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Climate limits vegetation green-up more than slope, soil erodibility, and immediate precipitation following high-severity wildfire

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Abstract

Background In the southwestern United States, post-fire vegetation recovery is increasingly variable in forest burned at high severity. Many factors, including temperature, drought, and erosion, can reduce post-fire vegetation recovery rates. Here, we examined how year-of-fire precipitation variability, topography, and soils influenced post-fire vegetation recovery in the southwestern United States as measured by greenness to determine whether erosion-related factors would have persistent effects in the longer post-fire period. We modeled relationships between post-fire vegetation and these predictors using random forest and examined changes in post-fire normalized burn ratio across fires in Arizona and New Mexico. We incorporated growing season climate to determine if year-of-fire effects were persistent during the subsequent 5 years or if temperature, water deficit, and precipitation in the years following fire were more influential for vegetation greenness. We expected that post-fire factors that drive erosion would reduce greenness; however, these effects would explain less variability in post-fire greenness than growing season climate.

Results We found reductions in post-fire greenness in areas burned at high severity when heavy and intense precipitation fell on more erodible soils immediately post-fire. In highly erodible scenarios, when accounting for growing season climate, coefficient of variation for year-of-fire precipitation, total precipitation, and soil erodibility decreased greenness in the fifth year. However, more of the variation in greenness was explained by variability of growing season vapor pressure deficit and growing season precipitation.

Conclusions Our results suggest that while the factors that contribute to post-fire erosion and its effects on vegetation recovery are important, at a regional scale, the majority of the variability in post-fire greenness in high-severity burned areas in southwestern forests is due to climatic drivers such as growing season precipitation and vapor pressure deficit. Given the increasing scale of area burned at high severity and the potential for more post-fire erosion, quantifying how these factors alter ecosystem development is central to understanding how different ecosystem types will be distributed across these landscapes with additional climate change.

Keywords Southwestern United States, Fire, Precipitation, Landsat, Vegetation recovery

Resumen

Antecedentes En el sudoeste de los Estados Unidos, la recuperación de la vegetación en el post-fuego es incrementalmente variable en bosques quemados a alta severidad. Diversos factores, incluyendo la temperatura, sequias, y erosión, pueden reducir las tasas de recuperación de la vegetación. En este trabajo, examinamos cómo la variabilidad

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en la precipitación en el año en que ocurren los incendios, la topografía, y los suelos, influencian la recuperación de la vegetación post-fuego en el sudoeste de los EEUU, medidos mediante un índice verde, para determinar si los factores relacionados con la erosión pueden tener efectos persistentes en períodos largos luego de los incendios. Modelamos las relaciones entre la vegetación post-fuego y esos predictores usando el programa Random Forest y examinamos los cambios en la relación normalizada de quema (post-fire normalized burn ratio) en fuegos ocurridos en Arizona y Nuevo México. Incorporamos el clima de la estación de crecimiento para determinar si los efectos del año en que ocurrió el fuego eran persistentes durante los siguientes cinco años, o si la temperatura, el déficit hídrico, y la precipitación en los años posteriores al fuego tuvieron más influencia en el reverdecimiento de la vegetación. Esperamos que los factores post-fuego que producen erosión puedan reducir el reverdecimiento de la vegetación. De esa manera, estos efectos podrían explicar el menor reverdecimiento post fuego que el clima de la estación.

Resultados Encontramos reducciones en el reverdecimiento de la vegetación en áreas quemadas a alta severidad cuando precipitaciones muy fuertes e intensas cayeron sobre suelos muy erosionables en el post-fuego inmediato. En escenarios altamente erosionables, cuando se tiene en cuenta el clima de la estación de crecimiento, el coeficiente de variación para la precipitación del año de ocurrencia del incendio, la precipitación total, y la erosión del suelo, decrecieron el reverdecimiento de la vegetación en el quinto año. Sin embargo, la mayoría de la variación en el reverdecimiento de la vegetación fue explicado por la variación del déficit de presión de vapor de la estación de crecimiento y la precipitación en esa misma estación.

Conclusiones Nuestros resultados sugieren que mientras los factores que contribuyen a la erosión en el post-fuego y sus efectos en la recuperación de la vegetación son importantes, a escala regional, la mayoría de la variabilidad en el reverdecimiento de la vegetación en el post fuego, en áreas severamente quemadas en los bosques del sudoeste de los EEUU, es debido a los conducentes climáticos como la precipitación en la estación de crecimiento y el déficit de presión de vapor. Dado el incremento en la escala de incendios de alta severidad y el potencial para una mayor erosión en el post fuego, el cuantificar cómo estos factores alteran el desarrollo de los ecosistemas es central para entender cómo diferentes tipos de ecosistemas se distribuirán a lo largo de esos paisajes teniendo en cuenta el adicional que implica el cambio Climático.

Background

Wildfire profoundly influences ecosystem dynamics globally (Bowman et al. 2009), and in the southwestern United States, the area impacted by high-severity wildfire has increased at all elevations (Singleton et al. 2019). Historically, many southwestern forests burned frequently at low severity leading to a mosaic of size classes and species, but in the twentieth century, fire suppression and other land use in the region increased forest density and changed species compositions in low- and mid-elevation forests (Hurteau et al. 2014; Naficy et al. 2010; Covington and Moore 1994), leading to a sharp decrease in fire occurrence, contributing to larger areas burned at high severity in recent years (Prichard et al. 2021). Post-fire reforestation in high-severity burned areas occurs at variable rates mostly due to temperature and moisture conditions (Chambers et al. 2016; Savage and Mast 2005). However, grasses and shrubs typically precede tree establishment and initial conditions related to topography and precipitation could explain variability in post-fire vegetation recovery in recently burned areas. These factors can contribute to erosion and reduce available nutrients and substrate. Because initial vegetation recovery following wildfire is important for stabilizing soils and promoting future tree establishment (Cerdà and Doerr 2008;

Swanson et al. 2011; Crockett and Hurteau 2022), exploring the effects of early precipitation and topography is essential to developing accurate projections of post-fire forest recovery and locating where additional post-fire management may be necessary.

Severely burned landscapes are dominated by bare and transformed soils with limited vegetation remaining to stabilize soil structure (Certini 2005). The combination of decreased litter and ground cover, and highly erodible soil types (e.g., sandy soils), makes post-fire landscapes susceptible to erosion (Shakesby and Doerr 2006). In particular, longer and steeper slopes speed overland flow while slope shape can concentrate flows in channels (Orem and Pelletier 2016). When precipitation falls on these soils, substantial sediment transport is possible and can quickly remove available soil organic and inorganic matter, creating additional resource limitations for early successional plant species (Bormann et al. 2008; Benavides-Solorio and MacDonald 2005; Orem and Pelletier 2016). These effects are seen following erosion on mine tailings, in which vegetation recovery can be slowed until sufficient cover is retained to intercept precipitation (Moreno-de Las Heras et al. 2011; Vidal-Macua et al. 2020). Whether this is the case in southwestern forests burned at high-severity fire is an open question.

Determining the potential for post-fire erosion to alter vegetation recovery is complicated by the altered thermal and moisture environment in burned forests. The elimination of tree canopy by high-severity fire exposes soils to sunlight which elevates temperatures and exacerbates soil moisture loss, and consequently, in dry systems, early successional stages are often characterized by pioneering herbaceous plants rather than trees (e.g., Turner et al. 1997; Coop et al. 2016; Abella and Fornwalt 2015). This initial vegetation can increase nutrient retention and mineralization, decrease microclimate extremes, and stabilize soils by reducing splash erosion that can lead to soil losses, thus altering the heterogeneity of future forests (Swanson et al. 2011) However, high-severity fire can reduce the abundance of seed banks and the loss of soil during post-fire erosion events can additionally remove embedded roots and seeds (Shi et al. 2022). Loss or slowed recovery of herbaceous ground cover could cause a positive feedback in which soil losses reduce vegetation, limiting the interception of precipitation and thus leading to further soil losses and vegetation loss (Moreno-de Las Heras et al. 2011; Vidal-Macua et al. 2020). Furthermore, prompt vegetation recovery can maximize the retention of soil nutrients, thus enhancing additional establishment (Johnson and Curtis 2001; Certini 2005).

Interactions between high-severity fire, precipitation, topography, and soils are likely in any topographically complex and fire-prone location. However, the seasonality of fire and precipitation in the southwestern United States increases the likelihood that these factors will intersect and influence vegetation recovery. Given the importance that early vegetation establishment has for providing resources for future tree establishment, we examined how the year-of-fire effects of post-fire precipitation totals and precipitation variability, topography, and soil erodibility following high-severity fire influenced post-fire vegetation establishment in the southwestern United States. To examine relationships between post-fire vegetation establishment and climate, soil, and topographic variables, we built random forest models for each of the 5 years following fires for forested areas in New Mexico and Arizona (hereafter, the southwest) between 1985 and 2017 (Breiman 2001). We included the growing season climate of subsequent years to investigate whether the year-of-fire effects were impactful or would be negligible relative to recognized drivers of post-fire vegetation recovery.

We expected that large amounts of intense precipitation in forests burned at high severity would delay post-fire vegetation establishment relative to lower amounts of less variable precipitation. Additionally, we expected that longer and steeper slope lengths burned by high-severity fire would delay post-fire vegetation establishment

more than shorter and shallower slopes. While we did not include changes in water-repellency due to fire, we expected that sand-dominated soils with coarser textures relative to soils with textures that are less prone to erosive loss would additionally decrease greenness. However, even if factors that increase erosion were to decrease greenness, we hypothesized that they would explain less variability in post-fire greenness than growing season climate.

Methods
Study area
We selected fires from semi-arid forests of the southwestern United States (Arizona and New Mexico, Supp. Fig. 1), which occupy 14.6 million ha across an elevation gradient that consists of ponderosa pine (*Pinus ponderosa*) and Gambel oak (*Quercus gambelii*) at lower elevation, mixed conifer forests at mid-elevation, then sub-alpine conifer forests at the highest forested elevations. Historically, the fuel-limited forests at low and mid-elevations burned frequently at low severity leading to a mosaic of size classes and species, but in the twentieth century, fire suppression, logging, and grazing in the region changed species compositions in low- and mid-elevation forests (Hurteau et al. 2014; Covington and Moore 1994), leading to a sharp decrease in fire occurrence, followed by larger areas burned at high severity. Dry pine forests historically burned frequently at low severity at approximately 5–10 year intervals (Covington et al. 1994; Swetnam and Baisan 1996; Allen et al. 2002). At higher elevations, mixed conifer forests consisting of ponderosa pine, Douglas-fir (*Pseudotsuga menziesii*), southwestern white pine (*P. stobiformis*), and other conifers burned at a range of frequencies and severities, with low-severity fires occurring at 5 + year intervals on drier sites and during drought periods (Margolis and Balmat 2009). Upper montane forests had repeated low severity fires with a 5–10-year frequency, with evidence suggesting that stand-replacing fires occurred only rarely (Margolis et al. 2011). However, increasing tree density from fire-exclusion and climate change in the twentieth and twenty-first centuries have increased fire severity and area burned at high severity in ponderosa pine and mixed conifer forests (Singleton et al. 2019; Parks et al. 2023).

Precipitation in the region is bimodal and split between cold winter precipitation and intense late summer monsoonal rains from the North American Monsoon (Williams and Ehlerginer 2000; Sheppard et al. 2002). Forest soils are highly variable, and all soil orders except for Ultisols and Oxisols are present in forests in the region, with Inceptisols, Alfisols, and Andisols occurring at the highest rates (Meurisse et al. 1991). Post-fire erosion

is more likely to occur due to intense monsoon rainfall causing the end of fire season.

Data

We used the LANDFIRE Existing Vegetation Type layer (LANDFIRE 2016) to select ponderosa pine, mixed conifer, and sub-alpine forests and then selected burned areas using Monitoring Trends in Burn Severity (MTBS) fire perimeters for the period 1985–2017. The MTBS program maps fire severity for fires with a minimum burned area of 404 ha (Eidenshink et al. 2007). We only included fires through 2017 to ensure that we had at least 5 years of post-fire data for all fires in the dataset.

Within each fire perimeter, we selected MTBS-designated high-severity burned pixels and aggregated gridded climate data, remotely sensed vegetation metrics, topography, and soil metrics. Unless otherwise stated, the following descriptions refer to pixelwise calculations. We calculated normalized burn ratio (NBR) for each fire year -1 to fire year $+5$ (Eq. 1), which describes both the amount and greenness of vegetation in a pixel. Compared with other metrics such as normalized difference vegetation index, NBR is more sensitive to post-fire recovery than other indices, and while the delta NBR (dNBR) is widely utilized to assess burn severity, NBR in high-severity burned areas assesses the absolute change of greenness that could be affected by erosion (Pickell et al. 2016). The study period encompassed multiple Landsat missions (5 TM, 7 ETM+, and 8 OLI), with 30-m resolution and 16-day return intervals. We imported perimeters accessed from MTBS into Google Earth Engine (GEE); then, for each perimeter, we excluded pixels identified by the USGS quality band as clouded, water, etc., and applied coefficients and offsets from Roy et al. (2016) to Landsat 5 TM and 7 ETM+ products to allow for continuous data between Landsat 5 TM, 7 ETM+, and 8 OLI imagery (Gorelick et al. 2017). For the non-masked pixels, we calculated the normalized burn ratio (NBR, Eq. 1) as:

$$NBR = SWIR - RED/SWIR + RED \qquad (1)$$

where SWIR is the short-wave infrared band, and red is the red band. We selected scenes between June 20 and September 20 to minimize snow cover and capture peak summer greenness in southwestern United States (Notaro et al. 2010). We then used a GEE implementation of the Landtrendr algorithm to segment and fit pixelwise curves to time series of imagery to summarize each year's peak greenness of vegetation with a single image of each pixel's maximum NBR (Kennedy et al. 2018). Finally, we excluded pixels in which the pre-fire NBR was less than

50, a threshold that corresponds to hard surfaces and rock (Lutes et al. 2006).

We selected year-of-fire effects based on the potential for substrate loss on post-fire slopes and used variables related to those in the Universal Soil Loss Equation (USLE), which predicts long-term average soil loss based on rainfall, topography, soil characteristics, and vegetation characteristics in agricultural settings (Wischmeier and Smith 1978). Here, we used slope length factor, soil erodibility, total precipitation, and coefficient of variation of precipitation between the fire date and the end of the fire year, which are similar to the topographic, soil conditions, and rainfall used in the USLE to predict long-term soil loss. These variables are strongly predictive of first year hillslope erosion in mountainous environments, though we substituted soil erodibility factor for percent rock to accommodate a wider array of soil textures and makeups (Miller et al. 2011). We accessed gridded, daily precipitation data (resolution: 1000 m) from the Daymet V4 repository hosted on GEE (Thornton et al. 2022). We selected precipitation between the fire date and December 31 of the year of fire and then calculated the coefficient of variation and total precipitation that occurred in that period. We used the RSAGA tool ls_factor to calculate landscape slope factor from the USGS 3DEP 10 m Digital Elevation Model, in which lower values correspond to shallower, shorter slopes and higher values correspond to steeper, longer slopes (U.S. Geological Survey n.d.). We accessed soil erosion likelihood from SSURGO and used ArcMap 10.8.1 to calculate the k-factor erosion potential of soils, in which values > 0.4 correspond to more erodible soils (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture n.d.).

We accessed monthly Terraclimate data to use for the growing season climate variables (Table 1, 4000 m) (Abatzoglou et al. 2018). We calculated the growing season (April through October) mean and sum of the climate variables for each post-fire year. We thinned the full dataset by randomly selecting 20% of pixels to reduce the likelihood of spatial autocorrelation and retained the remaining 80% for final model fit assessment.

Modeling

We modeled relationships between post-fire vegetation and predictors with random forest using the Ranger package (Wright and Ziegler 2017) to determine how much of the variability of post-fire greenness could be explained by erosion-related factors. The random forest algorithm can capture complex, nonlinear relationships and interactions between response and predictor variables, without making a priori assumptions about these relationships.

Table 1 Variables and their descriptions used for random forest models annual normalized burn ratio models. Variables are grouped by year-of-fire (i.e., factors that occurred between fire date and 12/31 of the fire year) and growing season (i.e., factors that occurred between April and October of the post-fire year being analyzed)

Variable	Source	Description
Normalized burn ratio years 1, 2, 3, 4, 5	Landsat + LandTrendr (30 m)	Normalized burn ratio for years 1 through 5
Year-of-fire effect variables		
Soil erodibility (K-factor)	gSSURGO, processed in ArcMap	Unitless factor denoting a soils susceptibility to erosion and rate of runoff
Slope length factor (LS-factor)	DEM (National Map 10 m)	Unitless factor representing the ratio of soil loss per unit area to the loss from a 22.1-m long plot with a 9% slope
Precipitation total, fire date to end of year	Daymet (daily, 1000 m)	Sum of daily precipitation between fire date and end of year (mm)
Precipitation seasonality (coefficient of variability), fire date to end of year	Daymet (daily, 1000 m)	Coefficient of Variation of daily precipitation between fire date and end of year (mm)
Growing season variables		
Growing season VPD	Terraclimate (monthly, 4000 m)	Mean vapor pressure deficit, April through October, model year (kPa)
Growing season tmax	Terraclimate (monthly, 4000 m)	Mean temperature maximums, April through October, model year (C°)
Growing season PPT	Terraclimate (monthly, 4000 m)	Total monthly precipitation, April through October, model year (mm)
Growing season CWD	Terraclimate (monthly, 4000 m)	Mean climatic water deficit, April through October, model year (mm)
Other		
Month of fire	MTBS	

For each of the five post-fire years, we built fivefold cross validated models with all predictors in Table 1 using the Ranger implementation of random forest in R with 500 trees and the square root of the number of variables per node split (R Core Team 2023). To determine the optimal number of variables, we used recursive variable elimination in a ten-fold cross-validation, repeated five times using the "rfe" function from the "caret" package and used root mean squared error (RMSE) as our performance metric, with sets of 1, 3, 6, and 9 variables. We refit a final model based on the optimal number of variables from the algorithm and calculated the permutation feature importance. We assessed final model fit by calculating the root mean squared error (RMSE) of model predictions and the coefficient of determination (R^2) of a linear regression between observations and predictions of the 80% of data withheld from model development.

To examine the underlying relationships between variables and outcomes, we used tools from the "iml" package to make global and local inferences (Molnar et al. 2018), and the strength of interactions between all variables to determine (1) whether variables did not meaningfully contribute to the models and (2) whether year-of-fire variables were influential when interacting with growing season variables, indicating their effects over longer periods. The interaction strength is the excess variance of the 2-dimensional partial dependence function greater than the sum of the two 1-dimensional partial dependence functions, measured by Friedman's H statistic, with higher values corresponding to greater connections to all other variables.

To examine how a particular variable affected outcomes over its entire range, we calculated accumulated local effects (ALE) for all individual variables and for pairwise combinations of year-of-fire variables to show the relative change in the prediction caused by a change in the variable, setting grid intervals to 20 units to extract clear trends (Apley and Zhu 2020). Finally, we calculated Shapley Additive exPlanations (SHAP) values for a likely highly erodible scenario using the year 5 models to decompose how changes in year-of-fire variables can affect the baseline NBR value while still accounting for any interacting effects with growing season climate (Table 2, Strumbeli and Kononenko 2014). The SHAP values decompose predictions into the contributions from

Table 2 Model statistics for data withheld from model development. Root mean squared error (RMSE), mean normalized burn ratio (NBR) and standard deviation (S.D.), and R^2 of a linear regression of observed and predicted Normalized burn ratio for each model year. Models were built using 20% of observations, with the remaining 80% withheld for validation

	RMSE	Mean (NBR)	S.D.	Observed NBR ~ predicted, R^2
Year 1	0.73	− 60.09	128.88	0.6
Year 2	0.46	15.16	115.25	0.65
Year 3	0.13	91.07	115.66	0.71
Year 4	0.27	167.02	129.38	0.75
Year 5	0.71	242.65	152.46	0.74

each variable, showing how the difference from a baseline value is achieved. We used a scenario from a dataset consisting of mean climate, fires occurring in June, and 100 samples from the top 10th percentile of year-of-fire variables to decompose how year-of-fire variables can affect the baseline NBR value while still accounting for any interacting effects with growing season climate in a highly erodible post-fire scenario (see Fig. 4, *y*-axis for values used).

Results

Over the period 1985–2017, there were 2003 large (> 404 ha) recorded fires in the southwestern United States that burned a combined 6,307,860 ha. Of the total burned area, 124,430 ha was burned at high severity in ponderosa pine, mixed conifer, or sub-alpine forest (Supp. Fig. 1). Greenness (NBR) increased over the 5 years following fire in all three forest types (Table 2, Supp. Fig. 2). Recursive variable elimination indicated that models using all nine variables, including the year-of-fire variables, minimized RMSE (Supp. Fig. 3). Of these full models, year 1 and year 5 models had the highest RMSE, and year 3 had the lowest RMSE. This corresponded to the variability of NBR in each year, as years 1 and 5 also had the largest standard deviation of NBR across the entire region, indicating that within areas designated by MTBS as high severity, vegetation was most variable immediately following fires and after 5 post-fire years (Table 2). The R^2 increased with the

inclusion of more variables and was highest in years four and five models (Table 2).

While including all variables increased model fit, importance scores indicated that year-of-fire variables were not as influential as subsequent growing season climate variables. Climatic water deficit, precipitation, and VPD had the highest variable importance scores, and growing season precipitation and VPD were ranked highest in all years, while soil erodibility and slope length were ranked lowest (Fig. 1), Most interaction effects between variables were greater than 0.25, indicating that interactions explain a greater portion of the variance than the sum of individual effects (Fig. 2). Growing season precipitation, climatic water deficit, and year-of-fire precipitation total had interaction strengths greater than 0.5 in all years, suggesting that interactions with moisture availability were key factors in determining post-fire greenness.

We plotted the accumulated local effects (ALE) of each variable for all post-fire years, which show the change in modeled NBR as each variable increases, with respect to the mean predicted by the model (Fig. 3). The year-of-fire variables (soil erodibility factor, slope length factor, month of fire, postfire precipitation total, and coefficient of variation) had close to zero effect on predicted NBR that were near the average prediction. Precipitation total above 500 mm decreased NBR in the year 1 model, which supports our hypothesized relationship between high initial precipitation and lower greenness. However, this
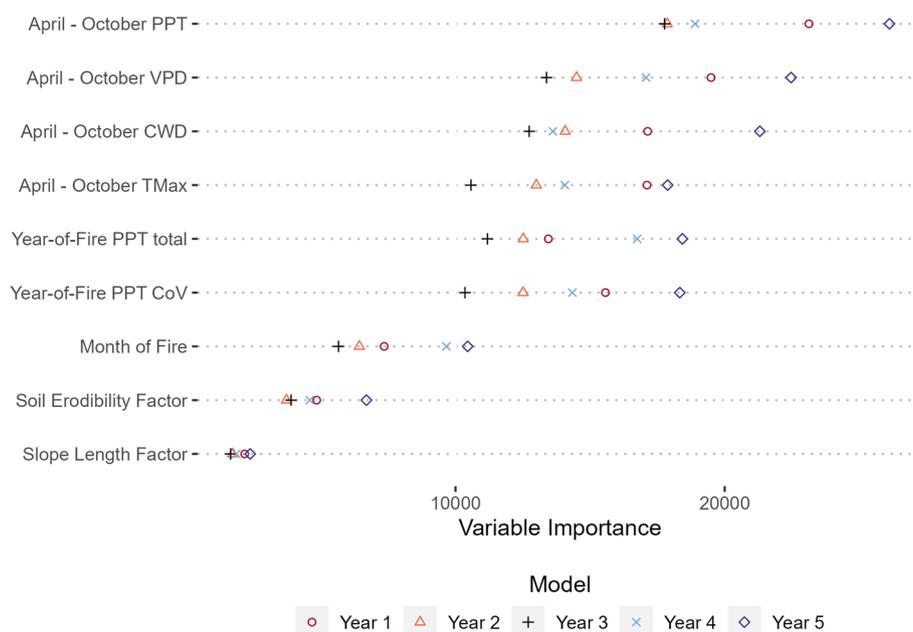

Fig. 1 Permutation importance scores for each model year. VPD, vapor pressure deficit; T max, maximum temperature; PPT, precipitation; CoV, coefficient of variation; CWD, climatic water deficit
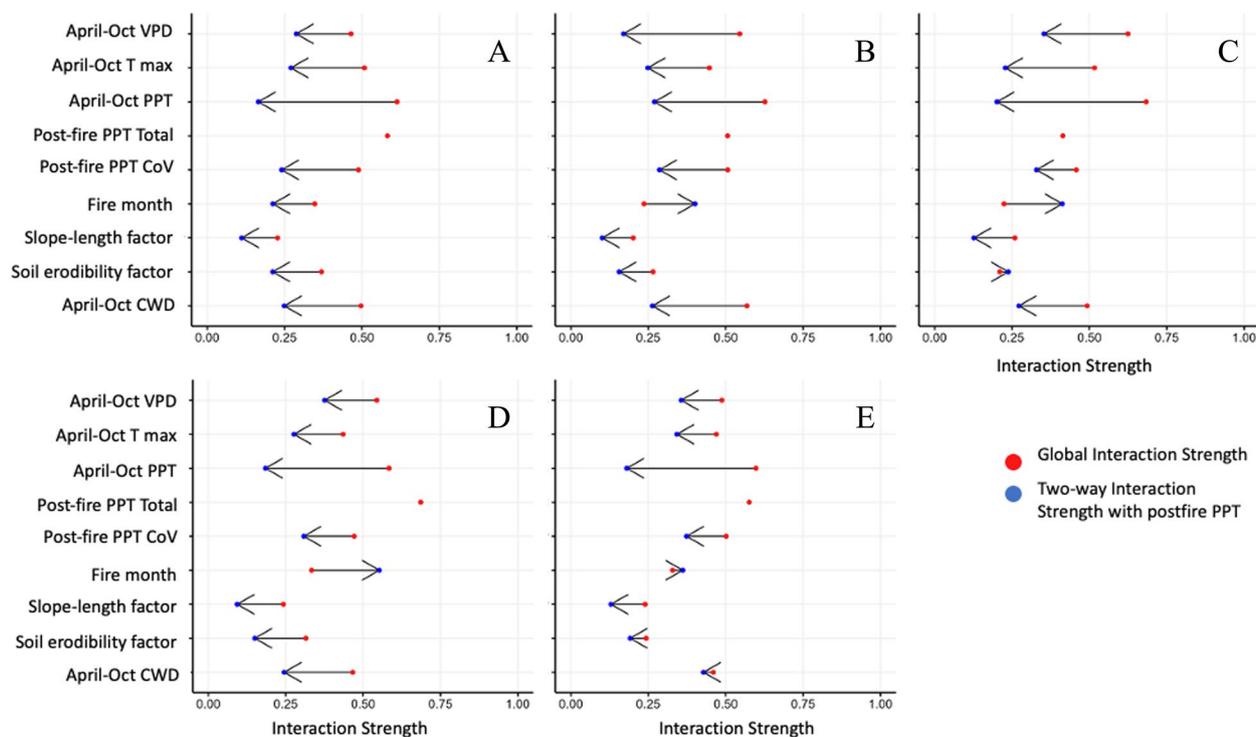
Fig. 2 Global interaction strength and two-way interaction strength with postfire precipitation total for each model (**A** fire year + 1; **B** fire year + 2; **C** fire year + 3; **D** fire year + 4, **E** fire year + 5). The interaction strength ranges from 0 (a variable does not interact with any other variable) to 1 (full interaction with other variables). Arrows show the direction of change from global to two-way interaction strength. VPD, vapor pressure deficit; T max, maximum temperature; PPT, precipitation; CoV, coefficient of variation; CWD, climatic water deficit

effect was not seen in the year 5 model. Additionally, fires that occurred between June and December were associated with a lower predicted NBR in the year 1 model. Yet, the range of the effects of year-of-fire variables was smaller (− 20 to 20) than that of growing-season climate, in particular VPD and growing season precipitation (− 100 to 100+).

In our evaluation of the year 5 model using SHAP values to decompose predictions from highly erodible scenarios, we found that the coefficient of variation of post-fire precipitation and post-fire precipitation total reduced SHAP values (Fig. 4). Soil erodibility further reduced NBR, while slope-length had a positive effect on it when mean growing season climate in year 5 is considered. Using the mean values of growing season climate resulted in neutral effects on NBR, except for maximum growing season temperature, which at a value of 22.3 °C increased NBR.

Discussion

Plant cover is a key factor in reducing post-fire erosion and enhancing conifer establishment in the southwestern US (Benavides-Solorio and MacDonald 2005; Crockett and Hurteau 2022). Evidence of substantial erosion

post-fire is widespread, and given observed losses of productive soils after fire, plant establishment could be slowed (Bormann et al. 2008). Hence, we hypothesized that factors related to post-fire erosion (year-of-fire effects) would result in changes in post-fire vegetation across a large region that experiences prevalent post-fire erosion. We found evidence that factors related to erosion that occur in the year-of-fire altered vegetation for multiple years post-fire, but this was limited to situations likely to result in erosion (i.e., high coefficient of variation of year-of-fire precipitation, high precipitation totals, and high soil erodibility factors (Fig. 4)). However, we also found that year-of-fire variables had much smaller effects relative to the climate of subsequent years across the greater region, specifically growing season precipitation (Figs. 1 and 3). Thus, the relative scale of these effects to growing season climate suggests that erosion may be locally important, but at the regional scale, weather and climate in the post-fire period is likely to obscure their impact (Fig. 3).

We found that factors contributing to post-fire erosion have a small effect on vegetation recovery in southwestern forests burned at high severity, relative to growing season climate, but in other disturbed systems, erosion
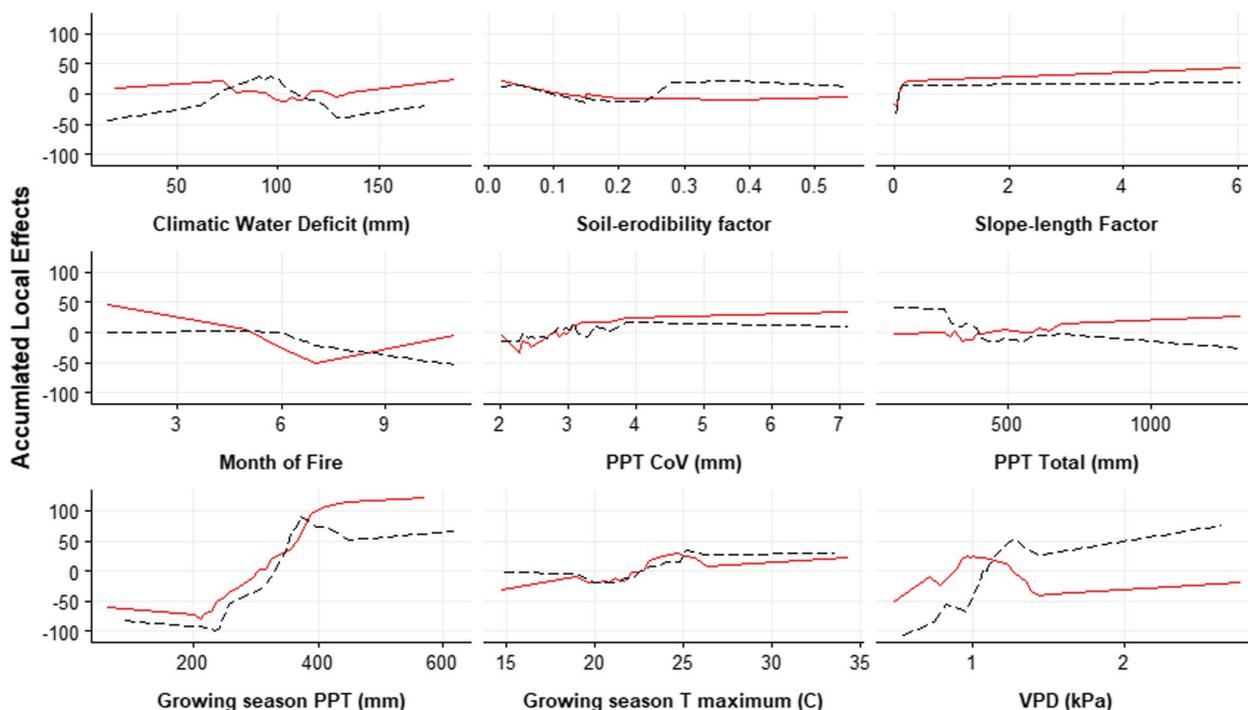
Fig. 3 Accumulated local effects plot of each variable showing the change in prediction due to a change in that variable. Values are centered at the mean predicted NBR of the variable, such that positive values correspond to relatively higher greenness. Colors indicate model years. NBR, normalized burn ratio; VPD, vapor pressure deficit; T max, maximum temperature; PPT, precipitation; CoV, coefficient of variation; CWD, climatic water deficit

has been found to significantly limit vegetation recovery on disturbed slopes, especially at the plot-level (Moreno-de Las Heras et al. 2011; Vidal-Macua et al. 2020; Hotta et al. 2024). For example, decreased vegetation recovery is linked to decreased soil moisture availability due to severe rill erosion on slopes with higher erosion risk (Moreno-de las Heras et al. 2011; Vidal-Macua et al. 2020). The retention of soil can increase vegetation establishment, while its loss can result in reduced coverage (Whisenant et al. 1995). The positive feedback from strong vegetation recovery immediately following fire reduces erosion risk, further increasing the rate of vegetation recovery (Espigares et al. 2011). While post-fire erosion occurs frequently, it may not affect all parts of a burned area, or it may affect it in different ways (Wondzell and King 2003). For example, rill or gully erosion can cause deep cuts and erode large quantities of soil in a narrow band with limited impact on the majority of the burned area surface. Sheet erosion, in contrast, removes topsoil from a wider area, which could have observable effects on vegetation (Horton and Kraebel 1955). Furthermore, the slope position could determine recovery rates, as lower parts of slopes are associated with more stable soils and faster recovery rates of soil carbon and nitrogen stocks (Hotta et al. 2024). However, these differences may be obscured at regional scales (Boix-Fayos et al. 2006). Thus, while local effects due to erosion can be important, our findings suggest that when aggregated across multiple years and large areas, ongoing climate has stronger controls over post-fire vegetation.

The availability of moisture is a limitation to early plant life stages and can be a limiting factor on burned landscapes (Stielstra et al. 2015; Crockett & Hurteau 2023; Davis et al. 2019a). Thus, we found that high growing season precipitation increased NBR in all years. Additionally, growing season VPD in year 5 had overall negative effects on NBR (Fig. 3), as the reduction of canopy cover can increase solar radiation experienced at the soil level, increasing evaporative loss especially on southern aspects (Davis et al. 2019b). This could also explain our finding that greater slope-length factor contributes to greater post-fire NBR, contrary to the hypothesized relationship that steeper and longer slopes would reduce NBR. Slope length factor interacts here with all variables (Fig. 2); thus, longer slopes, southwestern aspects excepted, may have had a positive effect due to reduced temperatures and increased moisture retention (Marsh et al. 2022; Dobrowski 2011). Determining the climatic impact of aspect here may require finer scale measurements beyond that which was available. Finally,
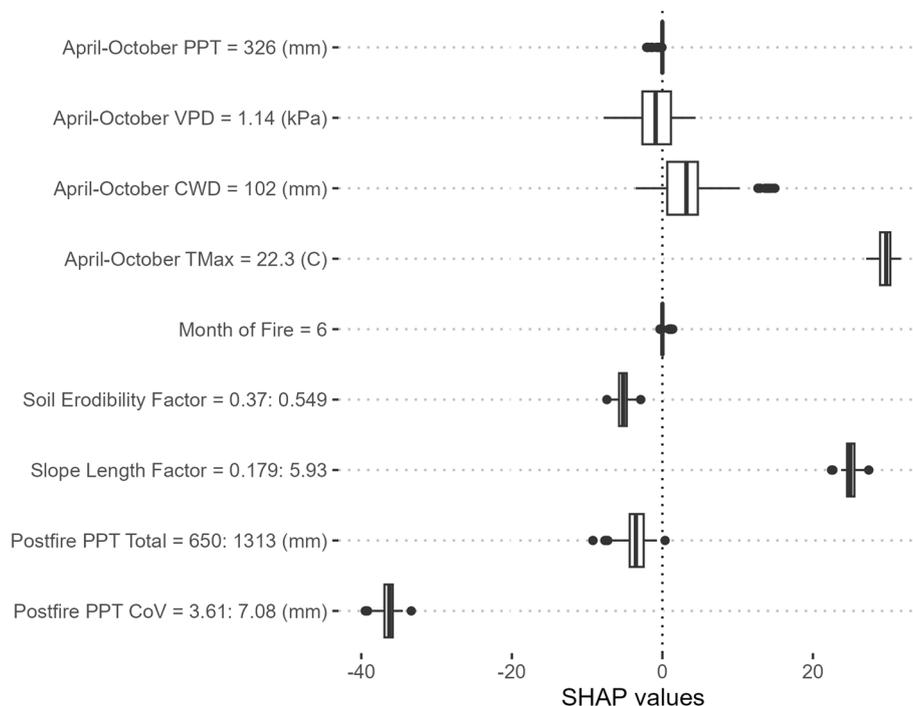
Fig. 4 Boxplots of Shapley additive explanative (SHAP) values decomposing contributions of each variable to the expected outcomes from the year 5 random forest model applied to mean climate + highly erodible year-of-fire scenarios. The baseline (0) is the mean NBR value predicted from the entire dataset (NBR = 243), positive and negative values indicating the direction and magnitude of the contribution of each variable. SHAP values were calculated from 100 draws from mean climate + 90th percentile and above of year-of-fire values, with the mean climate values and range of year-of-fire values used on the *y*-axis. VPD, vapor pressure deficit; T max, maximum temperature; PPT, precipitation; CoV, coefficient of variation; CWD, climatic water deficit

our models showed that growing season temperature increased greenness until approximately 22 °C (Fig. 3). The positive effect of lower temperatures may be due to the balance between cellular respiration, photosynthesis, and water availability (i.e., lower VPD, lower evaporation rates from soils), but above 25 °C, cellular efficiency likely decreases and moisture demand increases (Grossiord et al. 2020; López et al. 2021).

Specific post-fire plant communities may have outsized effects on enhancing vegetation connectivity, particularly in areas burned multiple times. Resprouting species, such as Gambel oak, are common in southwestern post-fire environments, though annual grasses are also common (Guiterman et al. 2018). Shrubs and other resprouters are capable of regrowing quickly following fire, especially in forests where they had been light limited (Paritsis et al. 2015). Their extensive root structures can reduce substrate loss if they survive through high-severity fire (see Fernández et al. 2013; Underwood et al. 2022). Additionally, we did not examine the prevalence of invasive grasses and forbs in the initial communities, though these can displace native species and alter ecosystems (Brooks et al. 2004). While invasive vegetation could alter greenness trajectories, determining community makeup was not

our goal, instead determining if physical properties of the landscape and weather were sufficient to explain differences in post-fire greenness. As invasive species are characterized by high fecundity and fast growth rates, this could more quickly stabilize slopes and reduce bare soils. However, some invasive species are linked to increased rates of erosion in riparian zones (Greenwood and Kuhn 2014). Accurately characterizing post-fire plant communities could improve our understanding of whether the underlying physical processes we analyzed are dependent on specific plant community composition. Our use of 30 m Landsat imagery obscures the mix of vegetation, which could have implications for whether climate or year-of-fire variables are more impactful over time.

There are several considerations that could influence our results, for which we were unable to account. Soil can be altered by wildfires depending on temperatures sustained during burning, with those burned at high temperatures likely to develop water-repellent layers at depth (DeBano 2000; Shakesby and Doerr 2006). We did not capture post-fire hydrophobicity in the analysis, which could affect susceptibility to detachment (Huffman et al. 2001). Additionally, post-fire management actions could influence the scale of any post-fire erosion. The risk of

post-fire flooding and erosion in some landscapes can lead to management actions such as seeding forbs and grasses, which could influence measured greenness values by increasing colonization rates. The Burned Area Emergency Response (BAER) program assesses stabilization issues arising from fire and apply a variety of treatments, including seeding, mulching, and installation of erosion control devices. These treatments can have variable efficacy (Peterson et al. 2007) and outcomes (Robichaud et al. 2009). For example, following BAER treatments of three fires in Colorado between 2006 and 2008, large soil loss was reported but was followed by extensive ground cover recovery after 1 year (Foltz and Robichaud 2013). While these treatments were likely applied in some of the fires we analyzed, spatial data of BAER treatments is limited, and due to the variable efficacy and vegetation outcomes, we did not include it as a confounding variable.

Conclusions

Factors affecting burned landscapes that occur early after fires in the southwestern US can influence the future trajectory of these ecosystems. Here, we show that year-of-fire precipitation can reduce greenness for up to 5 years post-fire, but the reductions in greenness in year 5 due to greater amounts of year-of-fire precipitation were offset by enhancements from other factors, including soil erodibility and growing season climate. This suggests that these systems can be resilient to post-fire erosion at the regional scale and that with warmer and drier growing seasons, reductions of post-fire vegetation establishment is likely to occur over the 5 years following wildfire. Given the increasing area burned at high severity and the potential for more post-fire erosion, quantifying how these factors alter ecosystem development is central to understanding how different ecosystem types will be distributed across these landscapes with additional climate change.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-024-00264-0.

Additional file 1: Supplemental Figure 1. Fire perimeters between 1984 and 2016 in the southwestern United States (yellow) and forested pixels classified by LANDFIRE (purple). **Supplemental Figure 2.** Normalized burn ratio (NBR) by year by forest type. Bar heights show mean NBR for all screened pixels with ± standard deviation. Higher NBR corresponds to greater vegetation. **Supplemental Figure 3.** Mean absolute error and R^2 values, ± 1 s.d., by model year and by subsets of 1, 3, 6, and 9 variables from a fivefold cross validation. Colors shows model year and mean ± 1 s.d. are shown in black within each point.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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