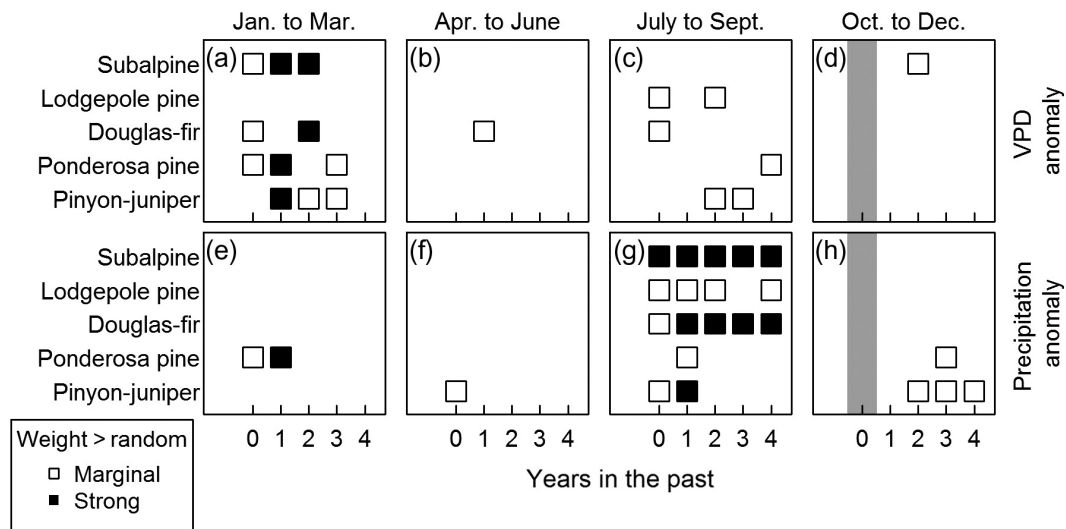


Fig. 5. Summary of current (year 0) and past (years 1–4) climate contributions to the (a–d) vapor pressure deficit (VPD) and (e–h) precipitation antecedent climate anomaly variables shown by season: (a, e) January–March, (b, f) April–June, (c, g) July–September, and (d, h) October–December. Contributions are displayed as strong ($P(\text{weight} > \text{random}) > 0.95$) and marginal ($0.75 > P(\text{weight} > \text{random}) \leq 0.95$). Climate anomalies during October–December of the current year were not used in our analysis (gray areas; d, h).

FTGs except Douglas-fir and the 95% credible intervals were greater than zero for subalpine, ponderosa pine, and pinyon-juniper FTGs (Fig. 6b). The magnitudes of anomaly effects were greatest for ponderosa pine and pinyon-juniper FTGs.

At the plot level, variation in effects ($\beta + \gamma_i$) was substantial, not only in terms of magnitude, but also in terms of direction. For precipitation anomalies, 18–100% of plot-level effects were negative, 58–100% when excluding the lodgepole pine FTG (Fig. 7a), indicating that low precipitation tended to precede forest canopy decline events, but not always. The greatest magnitude precipitation anomaly effects were observed in the southern portion of the study area (American Southwest and Southern Rocky Mountains; Fig. 8). In contrast to precipitation anomalies, plot-level VPD anomaly effects were both positive (23–71% of plots) and negative (0–23% of plots) for most FTGs (Fig. 7b), highlighting a less uniform effect of VPD on the probability of forest canopy decline. Interestingly, negative VPD anomaly effects were exhibited on nearly as many plots as positive effects for the Douglas-fir FTG (23% vs. 30% of plots). The greatest magnitude positive VPD anomaly effects were distributed in the southern portion of the study area

(American Southwest), while strong negative effects were observed in the northern portion of the study region (Northern Rocky Mountains; Fig. 9).

DISCUSSION

The integration of the TimeSync satellite image interpretation tool with the SAM framework provided a new perspective, identifying the key seasonal and interannual patterns of drought that impact the timing and duration of forest canopy decline events in the five coniferous forest type groups we examined. Similarity in seasonal and interannual climate signals (Figs. 4, 5) and climate anomaly effects on forest canopy decline probability (Fig. 6) indicate a common sensitivity of all five forest type groups to drought-induced change. The temporal patterns of climate-associated forest canopy decline provided evidence that hysteresis of prior drought events can induce ecological memory, the strength of which differs among and within biophysical settings. Although drought impacts on forest canopy decline were ubiquitous across forest types, variation in forest canopy decline sensitivities within forest type groups reveals a lack of uniformity in

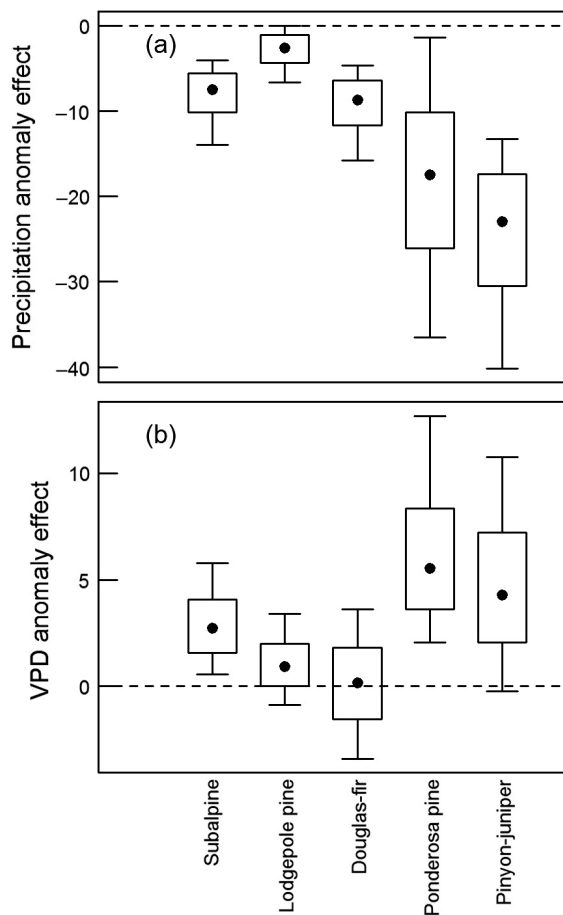


Fig. 6. Forest type group-level means (solid point), 68% credible intervals (box), and 95% credible intervals (whiskers) for the effects of the antecedent (a) precipitation and (b) VPD anomalies on forest canopy decline incidence.

forest responses to climatic stressors in the western United States.

Past climate (generally 1–3 yr in the past) contributed strongly to the antecedent climate variables used to predict forest canopy decline (Figs. 4, 5), similar to recent broad-scale assessments of tree growth responses to climatic water deficits (1- to 4-yr drought legacies; Anderegg et al. 2015a). Our results indicated that winter VPD and summer precipitation up to three years in the past were the most important part of the climate signal in mediating forest canopy decline across the forests examined (Fig. 5a, g). Warmer winters may be associated with snowpack reductions in forests of the western United States

(Mote et al. 2005) and earlier initiation of the growing season (Schwartz et al. 2006), contributing to elevated tree stress during the growing season. The contribution of January–March and October–December precipitation (Fig. 5e, h) in ponderosa pine and pinyon-juniper FTGs further supports the potential importance of winter snowpack in these lower elevation, dry forests. The contribution of summer precipitation to the antecedent precipitation variable suggests that moisture inputs during the summer may moderate drought effects. Remotely sensed shifts in seasonal water balance and land surface temperature based on MODIS (2003–2012) also found lengthening growing season and reduced summer precipitation contributing to late-season forest drought stress (Mildrexler et al. 2016).

The contributions of antecedent precipitation and VPD anomalies to forest canopy decline presented here contrast with dendrochronological studies of tree growth that highlight winter precipitation, summer temperature, or summer VPD (e.g., Chen et al. 2010, Williams et al. 2013), but are consistent with other studies emphasizing the role of summer water balance (e.g., Littell et al. 2008, Restaino et al. 2016). These studies of tree growth, or even survival, can be biased against the impact of extreme events that drive major tree mortality events because dendrochronological studies tend under-sample the individuals that died (Johnson et al. 1994). Furthermore, these studies rarely account for variation in the response of trees and forests to meteorological drought as a function of local factors such as soils, community composition, tree physiology, and physical damage from past drought (Anderegg et al. 2013). By focusing on the timing and duration of forest canopy decline events across an array of forest ecosystems in the western United States, we were able to address both the temporally complex nature of the contribution of climate to drought and plot-level variation in forest canopy decline responses to drought. By recognizing the complex connections between climate and the mortality processes contributing to forest canopy decline, our results provide a nuanced assessment of drought effects on forests.

The magnitude and direction of the plot-level random effects ($\beta + \gamma_i$; Fig. 7) compared to the

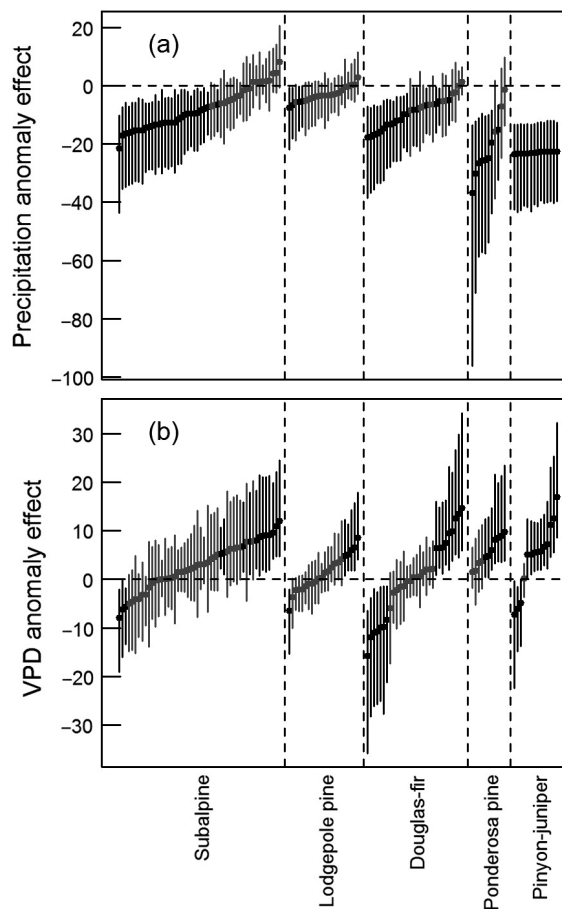


Fig. 7. Plot-level means and 95% credible intervals for the plot-level effects of the antecedent (a) precipitation and (b) vapor pressure deficit (VPD) anomalies on forest canopy decline incidence. Black intervals indicate that the plot-level effect is different from zero.

mean FTG-level effect (β ; Fig. 6) imply that local factors can amplify, dampen, and even reverse the apparent effects of drought on remotely sensed forest canopy decline occurrence within forest type. Plot-level effects might represent geographic variation in drought-induced tree mortality associated with variation in tree density and species composition (Bradford and Bell 2017) or stage of structural development (Reilly and Spies 2016), a hypothesis supported by the observed differences in the magnitude of FTG-level effects (β) as FTGs represent broad-scale variation in forest composition associated with biophysical setting. Geographic variation in tree genetics and mean climatic conditions could alter

the tree species adaptive capacity and exposure to drought, respectively (Smit and Wandel 2006). The geographic distribution of plot-level drought effects (Figs. 8, 9) might support genetic and/or climatic factors mediating the local drought response (Clifford et al. 2013, Restaino et al. 2016). Local topography or soil characteristics may also intensify or decouple tree growth, and presumably mortality, responses to climate (Chen et al. 2010). Despite the high degree of variation, precipitation effects were negative across the majority of plots (Fig. 8), possibly reflecting the importance of precipitation in constraining summer water balance for western tree species (e.g., Littell et al. 2008). Finally, timber harvesting, fire suppression, agriculture, and other land-use and disturbance legacies likely shape geographic variation in sensitivity. For example, the forest type groups where we observed the strongest and most consistent sensitivity to drought, ponderosa pine FTG and pinyon-juniper FTG, have experienced densification and expansion contributed to by land management practices (Covington and Moore 1994, Miller and Rose 1999, Baker and Shinneman 2004, Weisberg et al. 2007), resulting in greater competition for limiting resources, such as water, and greater exposure to drought as trees are growing beyond their historical distributions.

Another potential source of the high degree of variation in drought effects stems from the TimeSync attribution of forest canopy decline. TimeSync offers a powerful tool for interpreting satellite imagery with respect to key forest disturbance types (Cohen et al. 2016). Attributing causality to that disturbance is a key objective for global disturbance monitoring frameworks (McDowell et al. 2015). However, forest canopy decline as a disturbance type is not directly attributable to a single source from TimeSync because insect, disease, and drought are difficult to separate, whether through remote or field observation. Furthermore, different disturbance agents can have interactive, compound effects on tree stress and mortality (Allen et al. 2015, Anderegg et al. 2015b). Therefore, when modeling forest canopy decline as a single disturbance, we are combining multiple mortality processes that also contribute to the observations. For example, relatively poor performance of the model for the lodgepole pine FTG may be

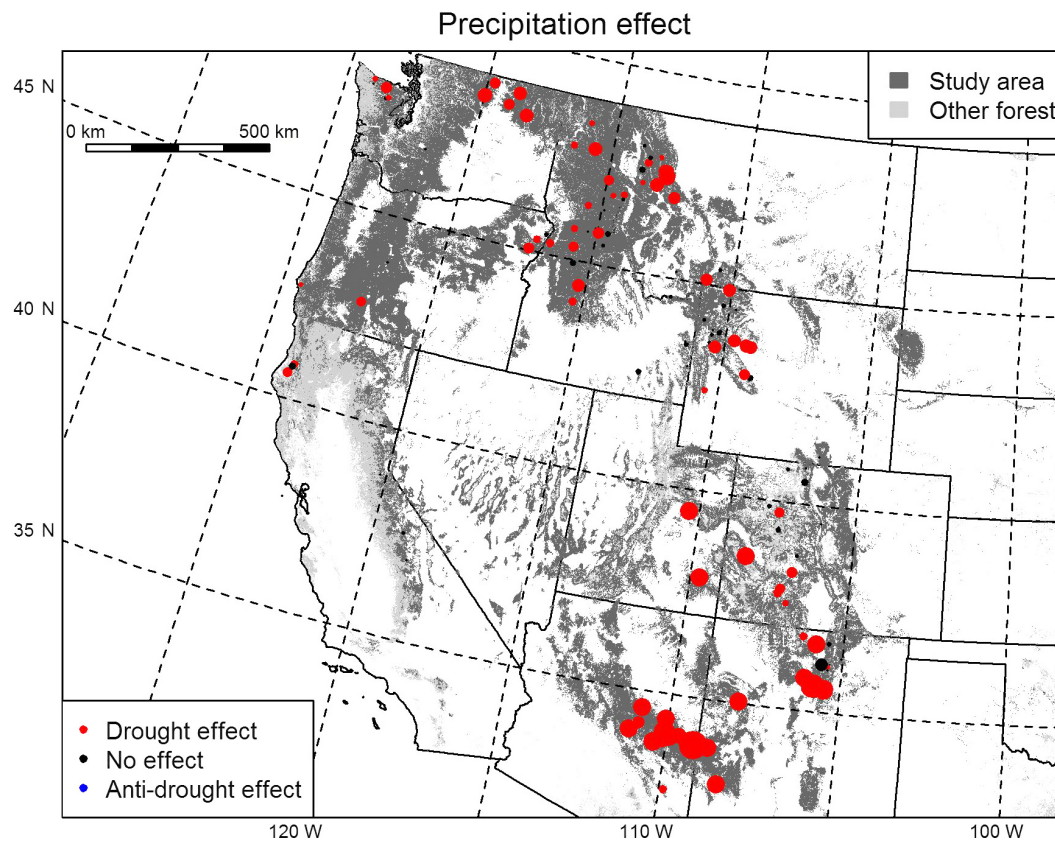


Fig. 8. Mapped effect sizes of precipitation at TimeSync interpretation plots observed experiencing forest canopy decline with symbol size indicating magnitude of effect on the probability of forest canopy decline and color indicating direction of effect: negative being consistent with drought-mediated decline (drought effect; red) and positive being inconsistent with drought-mediated decline (anti-drought effect; blue). Black indicates no significant effect. Dashed lines are graticules representing parallels of latitude and meridians of longitude.

explained by an epidemic of mountain pine beetle (*Dendroctonus ponderosae*) during recent decades. Recent mountain pine beetle outbreaks may act to decouple observed forest mortality patterns from climatically mediated moisture stress as local beetle population dynamics dominate patterns of mortality (Chapman et al. 2012). Similarly, because western spruce budworm (*Choristoneura freemani* Razowski) infestations depend most strongly on forest proximity to existing budworm infestations (Senf et al. 2017), landscape patterns of budworm infestation may explain non-significant or even significant effects in the opposite direction as drought effects (e.g., increasing probability of decline with decreasing VPD) for the subalpine FTG. Integrating improved agent attribution for forest decline

events, such as the aerial detection surveys (USDA 2017), could provide additional insights into the role of insects and disease in modifying forest responses to drought.

The presence of high plot-level variation in forest canopy decline sensitivity to drought suggests the existence of forest resistance to drought in some landscapes. Some of this may be due to the coarse scale of our climate data, as some topographic settings may be decoupled from broad-scale climate anomalies due to differences in aspect, insolation, and cold-air drainages (Dobrowski 2011). Such settings may provide refugia and may become important in maintaining forest ecosystems (e.g., Gavin et al. 2014) if hotter droughts become more common under future climate change (Allen et al. 2015). Without

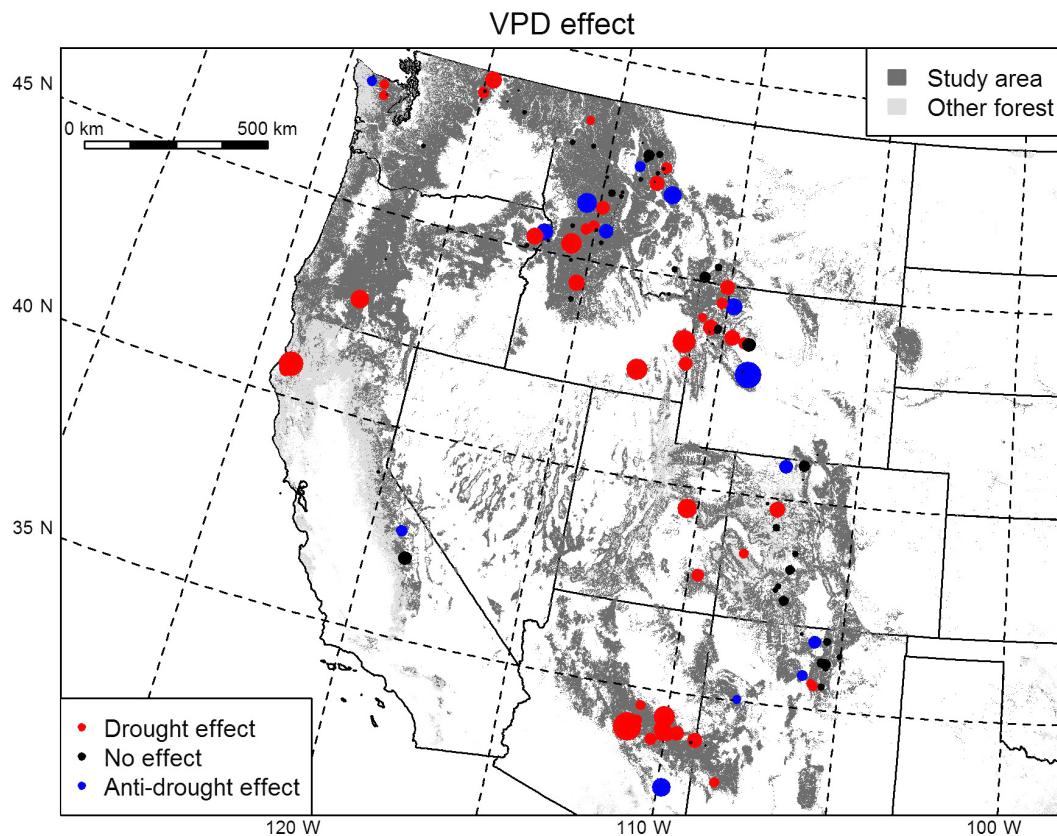


Fig. 9. Mapped effect sizes of vapor pressure deficit (VPD) at TimeSync interpretation plots observed experiencing forest canopy decline with symbol size indicating magnitude of effect on the probability of forest canopy decline and color indicating direction of effect: positive being consistent with drought-mediated decline (drought effect; red) and negative being inconsistent with drought-mediated decline (anti-drought effect; blue). Black indicates no significant effect. Dashed lines are graticules representing parallels of latitude and meridians of longitude.

knowing the drivers of the plot-level variation in drought effects on forest canopy decline, it is difficult to predict whether drought-resistant forest refugia will be broadly distributed or geographically isolated (Keppel et al. 2012, Morelli et al. 2016). Therefore, parsing the various, interactive local drivers that mediate forest drought response is an area of research requiring extensive attention. Although the drought effects on forest canopy decline probability described in this study are insightful, research is still needed to understand the magnitude of tree mortality associated with these disturbance events.

The integration of the TimeSync satellite image interpretation tool with the SAM modeling framework provides a promising approach for landscape and regional analysis of climate-induced

vegetation disturbance. This framework integrates high-quality observations of annual disturbance and recovery patterns for multiple decades (1985–2013) with a time series approach for identifying and characterizing hysteresis of lagged climatic drivers. We (1) identified seasonal and interannual climate anomalies driving drought related to forest canopy decline events (winter VPD and summer precipitation anomalies), (2) showed that all forest type groups responded similarly to these anomalies (i.e., increased probability of forest canopy decline when VPD anomalies were high and precipitation anomalies were low), and (3) found substantial differences in the sensitivity of forest canopy decline probability to drought within each forest type group. The impact of drought across

different forest type groups was ubiquitous, but not uniform within those forests. The high degree of plot-level variation in forest responses to drought emphasizes a substantial need to better understand how local abiotic (e.g., topography and soils) and biotic (e.g., forest structure and composition) factors mediate forest change. Such work is necessary for linking our ecological and physiological understanding of tree drought responses to forest and landscape responses of interest to land managers, decision makers, and the public at large (Clark et al. 2016).

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