



RESEARCH ARTICLE

Management strategy influences landscape patterns of high-severity burn patches in the southwestern United States

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Abstract

Context Spatial patterns of high-severity wildfire in forests affect vegetation recovery pathways, watershed dynamics, and wildlife habitat across landscapes. Yet, less is known about contemporary trends in landscape patterns of high-severity burn patches or how differing federal fire management strategies have influenced such patterns.

Objectives We assessed fires managed for ecological/resource benefit and fires that are fully suppressed and investigated: (1) whether spatial patterns of high-

severity patches differed by management strategy, (2) whether spatial patterns were related to fire size and percent high-severity fire, and (3) temporal trends in spatial patterns.

Methods We examined high-severity spatial patterns within large fires using satellite-derived burn severity data from 735 fires that burned from 1984 to 2017 in Arizona and New Mexico, USA. We calculated a suite of spatial pattern metrics for each individual fire and developed a method to identify those which best explained variation among fires.

Results Compared to managed fires, spatial pattern metrics in suppression fires showed greater patch homogeneity. All spatial pattern metrics showed significant relationships with fire size and percent high-severity fire for both management strategies. Mean annual spatiotemporal trends in suppression fires have moved toward smaller, more complex, fragmented patches since the early 2000s.

Conclusions Increases in fire size and proportion high-severity fire are driving more homogenous patches regardless of management type, with percent high-severity more strongly driving average temporal trends. Anticipated shifts in fire size and severity will likely result in larger, more contiguous, and simple-shaped patches of high-severity fire within southwestern conifer forests.

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Keywords Patch dynamics · Spatial pattern · RdNBR · Stand replacing patches · High-severity · Heterogeneity · Fire ecology

Introduction

Wildfire is an important disturbance process and a major driver of landscape dynamics in forests of western North America (Hessburg et al. 2019). Wildfire is inherently a spatially contiguous process, generating spatial patterns of burned vegetation that vary in size, shape, and severity as the fire spreads. Fire severity (i.e., the degree of aboveground loss of dominant vegetation due to fire; Lentile et al. 2006; Keeley 2009) is a key spatially explicit outcome of fire. Within forests, fire severity is generally categorized by the proportion of aboveground tree foliage killed by fire within a given area (from a satellite pixel to an entire burned landscape), with “high-severity” or “stand-replacing” fire describing areas where most to all overstory trees are killed (Lentile et al. 2006). High-severity fire effects are of particular importance because of the immediate changes in vegetation structure, wildlife habitat (Wan et al. 2019), watersheds (Neary et al. 2003), and carbon storage (Rogers et al. 2011) that have lasting effects on forest ecosystem processes over large spatial and temporal scales.

Given the ecological and social significance of high-severity fire, it is important to understand its temporal trends and key drivers in forests across western North America. A number of studies have investigated trends and drivers of high-severity fire by assessing basic metrics describing high severity fire, namely area burned severely and proportion burned severely (Miller et al. 2009; Dillon et al. 2011; Miller and Safford 2012; Picotte et al. 2016; Singleton et al. 2019). Evidence is mixed, but broadly suggests an increase in these variables over time in some (Miller et al. 2009; Miller and Safford 2012; Reilly et al. 2017; Singleton et al. 2019; Mueller et al. 2020) but not all (Dillon et al. 2011; Picotte et al. 2016; Parks and Abatzoglou 2020) regions in the western US. These trends have been attributed to well-documented increases in surface and canopy fuels and stand density following over a century of grazing, logging, and fire exclusion (Covington and Moore 1994; Safford and Stevens 2017; Parks et al. 2018b), as well as increasing temperature, water deficit, and other climate parameters that have been linked to anthropogenic climate change (Abatzoglou and Williams 2016; Westerling 2016; Mueller et al. 2020; Parks and Abatzoglou 2020).

Concurrently, there has been recognition that while metrics that describe area and proportion burned severely are indicative of broad trends in fire effects, they do not explicitly account for the spatial pattern and configuration of high-severity burn patches (Collins et al. 2017). By spatial pattern we refer to the size, shape, and distribution of discrete patches of high-severity fire that represent treeless patches on the landscape. The spatial patterns of high-severity burn patches are critical from a vegetation perspective because most western US conifer forest types are dispersal-limited, and conifer regeneration in high-severity patches has been clearly linked to distance from the nearest seed source (Haire and McGarigal 2010; Chambers et al. 2016; Welch et al. 2016; Owen et al. 2017; Haffey et al. 2018; Shive et al. 2018; Rodman et al. 2020). Landscapes with large high-severity patches, high patch aggregation, and minimal patch edge may exist in a prolonged state of non-forest vegetation (Coop et al. 2020), have significantly elevated water yield and flood peak flows (Neary et al. 2003), are less suitable for some forest-dependent wildlife species (Jones et al. 2020), and have reduced snowpack duration (Harpold et al. 2014; Stevens 2017). Thus, the relationship between fire size, severity, and spatial pattern of high-severity fire needs to be examined, especially as western US wildland fire management strategies have shifted in recent decades.

For over a century, land management agencies in the western US have primarily used full suppression strategies aimed at limiting fire extent to protect natural resources and rural communities (Busenberg 2004). This strategy largely excluded fire in forests resulting in the rapid accumulation of fuels culminating with larger and more severe fires in recent decades (Singleton et al. 2019). To combat this trend, agencies have begun using other fire management strategies including “managed fires,” which are naturally ignited wildfires managed, or allowed to burn to benefit resources (i.e., reduce fuel loads). Although this strategy has been widely used in more remote areas of the western US since the 1970s (Hunter et al. 2014), recent changes in wildland fire management have accelerated its use in most regions across the western US (Young et al. 2019). The main goal of this strategy is to reduce fuels across landscapes (North et al. 2015); however, it is less clear how spatial patterns within managed fires compare to

“suppression fires,” which are fires that often burn under more extreme weather conditions favorable to rapid fire spread (Stevens et al. 2017; Young et al. 2019). Such information is critical especially as managed fires are becoming more widely used to restore natural fire regimes in forested areas.

In recognition of the ecological significance of spatial pattern of high-severity patches, several studies have quantified various metrics of spatial pattern, and important drivers of these metrics across space and time (Cansler and McKenzie 2014; Harvey et al. 2016; Reilly et al. 2017; Stevens 2017; Steel et al. 2018). These studies have been largely regional in scope, leaving some regions of the western US unstudied. Further, there has not always been a systematic selection among the multitude of available metrics that describe spatial pattern, or a rigorous assessment of the relationship between spatial pattern metrics and the more conventional metrics of area and proportion of high-severity fire, as part of these analyses. Given the ecological significance of spatial pattern described above, there is increasing interest in whether managed fires might achieve spatial patterns more consistent with frequent fire regimes, compared to suppression fires, which may generate more homogenous spatial patterns of high-severity fire (Stevens et al. 2017). While the aforementioned regional studies investigate the impacts of fire weather on spatial pattern, fewer (e.g., Stevens et al. 2017; Steel et al. 2018) explicitly make the connection to a managed wildfire prescription.

The goal of this study was to investigate the consequence of differing federal fire strategies on landscape patterns of high-severity burn patches in a regionally focused assessment. We address current knowledge gaps by conducting the first comprehensive study of contemporary spatial pattern of high-severity burn patches in the southwestern US (Arizona and New Mexico)—a region perhaps most well-characterized for other aspects of historical fire ecology (Covington and Moore 1994; Fulé et al. 1997). Importantly, we first introduce a novel method for the systematic selection of the most relevant metrics of high-severity spatial pattern within an individual fire (hereafter “spatial pattern metrics”) among the multitude of available metrics. This method may be applied more broadly and comparatively in other regions. Then, with respect to selected spatial pattern metrics, we investigated the following

questions: (1) whether spatial pattern metrics differed by fire management strategy, (2) whether metrics that do not explicitly account for spatial pattern (hereafter “basic metrics”; e.g., area burned and proportion burned severely) were related to spatial pattern metrics within managed and suppressed fires, and (3) whether spatial pattern metrics within managed and suppressed fires have changed over the study period (1984–2017). Given recent changes in US federal fire policies over the past few decades and the need for increased burning on many landscapes, we hypothesized that managed wildfires would show distinct spatial patterns compared to suppressed fires and would be more consistent with the fine-grained landscape heterogeneity of historical frequent fire regimes. Second, based on seminal work relating landscape connectivity to spatial patterns of landscapes (Turner et al. 1989; Gustafson and Parker 1992), we expected a relationship with fire growth, severity, and spatially homogeneous patterns of high-severity patches in both fire types. Lastly, if we found a relationship between basic metrics and spatial pattern metrics in both managed and suppressed fires, we hypothesized that spatial patterns of high-severity burn patches would display a higher degree of patch size, aggregation, and connectivity over time. This work draws a connection between fundamental landscape ecology theory and practical applications of fire to achieve more desirable outcomes.

Methods

Study area

Our study region covers over 19 million ha of forest and woodland across Arizona and New Mexico, USA (Fig. 1). The climate is semi-arid and characterized by dual annual precipitation peaks which constitute the region’s primary sources of moisture (Sheppard et al. 2002). Late summer monsoonal rains, occurring from July through September, account for up to 50% of the moisture received annually and play a vital role in modulating fire extent and severity in the Southwest (Sheppard et al. 2002; Holden et al. 2007). From November through March, more than 75% of precipitation falls as snow over mountainous portions of the region (Sheppard et al. 2002). During the time frame of the study (1984–2017), Arizona had a mean annual

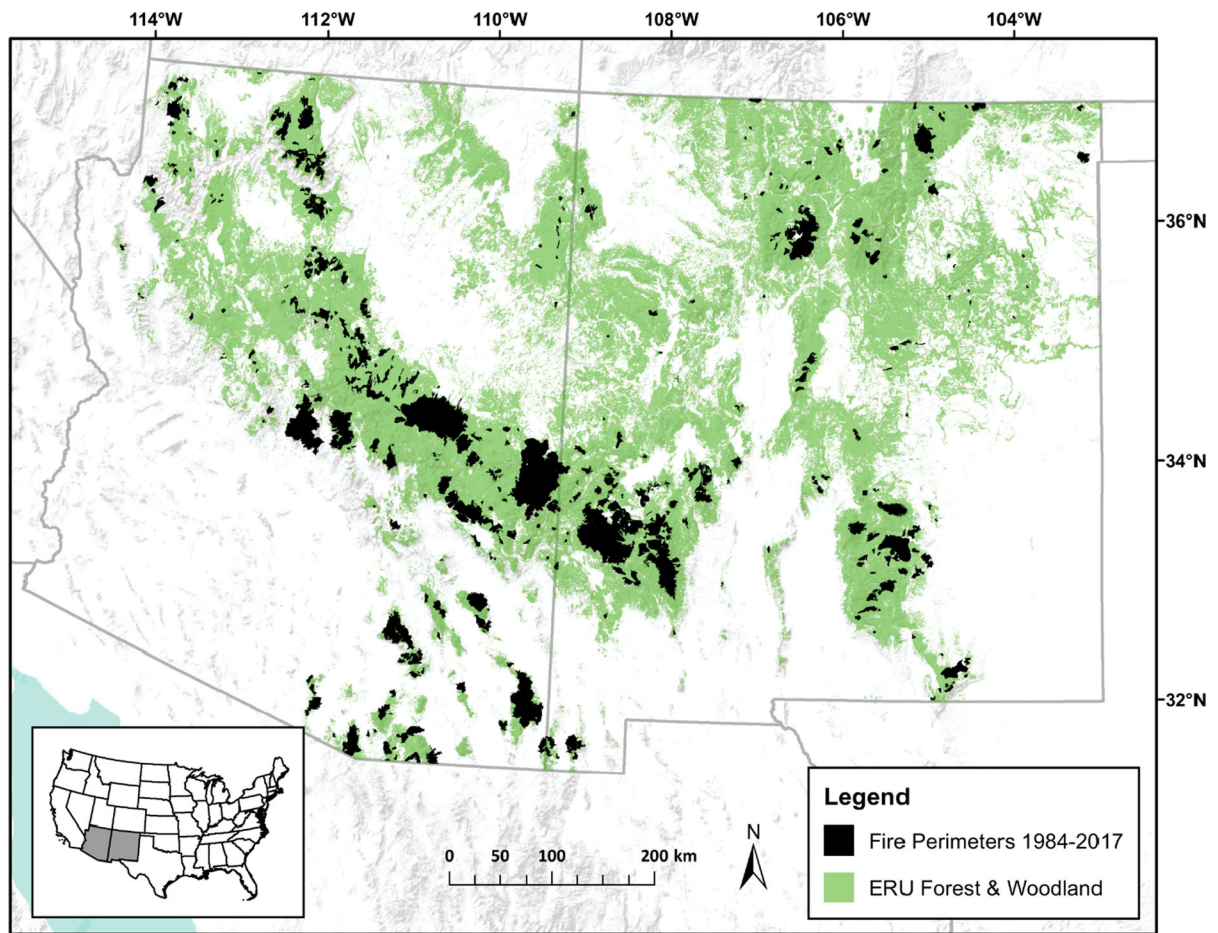


Fig. 1 Map of the study region in Arizona and New Mexico, USA showing location of the 735 large fires (> 404 ha) in this study that burned between 1984 and 2017. Fires were separated by management type (suppression fires $n = 493$; managed fires

$n = 242$) and sampled to analyze spatial patterns of high-severity fire. Green shading represents the distribution of forests and woodlands based on the Ecological Response Unit Framework (Whalberg et al. 2014). (Color figure online)

precipitation of 30.5 cm and New Mexico had a mean annual precipitation of 36.7 cm (NOAA 2019). Mean annual summer temperature ranged from 20.8–27 °C, while mean annual winter temperatures ranged from 0.78–8.4 °C across the region.

The forest and woodland vegetation of Arizona and New Mexico vary widely along climate and elevational gradients (elevation ranges from 448 to 3990 m above sea level). The dominant species at lower elevations include Pinyon pine (*Pinus edulis*) and Juniper spp. (*Juniperus* spp.), ponderosa pine (*Pinus ponderosa*) at mid-elevations, and Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*) at higher elevations. Within the study region, we distinguished forest and woodland vegetation using the Southwest Ecological Response Unit

vegetation framework (ERUs; Whalberg et al. 2014) which groups homogenous vegetation classes based on similar site potential and natural disturbance regimes prior to European settlement (Whalberg et al. 2014). Our study does not include non-forested areas of the region (Fig. 1).

Data

We mapped burn severity for all large fires (> 404 ha) in Arizona and New Mexico from 1984 to 2017 across all ownerships of forested land (Fig. 1). For each fire, we derived Landsat-based severity data (RdNBR; Miller and Thode 2007) by implementing Parks et al. (2018b) novel burn severity mapping methodology within the Google earth engine (GEE) platform. We

obtained fire perimeter shapefile data for Arizona and New Mexico from the Monitoring trends in burn severity (MTBS) project and input these data into Parks et al. (2018b) open-source code within GEE (Eidenshink et al. 2007; Voss et al. 2018). We selected the ‘RdNBR with offset’ calculation and set the scene-stacking date range from April to June (*sensu* Parks et al. 2018b). We chose the RdNBR index over other burn severity indices (e.g., dNBR or RBR) to account for change relative to pre-fire vegetation cover and to facilitate comparisons among multiple fires (Miller and Thode 2007). The offset calculation is applied to RdNBR images to account for potential phenological differences in pre- and post-fire scenes. For each fire, the offset is determined by averaging dNBR values within a 180 m ring outside the fire perimeter and subtracting this value from the dNBR raster (Parks et al. 2018b).

We used the ERU layer to map RdNBR pixels that burned in forest or woodland vegetation types (Whalberg et al. 2014) and retained all fires that burned $\geq 40\%$ of its area within forests and woodlands for analysis. Then, for each fire, we classified continuous RdNBR data into a single binary class representing high-severity by applying a field-validated threshold value. We used regression analysis to model the relationship between 1283 field measurements of burn

severity (composite burn index; CBI) and their corresponding RdNBR values (Fig. 2). From this model, we calculated a high-severity threshold equivalent to a $\text{CBI} \geq 2.25$ ($\text{RdNBR} \geq 687$). Field-measured CBI values ≥ 2.25 represent $\geq 95\%$ basal area mortality (Rivera-Huerta et al. 2016; Lydersen et al. 2016). The CBI plot field measurements were taken in fires that burned in the Grand Canyon National Park, Coconino, and Gila National Forests (Gdula and Brannfors 2014).

Fires were also classified based on management strategy and were categorized as either “suppression fire” or “managed fire”. We define managed fires as prescribed burns, Wildland fire use (WFU), or resource objective fires. We used the MTBS database to classify fires from 1984 to 2008 then used Young et al. (2019) suppression containment model along with Inciweb reports to identify the dominant management strategy from 2009 to 2017 (inciweb.nwcg.gov). MTBS classifications were not used after 2008 due to the release of the Guidance for Implementation of Federal Wildland Fire Management Policy in 2009, which effectively removed the classification of fires as Wildland Fire Use (US DOI/USDA 2009). In cases where we were unable to identify a fire’s dominant management strategy, they were excluded from the study ($n = 83$).

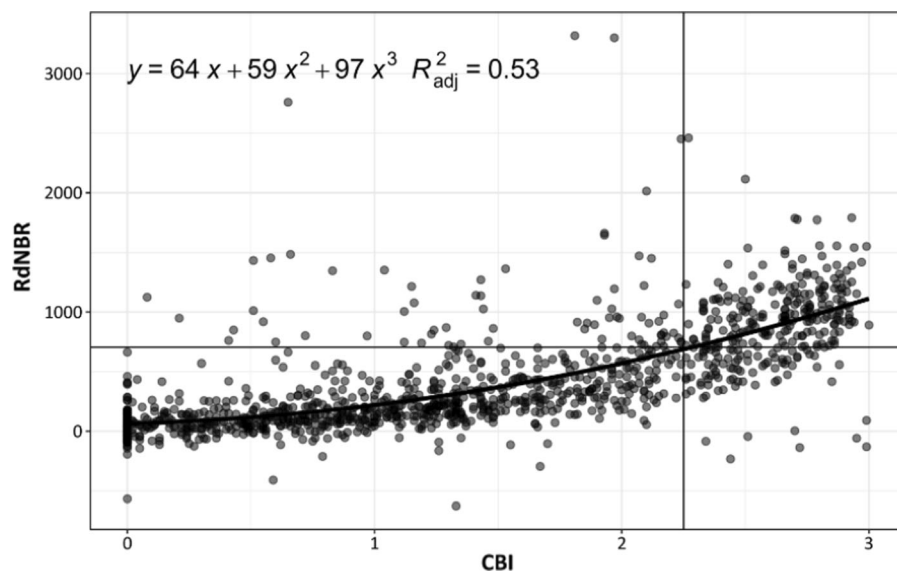


Fig. 2 Quadratic regression model of 1283 field-measured Composite burn index (CBI) plots as a function of the relativized differenced normalized burn ratio (RdNBR). RdNBR images

were derived using Parks et al. (2018b) Google Earth Engine mean composite approach. Crosshairs indicate threshold for high-severity fire ($\text{RdNBR} \geq 687$) equivalent to a $\text{CBI} \geq 2.25$

Metric selection analysis

Spatial pattern metrics (hereafter “metrics” in this section) summarize the cumulative properties of discrete patches of high-severity fire within a single fire perimeter. A number of studies have quantified spatial patterns of burn severity across various regions in the western US and have done so by selecting metrics a priori (Cansler and McKenzie 2014; Harvey et al. 2016; Meddens et al. 2018; Steel et al. 2018). Here, we selected the most relevant metrics more systematically by using Principal component analysis (PCA) and K-means clustering methods to identify metrics that explained the most variation within our dataset (Cushman et al. 2008). First, using FRAGSTATS version 4.2, we calculated relevant metrics on the high-severity class of mapped fires ($n = 867$; McGarigal and Marks 1995; Table S1). In FRAGSTATS, metrics are calculated for individual discrete high-severity burn patches, of which there are usually multiple per fire. To develop a single metric for an entire fire, individual metrics are either averaged or summed depending on the type of metric used. We performed all calculations using the 8-cell-neighborhood rule with a minimum high-severity patch size of 900 square meters (1 pixel; Harvey et al. 2016). Prior to the PCA, we removed fires that had less than one hectare of total high-severity area because it rendered some metrics incalculable or caused them to perform poorly (removed $n = 132$; McGarigal et al. 2000; Cansler and McKenzie 2014). In total, we calculated 44 metrics (Table S1) for 735 fires (of which 493 are suppression fires and 242 are managed fires).

Since all metrics in FRAGSTATS can belong to one of four categories (1) area/edge, (2) shape complexity, (3) aggregation and, (4) core area, our goal was to identify the strongest metric in the PCA and cluster analysis for each of these four categories to more fully quantify high-severity burn patch composition and configuration. We performed the PCA and cluster analyses using the FactoMineR version 2.3 (Le et al. 2008) and factoextra packages version 1.0.6 (Kassambara and Mundt 2019) in R version 4.0.2, respectively (R Core Development Team 2019). We retained seven principal components (PC) based on the latent root criterion (eigenvalues > 1) which were found to explain 88.81% of the variation for high-severity (McGarigal et al. 2000). We calculated the contribution of each metric on PC 1 through 7

(Fig. S1) then performed a cluster analysis of similar metrics on the first two principal components (PCA biplot) using the K-means algorithm (Fig. S1). To determine the optimal number of clusters within our dataset, we used the gap statistic method (Tibshirani et al. 2001). This method resulted in an 11-cluster solution, from which, four metrics were selected (Table 1) based on two criteria: (1) metrics must be from separate clusters (Fig. S2), and (2) must hold the highest contribution (explained the most variability) in principal components 1–7 (Fig. S2) in each of the four aforementioned patch characteristic categories.

Metrics that parsed out the most variability were: (1) area-weighted mean radius of gyration (GYRA-TE_AM), (2) area-weighted mean perimeter area ratio (PARA_AM), (3) Percentage like adjacencies (PLADJ), and (4) Total core area (TCA; Table 1; McGarigal and Marks 1995). In addition to these four metrics identified from the PCA and cluster analysis, we selected two other metrics for evaluation: Class area (CA) and the stand-replacing decay coefficient (SDC; Table 1). CA is a commonly reported ‘basic’ metric that describes the total high-severity area within individual fire perimeters and was selected to draw comparisons to recent burn severity analyses (Dillon et al. 2011; Harvey et al. 2016; Steel et al. 2018). We also included the novel SDC metric because it utilizes an ecological-based approach to quantify the relationship between percent high-severity and the distance to patch edge (Collins et al. 2017; Stevens et al. 2017). The SDC metric is unique in that it encompasses multiple patch characteristic categories including patch size, shape, and core area. In total, we used six metrics to quantify the spatial pattern of high-severity fire in the southwestern US. All metrics used in this analysis are described in Table 1.

Statistical analysis

To address objectives one and two, we investigated differences in spatial pattern of high-severity burn patches as a function of fire management strategy (managed vs suppression fires), fire size, and percent high-severity. To test for significant differences in spatial pattern metrics of high-severity burn patches by management strategy, we used the nonparametric one-way Kruskal–Wallis ANOVA test ($\alpha = 0.05$; Hollander and Wolfe 1973). To test if fire size and percent high-severity were significant predictors of

Table 1 Description and interpretation of spatial pattern metrics applied to high-severity burn patches in 493 suppression fires and 242 managed fires that burned between 1984 and 2017 in Arizona and New Mexico, USA

Patch category	Metric acronym	Description	Meaning of low values	Meaning of high values	Units	Range
Area	CA	<i>Class area:</i> Basic measure of landscape composition equaling the sum of all high-severity patch areas within a fire	Less high-severity area	Greater high-severity area	Hectares	CA > 0, without limit
Reach	GYRATE_AM	<i>Area-weighted mean radius of gyration:</i> Measure of patch reach or extent equaling the mean distance between each cell in the patch and the patch centroid	Smaller and/or more compact patches	Elongated, large, contiguous patches	Meters	GYRATE ≥ 0, without limit
Shape complexity	PARA_AM	<i>Area-weighted perimeter-area ratio:</i> Measure of patch shape representing edge (m ²) to area (m) relationship	Large and/or simple in shape	Small and/or complex in shape	None	PARA > 0, without limit
Aggregation	PLADJ	<i>Percentage of like adjacencies:</i> Measure of spatial distribution. Sum of cells sharing same border (like adjacencies) divided by the total number of cell adjacencies	Dispersed, fragmented patches	Highly aggregated patches	Percent	0 ≤ PLADJ ≤ 100
Core area	TCA	<i>Total core area:</i> Measure of patch interior. Sum of all high-severity areas > 200 m from patch edge within in a fire	Less high-severity area within patch interior	Greater high-severity area within patch interior	Hectares	TCA ≥ 0, without limit
Decay	SDC	<i>Stand-replacing decay coefficient:</i> Measure of high-severity patch size, shape complexity, and core area. SDC is the continuous relationship between remaining patch area in a fire and distance inward from patch edges (Collins et al. 2017)	Faster decay, large, homogenous, contiguous patches	Slower decay, small and/or more complexly shaped, patches	None	0 ≤ SDC 0 ≤ 1

CA, GYRATE_AM, PARA_AM, PLADJ, and TCA were calculated using FRAGSTATS (McGarigal and Marks 1995). GYRATE_AM, PARA_AM, PLADJ, and TCA were selected based on PCA and cluster analysis; CA and SDC were selected a priori

each spatial pattern metric, we used simple linear regression and beta regression models ($\alpha = 0.05$). Specifically, we used ordinary least squares (OLS) models for CA, GYRATE_AM, TCA, PARA_AM, SDC data and beta regression models for PLADJ data since these models are designed to accommodate common issues with rate or proportion data such as

heteroskedasticity and asymmetrical distributions (Cribari-Neto and Zeileis 2010; Schmid et al. 2013).

To assess whether spatial patterns are changing in suppression and managed fires over time, we analyzed average temporal trends for each spatial pattern metric from 1984 to 2017 by fire management type. Although testing for linear changes (i.e., changes in slope of a

linear function) are important in describing general trends over time (Singleton et al. 2019; Mueller et al. 2020), our goal was to identify best-fitting models because they can provide a more nuanced understanding of spatiotemporal trends and potentially provide insight into underlying ecological processes. This is an important distinction because this approach and its corresponding results are not directly comparable to most studies that have assessed temporal trends in burn severity in the western US (Dillon et al. 2011; Picotte et al. 2016; Reilly et al. 2017; Singleton et al. 2019; Mueller et al. 2020; Parks and Abatzoglou 2020).

We performed regression analyses on the mean of each metric by year (*sensu* Stevens et al. 2017) and eliminated years where only one fire occurred. Since time series data tend to be autocorrelated, we tested for serial dependence using the Durbin–Watson test ($\alpha = 0.05$) and by examining patterns in autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs). In cases where data exhibited autocorrelation, we used generalized least squares models (GLS) with either a first-order autoregressive structure or first-order moving average structure (Dillon et al. 2011). When data were not autocorrelated, we used ordinary least squares regression and beta regression models for proportion data. If higher-order terms were included in models, we mean-centered the predictor variable to mitigate collinearity.

Prior to OLS and time-series regression analyses, we natural log (ln) transformed fire size, CA, GYRATE_AM, TCA, PARA_AM, and SDC data and logit transformed percent high-severity to satisfy OLS model assumptions and to stabilize time-varying heteroskedasticity. When modeling SDC data, we removed fires with a null SDC value (total remaining suppression fires $n = 400$ and managed fires $n = 175$) since fires must have at least one cluster of 3×3 high-severity pixels to render a SDC value. We compared all competing models and tested goodness-of-fit using the Akaike information criterion (AIC), and selected models with the lowest AIC value (Burnham and Anderson 2004; Shumway and Stoffer 2010). In OLS models, we tested for significant trends ($\alpha = 0.05$) using the P -value of the slope estimate for linear models and used the overall P -value of the F -test for quadratic models. For beta regression and generalized least square models, we performed likelihood ratio tests and calculated the P -value of the fitted models

against the null model. Ordinary least squares, beta regression, and generalized least squares models were analyzed using the *stats* package version 4.0.2 (R Core Development Team 2019), *betareg* package version 3.1–3 (Cribari-Neto and Zeileis 2010), and the *nlme* package version 3.1–151 (Pinheiro et al. 2021) respectively.

Results

Differences between managed and suppression fires

Area burned severely represented 20% of the burned forested landscape in suppression fires and 5% in managed fires (Table 2). Means for all six spatial metrics in the high-severity class were significantly different between management strategy types ($P < 0.0001$; Fig. 3). Compared to spatial pattern metrics in managed fires, high-severity burn patches in suppression fires had significantly greater high-severity area (CA), larger patch reach (GYRATE_AM), greater high-severity area ≥ 200 m from patch edges (TCA), were simpler in shape (PARA_AM), were more aggregated (PLADJ), and decayed slower (SDC; Fig. 3).

Relationships between basic metrics and spatial pattern metrics

From 1984 to 2017, the 735 large fires observed in this study burned a total of 2,661,819 ha in forests and woodland systems with 17% burning severely (Table 2). Fire size was a significant predictor of all metrics ($P \leq 0.005$; Table 3; Fig. 4) and was most strongly correlated with class area (CA) for both managed and suppression fires ($R^2 = 0.44$ and $R^2 = 0.16$, respectively; Table 3; Fig. 4A). Percent high-severity fire was also a significant predictor of all six spatial pattern metrics and was a stronger predictor than fire size based on higher correlations values ($P < 0.0001$; Table 4; Fig. 5). In general, percent high-severity in suppression models had stronger correlations with spatial pattern metrics compared to managed fire models (Table 4; Fig. 5). Percent high-severity had the highest correlations with patch reach (GYRATE_AM) in suppression fires and class area (CA) in managed fires (Table 4).

Table 2 Summary statistics of spatial pattern metrics of high-severity burn patches calculated within 493 suppression fires and 242 managed fires in Arizona and New Mexico, USA

	Suppression fires	Managed fires	Total
Total burned (ha)	2,111,062	550,757	2,661,819
Total class area (ha)	418,550	25,496	444,046
Total percent of landscape (%)	20	5	17
Median CA (ha)	85 (13, 455)	26 (7, 79)	51 (11, 252)
Median GYRATE_AM (m)	136 (50, 387)	63 (35, 125)	97 (40, 276)
Median PARA_AM	406 (251, 659)	603 (430, 776)	474 (298, 718)
Median TCA (ha)	0 (0, 3)	0 (0, 0)	0 (0, 0.2)
Median PLADJ (%)	70 (51, 81)	53 (35, 66)	64 (46, 78)
Median SDC	0.009 (0.004, 0.016)	0.011 (0, 0.018)	0.01 (0.003, 0.017)

'Total' column represents statistics for both suppression and managed fires ($n = 735$). Values for metrics indicate median (1st, 3rd) quantile

CA high-severity area, GYRATE_AM patch reach, TCA total core area, PARA_AM shape complexity, PLADJ aggregation, SDC patch decay

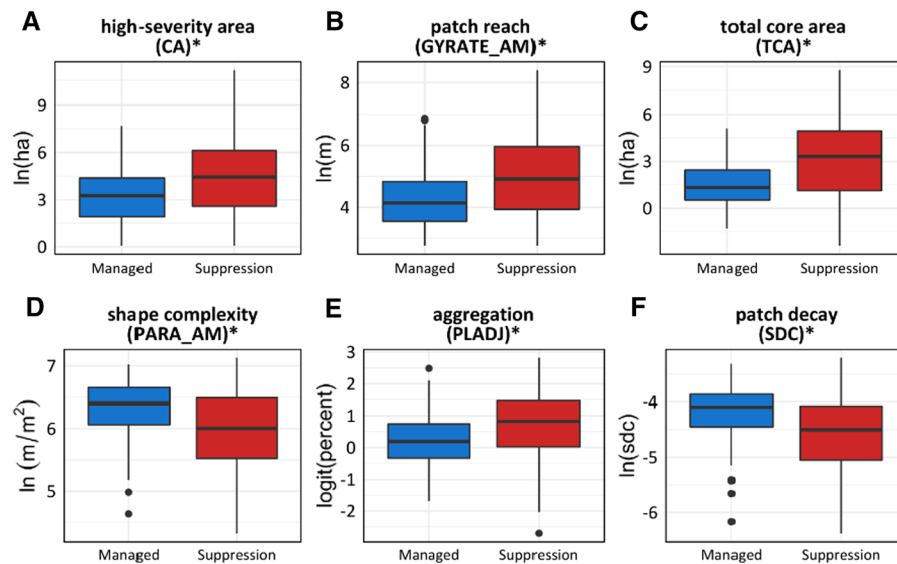


Fig. 3 Boxplots showing spatial pattern metrics of high-severity burn patches as a function of fire management strategy. High-severity burn patches in suppression fires (red) have greater (A) area, (B) extent, (C) total core area, (D) are simpler in shape, (E) have greater aggregation, and (F) decayed slower

than high-severity patches in managed fires (blue). Comparisons were made using non-parametric one-way Kruskal–Wallis ANOVA test. Graphs are in transformed units for interpretability. Asterisk (*) indicates significant differences ($\alpha = 0.05$; $P \leq 0.0001$). (Color figure online)

Trends in spatial patterns from 1984 to 2017

Over the 34-year time span, high-severity burn patch area (CA), reach (GYRATE_AM), total core area (TCA), shape complexity (PARA_AM), aggregation (PLADJ), and patch decay (SDC) showed significant quadratic relationships in suppression fires ($P \leq 0.032$, Table 5; Fig. 6). Spatiotemporal trends in

suppression fires followed a convex and unimodal trajectory, generally peaking between 2000 and 2004 then reversing direction (i.e., patches became smaller, more complexly shaped, less aggregated, and decayed faster) in the past ~ 13 years of the study (Fig. 6 B/D/E/F). In managed fires, class area showed a significant quadratic trend ($P \leq 0.038$) while trends in GYRATE_AM, TCA, PARA_AM, PLADJ, and SDC

Table 3 Results of regression analyses modeling the relationship between spatial patterns of high-severity burn patches as a function of fire size in 493 suppression fires and 242 managed fires across Arizona and New Mexico, USA

Fire size regression						
Model statistics	CA	GYRATE_AM	PARA_AM	TCA	PLADJ	SDC
Suppression fires						
Best model	Linear	Linear	Linear	Quadratic	Beta Reg	Linear
b ₀	– 5.742	0.916	7.604	2.727	– 1.888	– 2.938
b ₁	1.362	0.550	– 0.223	– 1.323	0.000009	– 0.218
b ₂				0.146		
P	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.002	< 0.0001
RMSE	1.709	1.147	0.609	1.674	0.872	0.633
R ²	0.435	0.218	0.139	0.317	0.012	0.132
AIC	1933.24	1540.421	916.672	1915.023	– 1113.83	775.052
Managed fires						
Best model	Linear	Linear	Linear	Quadratic	Beta Reg	Linear
b ₀	– 2.364	2.735	6.967	2.466	– 0.087	– 3.146
b ₁	0.777	0.210	– 0.090	– 0.886	0.00005	– 0.141
b ₂				0.078		
P	< 0.0001	0.001	0.005	< 0.0001	0.004	0.0001
RMSE	1.531	0.871	0.422	0.726	0.999	0.449
R ²	0.161	0.042	0.033	0.128	0.034	0.080
AIC	899.044	625.909	274.671	540.280	– 189.078	222.442

CA high-severity area, GYRATE_AM patch reach, TCA total core area, PARA_AM shape complexity, PLADJ aggregation, SDC patch decay

All models are significant ($P < 0.005$)

Bold typeface values indicate model significance ($\alpha = 0.05$). Table in units of transformed data. ‘Beta Reg’ represent beta regression models. Pseudo-R² reported for beta reg models

were non-significant ($P \geq 0.102$; Table 5, Fig. 6 B/C/D/E).

Discussion

Are spatial pattern metrics different between managed and suppression fires?

All six spatial pattern metrics of stand-replacing fire differed significantly between management strategies in the study area (Arizona and New Mexico). High-severity burn patches in suppression fires had greater area, reach, aggregation, total core area, were simpler in shape, and decayed slower than patches in managed fires. These results are likely a function of burning and weather conditions. Suppression fires generally coincide with extreme weather events which drive fire growth, severity, and subsequently, more

homogeneous spatial patterns (Collins 2014). Comparatively, managed fires are allowed to burn under mild or average weather conditions thereby inhibiting fire spread, intensity, and the potential for large patches (Young et al. 2019). Significant differences between fire management strategies also suggest that spatial patterns of high-severity burn patches in suppression fires are outside the historical range of variability (HRV) for some forest types. Based on tree-ring reconstructions, the largest stand-replacing patch sizes ranged from 200 to 1000 ha in southwestern mixed conifer-aspen and spruce-fir forests (Margolis et al. 2011; O’Conner et al. 2014) and were typically less than 1 ha (Pearson 1923) but up to 60 ha in ponderosa pine forests (Iniguez et al. 2009). Based on our results, the median and maximum area-weighted mean patch sizes in managed fires was within the HRV for both mixed conifer-aspen and spruce-fir and dry conifer forests (i.e., 2.3 ha and

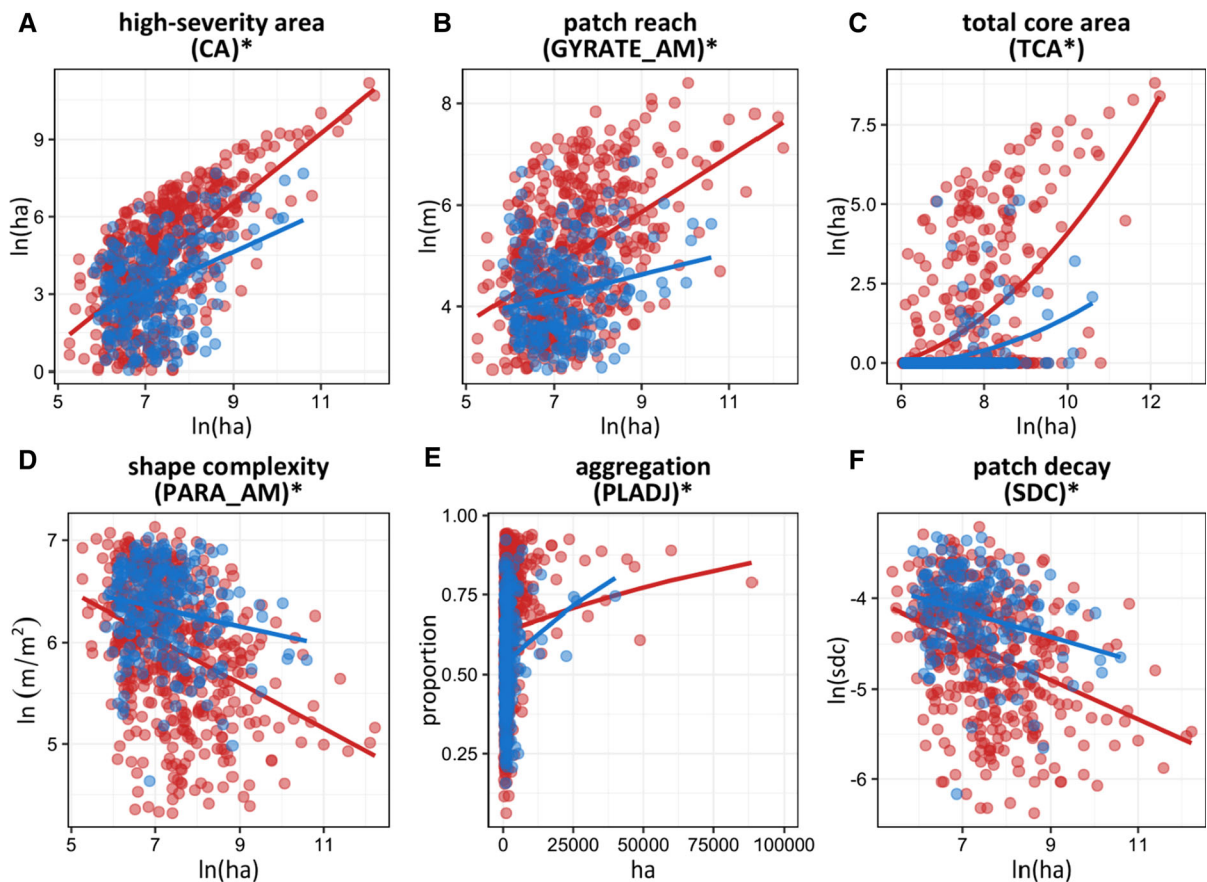


Fig. 4 Relationship between fire size (burned area) and high-severity spatial pattern metrics stratified by suppression fires (red) and managed fires (blue). As fire size increased, (A) area burned severely increased, (B) patch extent increased, (C) total

core area increased, (D) patch complexity decreased, (E) aggregation increased, and (F) decayed slower in both fire types. Asterisk (*) indicates significant relationship ($P \leq 0.005$) for both managed and suppression fires. (Color figure online)

581 ha respectively). Within suppression fires, the median area-weighted mean patch size (10 ha) was close to historical ranges in dry forest types, but the maximum patch size (7561 ha) was seven times larger than the HRV for upper elevation forests and at least 126 times larger than the HRV for dry forests. Due to inherent difficulties of reconstructing incomplete extant data, it is unclear whether other spatial metrics such as patch aggregation or shape are outside HRV. However, it is evident that contemporary fires under a suppression management strategy have resulted in significant departures from historical spatial patterns of high-severity fires, particularly related to patch size in dry conifer systems. This finding is concerning given that dry coniferous forests are not adapted to large and severe fire, and these vast and contiguous severely burned patches could potentially be at risk for

fire-facilitated vegetation conversion (Coop et al. 2020).

While spatial patterns appear to be changing in suppression fires, high-severity patch sizes in managed fires are closer to historical ranges and thus, are better aligned to function as they did historically. Although high-severity fire can adversely impact degraded conifer stands, the heterogeneity of severity classes within reintroduced fires is an important component towards increasing forest resilience. Managed fire that incorporates fine-grained patches of high-severity, along with a mosaic of unchanged, low, and moderate severity classes creates wildlife habitat diversity, promotes post-fire regeneration, and moves forests towards a more resilient state (Roberts et al. 2015; Huffman et al. 2017; Collins et al. 2018). In particular, moderate severity is effective in meeting

Table 4 Results of regression analyses modeling the relationship between spatial patterns of high-severity burn patches as a function of percent high-severity in 493 suppression and 242 managed fires across Arizona and New Mexico, USA

Percent high-severity regression						
Model statistics	CA	GYRATE_AM	PARA_AM	TCA	PLADJ	SDC
Suppression fires						
Best model	Linear	Quadratic	Quadratic	Quadratic	Beta Reg	Quadratic
b_0	7.338	7.041	4.897	4.275	0.342	– 5.563
b_1	1.032	0.923	– 0.513	1.965	0.045	– 0.609
b_2		0.051	– 0.035	0.208		– 0.054
P	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
RMSE	1.082	0.522	0.299	1.325	1.016	0.391
R^2	0.773	0.838	0.792	0.572	0.656	0.669
AIC	1483.100	766.119	218.428	1684.910	– 700.203	391.56
Managed fires						
Best model	Linear	Quadratic	Quadratic	Quadratic	Beta Reg	Quadratic
b_0	6.729	6.727	5.524	4.275	0.264	– 5.207
b_1	0.889	0.882	– 0.392	0.898	0.056	– 0.487
b_2		0.055	– 0.026	0.088		– 0.045
P	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
RMSE	0.860	0.498	0.294	0.659	1.004	0.387
R^2	0.735	0.686	0.528	0.287	0.394	0.318
AIC	619.928	357.678	103.019	493.597	– 297.127	172.121

CA high-severity area, GYRATE_AM patch reach, TCA total core area, PARA_AM shape complexity, PLADJ aggregation, SDC patch decay

All models are significant ($P < 0.0001$)

Bold typeface values indicate significance ($\alpha = 0.05$). ‘Beta Reg’ represent beta regression models. Adjusted R^2 was reported for OLS quadratic models and pseudo- R^2 was reported for beta regression models. P -value obtained from F -test in OLS models or from likelihood ratio test in beta regression models ($\alpha = 0.05$)

structural and hazardous fuel restoration targets in ponderosa pine stands (Huffman et al. 2017) and is important for decreasing risk of future crown fire and restoring natural fire regimes (Collins et al. 2018; Hunter et al. 2011). Managed fires that burn more actively are likely to have a more complex burn mosaic and high-severity fire effects are often a necessary trade-off in order to increase the representation of moderate effects on the landscape. Thus, current high-severity patch sizes in dry forests could be ecologically beneficial in order to achieve a matrix of severity classes.

Are spatial pattern metrics related to fire size and percent high-severity?

Our results showed that all six spatial pattern metrics were significantly related to fire size and percent

burned severely for both suppressed and managed fires. As fire size and percent high-severity fire increased, spatial patterns of high-severity burn patches were more contiguous, aggregated, simpler in shape, and decayed faster regardless of management strategy. Our results are consistent with relationships found between fire size and spatial pattern metrics of high-severity fire in the northern Cascade Range, northern Rocky Mountains, and California conifer forests (Cansler and McKenzie 2014; Harvey et al. 2016; Stevens et al. 2017). The consistency in results across the western US suggests that as fires become larger, they will generate more homogenous high-severity patch characteristics, regardless of region and other potential driving factors such as climate or topography.

Compared to the linear relationships with fire size, spatial pattern metrics generally exhibited strong,

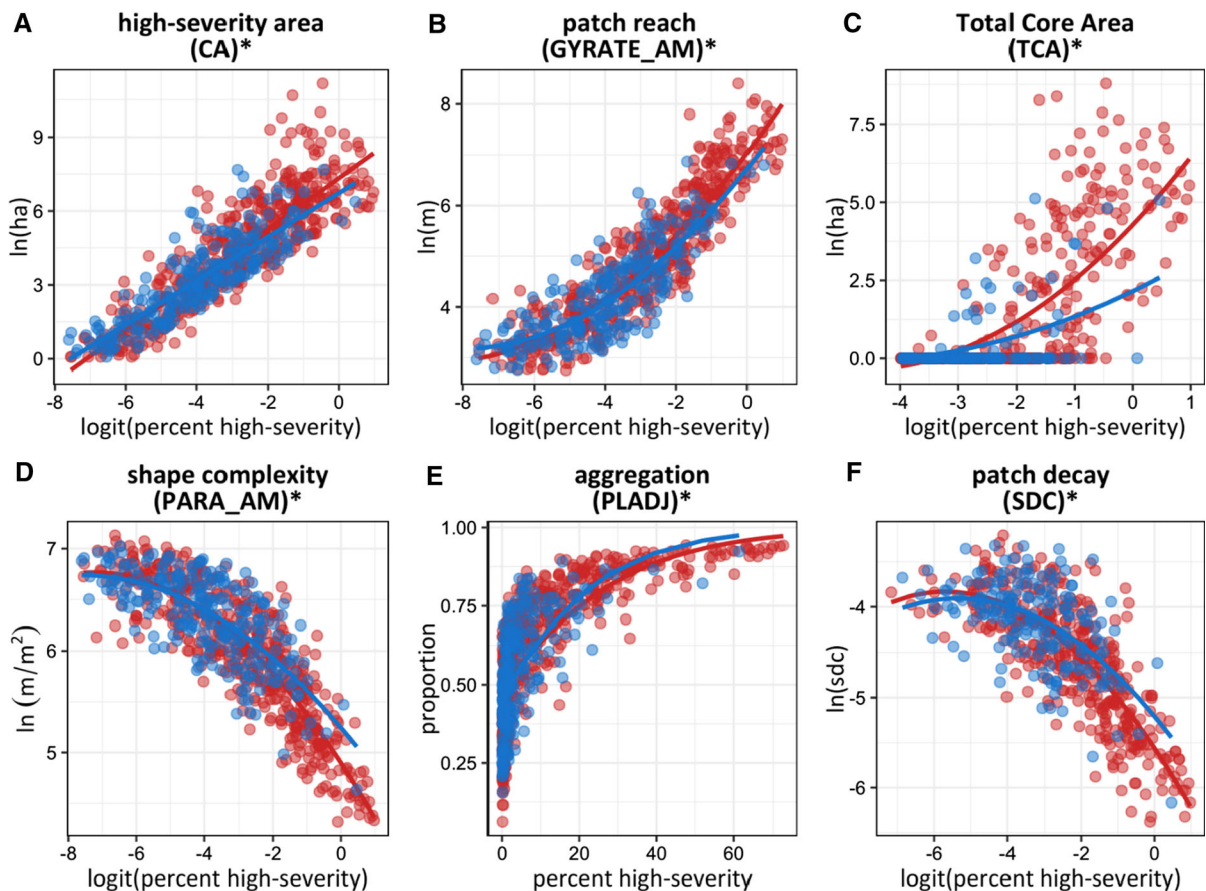


Fig. 5 Relationship between percent high-severity fire and spatial pattern metrics of high-severity burn patches stratified by suppression fires (red) and managed fires (blue). As the percent of high-severity fire increased, the spatial pattern of burn patches showed: (A) greater area, (B) greater extent, (C) greater

core area, (D) simpler shapes, (E) greater aggregation, and (F) slower decay in both fire types. Asterisk (*) indicates significant relationship ($P \leq 0.0001$) for both managed and suppression fires. For untransformed data, see Fig. S3. (Color figure online)

quadratic relationships with percent high-severity fire. These nonlinear responses were expected based on previous work showing the relationship between landscape processes and observed patterns (Gardner et al. 1987; Turner et al. 1989). As demonstrated in neutral landscape models, the connectivity of patches changes as a function of the proportion of a given class: As proportion increases, a network of clustering patches will develop and undergo a phase transition (i.e., nonlinear response) to a single spanning cluster once a critical threshold is reached (Gardner et al. 1987; Gustafson and Parker 1992; Villard et al. 2014; Harvey et al. 2016). In our analysis, patch shape (PARA_AM), aggregation (PLADJ), and decay (SDC) exhibited nonlinear behavior with increases in percent high-severity, suggesting that numerous

smaller patches eventually coalesced into fewer but larger homogenous patches after reaching a critical threshold (Fig. S3; Gustafson and Parker 1992). Similarly, a study in the Northern Rocky Mountains documented sharp increases in patch size and core area when percent high-severity exceeded a threshold of 35% (Harvey et al. 2016). Although quantifying critical thresholds was beyond the scope of this study, identifying these values for burn severity patterns in the Southwest have important implication for management where percent of high-severity fire might serve as an effective metric to better predict stand-replacing effects or trigger alternative suppression or management actions. More research is needed in assessing critical threshold values for spatial patterns of high-severity fire; however, current research offers

Table 5 Regression statistics of time series models. Models were used to analyze mean annual trends in high-severity spatial pattern in suppression and managed fires from 1984 to 2017 across Arizona and New Mexico, USA

Temporal trends						
Model statistics	CA	GYRATE_AM	PARA_AM	TCA	PLADJ	SDC
Suppression fires						
Best model	Quadratic (0, 1) [†]	Quadratic (0, 1) [†]	Quadratic (1, 0) [†]	Quadratic (0, 1) [†]	Quadratic (1, 0) [†]	Quadratic (0, 1) [†]
b ₀	6.355	5.990	5.946	3.827	0.909	− 4.567
b ₁	0.071	0.024	− 0.003	0.082	0.005	− 0.005
b ₂	− 0.007	− 0.005	0.002	− 0.010	− 0.003	0.002
P	0.001	0.003	0.016	0.008	0.004	0.032
RMSE	1.021	0.571	0.183	1.589	0.273	0.248
AIC	101.885	64.851	− 12.262	130.273	14.379	8.853
Managed fires						
Best model	Quadratic	Quadratic	Linear	Linear	Linear	Linear
b ₀	4.641	4.817	− 3.158	− 40.226	19.768	2.337
b ₁	0.041	0.005	0.005	0.020	− 0.009	− 0.003
b ₂	− 0.014	− 0.006				
P	0.038	0.102	0.374	0.509	0.295	0.699
RMSE	0.795	0.360	0.148	0.856	1.056	0.201
AIC	57.945	24.643	− 14.712	59.048	− 47.812	− 1.094

CA high-severity area, GYRATE_AM patch reach, TCA total core area, PARA_AM shape complexity, PLADJ aggregation, SDC patch decay

Bold typeface values indicate model significance ($\alpha = 0.05$). Table in units of transformed data

P-value obtained from F-test in OLS models or from likelihood ratio test in GLS models

[†]Generalized least squares (GLS) regression models with first-order autoregressive (1, 0) or moving average (0, 1) structure

insight into predicting patterns of high-severity fire based on climate data. Mueller et al. (2020) have modeled the relationship between average maximum monthly vapor pressure deficit (VPD) and the probability of surpassing a certain percent high-severity fire threshold in the Southwest. Thus, for a given VPD value, it is possible to estimate the probability of percent high-severity fire and high-severity patch characteristics using Mueller et al. (2020) model predictions and graphs generated in this study (Fig. 5 and Fig. S1).

Trends in spatial pattern metrics from 1984 to 2017

Temporal trends in spatial patterns of high-severity fire varied by management strategy—all six spatial pattern metrics in suppression fires fluctuated similarly over time while managed fires showed inconsistent trends among metrics. Spatiotemporal trends in suppression fires were characterized by an increase in

homogenous patterns of high-severity burn patches until 2004, then subsequently reversed. Thus, high-severity patches within suppression fires appear to be moving toward a higher degree of heterogeneity within the last ~ 13 years of the study, and particularly in the last ~ 3 –4 years. This was surprising given known trends of increasing fire size and percent burned severely in the Southwest (Singleton et al. 2019) as well as the relationship between these metrics and selected spatial pattern metrics. As previously described, differences between Singleton et al. (2019) and this study are likely due to differences in methods and objectives, but also likely due to sampling scale and size. For example, Singleton et al. (2019) sampled high-severity fire at a smaller scale (30m pixels), in a greater number of fires ($n = 1621$), over a shorter time period (32 years), and did not stratify fires by management type. Furthermore, temporal trends presented in Singleton et al. (2019) represent total annual area and percent burned severely at the pixel-level while

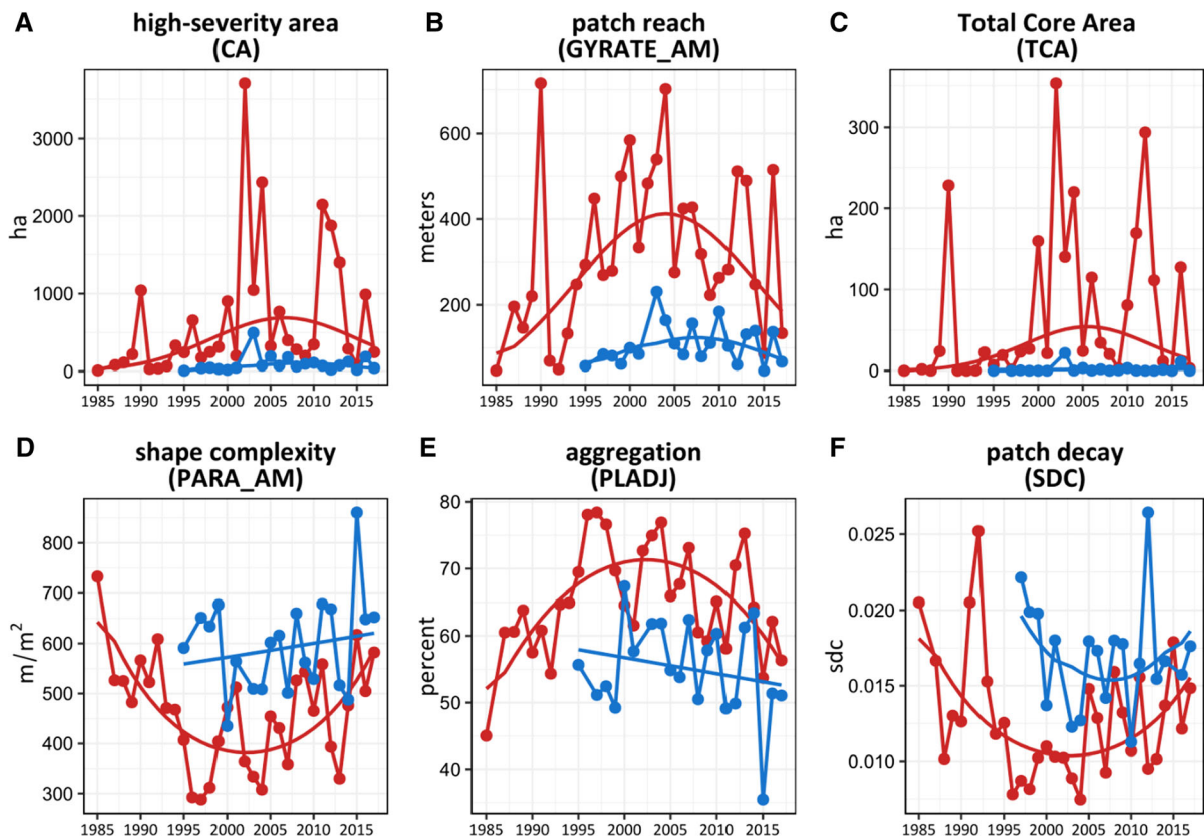


Fig. 6 Mean annual temporal trends in high-severity spatial pattern metrics from 1984 to 2017 by suppression fires (red) and managed fires (blue). Solid lines represent fitted trend lines that were back-transformed to each metric's corresponding native

units. All spatial pattern metrics (A–F) showed significant quadratic relationships in suppression fires ($P \leq 0.032$). Only class area (A) showed significant quadratic trends ($P = 0.038$) in managed fires. (Color figure online)

results in this study reflect average patch characteristics within individual fires (since metrics are averaged over all discrete patches with fire perimeters) and by year. In this study, each fire was considered and assessed as a distinct landscape while Singleton et al. (2019) assessed burned pixels across a single landscape (Arizona and New Mexico). Temporal trends were also sensitive to the number of fires per year and the range of spatial pattern metrics. Thus, because the number of fires in the Southwest has increased since the early 2000s (Mueller et al. 2020), and because we assessed mean statistics of temporal trends, the influence of large fires with the greatest high-severity area (e.g., 2011 and 2012) was dampened (Fig. 6). This effect is particularly true for metrics (i.e., SDC and PLADJ) whose range in values is more bounded than the range in values of high-severity area (Table 1). Finally, Singleton et al. (2019) explicitly tested for linear increases over time (i.e., changes in slope),

while this study applied the best-fitting model which may or may not have been linear.

To better understand the relationship between fire size, severity and spatiotemporal trends of high-severity fire within the context of this study, we analyzed average annual fire size and percent burned severely from 1984 to 2017 based on data and methods presented here (Fig. S4). From this exploratory analysis, fire size showed a significant linear increase over time in suppression fires ($P = 0.024$) but not in managed fires ($P = 0.192$; Fig. S4; Table S2). Thus, it appears that the relationship between fire size and spatial pattern metrics are independent of their respective average temporal trends (i.e., although fire growth is linked to more homogenous high-severity spatial patterns and fire size has increased over time, these results are not linked to more homogenous patterns of high-severity fire over time). Conversely, temporal trends in percent high-severity fire (Fig S4)

were generally reflective of trends among spatial metrics in suppression fires (i.e., relationships and trends in percent high-severity fire corresponded with temporal trends among selected metrics). Overall, these results indicate that larger percentages of high-severity fire are linked to more homogenous patterns across space and time. These results, along with stronger correlations with spatial pattern metrics compared to fire size (Table 4), also suggest that percent high-severity fire is potentially the primary driver of landscape patterns of high-severity burn patches. This finding is consistent with strong correlations found between proportion high-severity and spatial patterns of high-severity patches in the northern Rocky Mountain region (Harvey et al. 2016) as well as non-empirical studies linking increasing landcover proportion to changes in indices of spatial patterns in neutral landscape models (Turner et al. 1989; Gustafson and Parker 1992; Hargis et al. 1998). Ultimately, we can expect to see larger, more homogenous patches with increasing fire size and percent high-severity, but mean annual spatiotemporal trends are more strongly influenced by percent high-severity.

As emphasized above, our results represent average stand-replacing patch configurations across Arizona and New Mexico. Our goal was to assess, and document mean spatiotemporal patch characteristics, but our results minimize the impact of large fire events and/or fire years. Recent widespread fire years in the Southwest or outlier fire events such as the 2006 Warm Fire that produced the largest contiguous high-severity patch in our dataset (7561 ha), may outweigh the ecological impacts across landscapes compared to average conditions. A recent study found that under extreme climate conditions, outlier years (i.e., widespread fire years) accounted for the majority of high-severity area burned in dry conifer forests simulated in the Jemez Mountains (Loehman et al. 2018). Therefore, to better assess wildfire's impact on landscapes and to manage for long-term forest resilience, it may be become increasingly important to focus on extreme high-severity spatial patterns.

The importance of extreme weather and climate controls (Bessie and Johnson 1995; Westerling et al. 2006) on spatial patterns of high-severity burn patches is also evident in trend results. These influences were apparent in years 2000–2004 where trends in most spatial metrics in suppression fire

peaked, indicating a period in which average high-severity spatial patterns were most extreme. Given the synchronicity of trends among metrics and recent literature linking climate variables to high-severity fire in the Southwest (Mueller et al. 2020; Parks and Abatzoglou 2020), we speculate that extremes in spatial pattern metrics may be partially attributable to climate and weather patterns. For example, increases in daily maximum high temperatures were associated with larger, simpler shaped stand-replacing patches in California (Stevens et al. 2017) and increases in moisture deficit were associated with larger patch sizes, larger core areas, and simpler shaped high-severity patches in the northern Rocky Mountains (Harvey et al. 2016). These studies suggest that climate may strongly control spatial patterns of high-severity fire, however; spatiotemporal trends in suppression fires are likely the result of multiple interacting factors and further work is necessary to identify primary drivers and their relative importance (e.g. Parks et al. 2018a, b).

Given that managed fires are allowed to burn under mostly milder weather conditions, extreme weather or shifts in climate patterns likely played a lesser role in influencing spatiotemporal trends in managed fires. Unlike suppression fires, trends in spatial pattern metrics in managed fires did not consistently change over the study period. Rather, contemporary trends in managed fires were characterized by lower annual means (or higher means for PARA_AM and SDC) and highly variable linear or quadratic trends among metrics. These results demonstrate that high-severity burn patches are more heterogenous and fine-grained than suppression fires, are more stable over time, and that different controls such as topography and fuels are potentially driving spatial patterns in managed fires.

Study limitations and future work

In our study, we used remotely sensed continuous data to classify burn severity into discrete categorical data. We calculated a single threshold value based on the relationship of RdNBR to CBI data in order to classify high-severity fire for the Southwest. Therefore, spatial patterns of high-severity would change if different field data or threshold values were used. We also recognize that the RdNBR and CBI data are generally linked to changes in canopy cover and are useful when inferring fire effects but are not direct measures of

specific ecological effects of severity (Morgan et al. 2014). However, CBI resulted in higher classification accuracies than percent change in canopy cover or basal area, and is correlated with basal area mortality in conifer systems in the West (Miller and Thode 2007; Miller et al. 2009; Cansler et al. 2012; Lyderson et al. 2016). Additionally, it was our goal to make coarse assessments of high-severity patches across the Southwest and our methods to classify burn severity adequately approximate stand-replacing effects at this scale. We further classified stand-replacing effects into discrete patches within fires, which is the traditional approach when assessing landscape pattern-process relationships. However, other studies have characterized ecological attributes by using continuous, multi-dimensional surface models in order to better capture spatial heterogeneity of landscapes (McGarigal et al. 2009; Cushman et al. 2010). Although many current surface metrics do not yet have clear relationships with ecological processes, future work could identify links to fire severity and incorporate gradient models to quantify burn severity patterns.

Finally, we offer spatial analysis in the high-severity class but acknowledge that it is important to document other severity classes (i.e., low and moderate) which are important for ecological resilience and function (Hunter et al. 2011; Huffman et al. 2017). For example, moderate severity fire can significantly reduce ladder and surface fuels and can create gaps in the canopy that are critical for shade-intolerant species regeneration (Collins et al. 2018). Fire is a disturbance process that affects the landscape in dynamic ways and documenting spatial patterns in all severity classes is important in capturing a more complete understanding of current fire regimes. Continuing to quantify burn severity spatial metrics will remain important in understanding fire-regime ecosystem interactions and transitions.

Conclusions

This is the first comprehensive study to quantify high-severity burn pattern, trends, and response to fire management practices in the Southwest and our results illustrate the degree to which management strategy has affected the burned landscape across space and time. We demonstrate that spatial pattern of high-severity burn patches in suppression and managed fires have

significantly diverged, with stand-replacing patch sizes in managed fires aligning more closely to historical ranges. We also show that fire size and percent high-severity fire are correlated with high-severity patch area, reach, total core area, shape complexity, aggregation, and decay regardless of management strategy. These findings are important because future climate change is predicted to increase fire activity across the Southwest, so the spatial structure of high-severity patches will likely shift with anticipated changes in fire size and severity.

Lastly, spatial patterns in managed fires appeared more stable over time while suppression fires showed synchronous unimodal quadratic trends. Notably, at the fire-level, we show that mean annual percent high-severity in suppression fires has decreased in the last ~13 years of the study, matching temporal trends in all six spatial pattern metrics. These results indicate that percent high-severity fire potentially controls patterns of severely burned patches both spatially and temporally. Importantly, suppression fires showed a consistent linear increase in all spatial metrics from the 1980s to the early 2000s but have subsequently trended toward smaller, more complex, fragmented patches and it remains unclear whether these downward trends will continue, or the extent to which these trends are driven by increases in numbers of fires. Despite uncertainties in future trends, contemporary large patches of stand-replacing fire have compounding effects through time and space and repeated burning could potentially drive abrupt vegetation transitions and subsequent fire patterns (Savage and Mast 2005; Coop et al. 2020). Given projected increases in temperatures and wildfire activity, future work focusing on drivers of extreme high-severity burn patches will have critical implications in mitigating potentially undesirable patch characteristics in future fires.

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Author contributions MS and AT conceived of the study. MS performed the formal analysis, curated data, and wrote the original draft. AJSM and JTS assisted with the methodology and validation of the analysis. JI acquired funding for the project and reviewed the draft. All authors contributed to writing and editing and all authors reviewed and approved the final manuscript.

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