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Evidence for strong bottom-up controls on fire severity during extreme events

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Abstract

Background Record fire years in recent decades have challenged post-fire forest recovery in the western United States and beyond. To improve management responses, it is critical that we understand the conditions under which management can mitigate severe wildfire impacts, and when it cannot. Here, we evaluated the influence of top-down and bottom-up fire severity forcings on 17 wildfires occurring during two consecutive record-setting years in the eastern Cascade Mountains of Washington State. Despite much of the area having been burned after an extended period of fire exclusion, nearly one-third of the forested area burned at low severity.

Results Using random forest modeling and Shapley local importance measures, we found that weather and fuels were both dominant drivers of fire severity, and past fuel treatments were successful at reducing severity—even during extreme fire progression days. First-entry fires were more typically driven by top-down climate and weather variables, while for reburns (i.e., overlapping fire footprints within the period of record), severity was largely mitigated by reduced fuels and a positive influence of topography (e.g., burning downslope). Likewise, reburns overall exhibited lower fire severity than first entry fires, suggesting strong negative feedbacks associated with past fire footprints. The normalized difference moisture index (NDMI)—an indicator of live fuel loading and moisture levels—was a leading predictor of fire severity for both first-entry fires and reburns. NDMI values < 0 (i.e., low biomass) were associated with reduced fire severity, while values > 0.25 (i.e., high biomass) were associated with increased severity. Forest management was effective across a variety of conditions, especially under low to moderate wind speeds (< 17 m·s^{-1}), and where canopy base heights were ≥ 1.3 m.

Conclusions Our findings support previous work demonstrating strong top-down weather and climate controls on fire severity along with bottom-up spatial controls of fuels and topography on patterns of fire severity. Local importance measures refined our understanding of the conditions under which bottom-up factors successfully mitigated fire severity. Our results indicate a clear role for fuels and fire management—including wildland fire use—to restore characteristic composition and structure to the landscape and to moderate fire severity.

Keywords Wildfire severity, Fire weather, Reburn, Fuel reduction treatment, Machine learning, Shapley local importance

Resumen

Antecedentes Los registros con records de años con incendios en décadas recientes en EEUU, han desafiado la recuperación de los bosques en el oeste de los EEUU y también en otros lugares. Para mejorar las respuestas de

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manejo, es crítico que entendamos las condiciones en las cuales el manejo puede mitigar los impactos de fuegos severos y cuando no. Evaluamos en este trabajo la influencia de las estrategias de información (*bottom up* y *top down*) como forzantes de la severidad del fuego en 17 incendios ocurridos en dos temporadas sucesivas en la región de las Montañas Cascadas en el estado de Oregon. A pesar de que la mayor parte del área fue quemada luego de un largo período de exclusión del fuego, en casi un tercio del área quemada, el fuego quemó a baja severidad.

Resultados Usando el Modelado de Bosques al Azar (*Random Forest Modeling*) y medidas de Shapley de importancia local, encontramos que el tiempo meteorológico y los combustibles fueron las dos fuerzas conductoras dominantes de la severidad del fuego, y que los tratamientos de combustibles realizados en el pasado fueron exitosos en la reducción de la severidad – aún en días de progresión de comportamiento extremo del fuego -. Las primeras entradas del fuego fueron conducidas por variables climáticas y meteorológicas del tipo *top-down,* mientras que para las quemas recurrentes (i.e. el solapado de incendios en el período de registro), la severidad fue largamente mitigada por la reducción del combustible y la influencia positiva de la topografía (la quema cuesta abajo). De la misma manera, las quemas recurrentes exhibieron en general una severidad más baja que los fuegos que ocurrieron por vez primera, sugiriendo una fuerte retroalimentación negativa asociada con las huellas de fuegos anteriores. Los valores del Índice de Diferencia de Humedad Normalizada (NDMI), -un indicador de la carga de combustible vivo y niveles de humedad- fue un predictor primordial de la severidad del fuego tanto para los incendios primigenios como las requemas. Los valores de NDMI <0 (i.e., baja biomasa) estuvieron asociados a una baja severidad del fuego, mientras que valores >0.25 (i.e., alta biomasa) estuvieron asociados a una alta severidad. El manejo forestal fue efectivo a través de una variedad de condiciones, en especial bajo vientos suaves a moderados (<17 m·s-1), y cuando la base del dosel estuvo a ≥1.3 m.

Conclusiones Nuestros resultados confirman trabajos previos que demuestran que las variables climáticas y meteorológicas (*top down*) ejercen un control sobre la severidad del fuego junto con las variables espaciales de control (*bottom up*) como son los combustibles y la topografía, en los patrones de severidad. La importancia de las medidas locales refinan nuestro entendimiento sobre las condiciones bajo las cuales los factores *bottom up* pueden mitigar exitosamente la severidad del fuego. Nuestros resultados indican un rol muy claro de los combustibles y el manejo del fuego –incluyendo el uso del fuego – para restaurar la composición y estructuras características de los paisajes y moderar la severidad de los incendios.

Introduction

Recent studies throughout interior western North America (wNA) have documented rising incidence, severity, and size of wildfires. Increased fire activity is strongly associated with longer and more severe wildfire seasons (Westerling et al. 2016, Abatzoglou and Williams 2016; Parks and Abatzoglou 2020). Across much of wNA, regional studies consistently find a strong positive relationship between forest fire severity, climatic water deficit (CWD), and extreme fire weather (Cansler and McKenzie 2014; Parks and Abatzoglou 2020; Ellis et al. 2022). Research suggests that these factors will likely continue to be dominant drivers of wildfire regimes in the region, as modeled estimates of annual area burned and area burned at high severity are projected to increase through mid- to late-century (*cf.* Abatzoglou and Williams 2016, Taylor et al. 2016, Roos et al. 2022, Swetnam et al 2016, Turco et al. 2023).

Future projections of wildfire spread and severity often assume that bottom-up spatial controls provided by local patterns of topography, soils, and fuels will have minimal influence on wildfire patterns in the future (Abatzoglou et al. 2021; McKenzie and Littell 2017; Stavros et al. 2014). However, some theoretical models of large system-level dynamics, such as self-organized criticality (Malamud and Turcotte 1999; Malamud et al. 2005) and highly optimized tolerance (Moritz et al. 2005) suggest these feedbacks are universal properties of complex systems and provide a mechanism by which resilience in frequently disturbed systems can be imparted. In natural systems, bottom-up factors provided by changes in vegetation and fuel patterns, variation in topo-edaphic conditions and landscape context, and past disturbances have shown the capacity to reduce fire spread and severity across environments (Povak et al. 2018, 2020a; Stevens-Rumann et al. 2016; Prichard et al. 2020). Internal feedbacks stemming from ongoing disturbances and their shifting spatial patterns imprint lagged ecological memories (sensu Peterson 2002) onto systems that can influence subsequent fire behavior for periods ranging from 5 to 30 years (Povak et al 2023; Parks et al. 2015; Davis et al. 2024). As such, these studies indicate that internal system controls are a dominant regulating feature, providing constraints on top-down climate controls, and imparting resilience on fire-prone systems.

Still other studies from wildfire and landscape ecology literature emphasize that spatial patterns within and among wildfire events are driven by the interactions between both large-scale contributing (top-down) and local-scale constraining (bottom-up) factors (Parks et al. 2012, 2014a; Cansler et al. 2022; Harris and Taylor 2017; Margolis et al. 2025). The strength of these bottom-up controls varies depending on the type, number, and arrangement of local controls, as well as the broad-scale environmental conditions within which the system is situated (Moritz et al. 2011). Across broad landscapes these interactions determine the capacity for a system to self-regulate and maintain conditions over space and time (Moritz et al. 2011; Parks et al. 2015, 2016). For example, as wildfires burn more area within wNA forested landscapes, the ecological memory associated with past fires, whether in dry, moist, or cold forests, will have an increasing impact on the extent and severity of future fires (Peterson 2002; Parks et al. 2014a; Johnstone et al. 2016). The additive role of bottom-up factors provided by patterns in topography (Povak et al. 2018), vegetation composition and structure provide further spatial and temporal controls on burned area and fire severity (Birch et al. 2015; Hessburg et al. 2015, 2019; Parisien et al. 2011; Parks et al. 2012). Combined, local controls on fire spread and severity can build over space and time to affect landscape resilience properties at larger scales (Wu and Loucks 1995).

Knowledge of effective bottom-up spatial controls on fire severity can help inform best forest and fuel management practices. In dry pine and mixed-conifer forests, pre-fire fuel reduction thinning and/or prescribed burning treatments are designed to mitigate future fire behavior through surface and ladder fuel reduction (Agee and Skinner 2005; McIver et al. 2012; Brodie et al. 2024). However, questions remain as to whether these treatments are effective when confronted with increasingly extreme fire weather (Urza et al. 2023). Knowledge of the conditions where treatments or past wildfires can mitigate future fire severity can inform expectations of treatments to provide positive ecological and social benefits.

Empirical modeling of fire severity patterns and their bottom-up drivers

Machine learning has been used in recent years to evaluate drivers of fire spread and severity (Kane et al. 2015; Zald and Dunn 2018; Povak et al. 2020a). Models are often trained on individual large fires, and measures of global variable importance, and modeled response functions are reported. Such models generally capture influences of broad climatic gradients, variability in forest types and fuel conditions, and other top-down influences as they contribute the greatest reductions in model error. However, fine- to meso-scale bottom-up factors are often overlooked as their contribution to reducing model error can be minimal. Hence, these contributions are generally minimized because fire-treatment interactions occur over a small area and often within fire-excluded landscapes (Prichard et al. 2020), and their influence on severity varies over the period of a fire (Povak et al. 2018, 2020a).

More recently, methods that employ machine learning offer expanded insight into driving variables that can best explain the fire severity response and corresponding variable importance. For example, machine learning can reveal the spatial variability of the dominant drivers of fire severity and how specific fire environments can influence burn severity outcomes using post hoc analysis tools such as local variable importance measures—collectively referred to as explainable AI techniques (Prichard et al. 2020; Povak et al. 2020a). This is particularly relevant for evaluating fuel reduction and time-since-treatment influences where treatment area is a minor feature of burned landscapes (Kolden et al. 2019). Thus, application of these methods can aid in quantifying the relative importance of top-down and bottom-up drivers to fire severity and provide insight as to the conditions under which bottom-up factors play a significant role in mitigating fire severity.

Study objectives

The Inland Pacific Northwest has experienced many large, regional wildfire events in recent decades (Westerling et al. 2016). North-central Washington alone has been transformed by large wildfire events with >40% of the region burning in the last 20 years (Cova et al. 2022). Prior to the record-setting 2014 and 2015 wildfire seasons, forests that historically received frequent, often restorative fires, were mostly left unburned for nearly a century or longer (Hessburg and Agee 2003; Hessburg et al. 2005). As fires return to the region, some are reburning in areas for a second or third time, allowing for evaluations of fire-fire interactions and their role in landscape dynamics. For example, in a recent study, Cansler et al. (2022) evaluated trends in fire severity within reburns from 2001 to 2019 and random forest (RF) modeling and found compelling evidence that fire severity was lower in reburned areas than in first-entry fires. However, reburns within post-fire logging and planting units showed slightly higher severity when surface fuels were left untreated by prescribed burning.

In the present work, we describe the characteristics of the 2014–2015 regional fire years within north-central Washington in terms of wildfire size, severity, and spatial patterns. We then used RF modeling to evaluate the main drivers of fire severity patterns and their variability across broad- and meso- spatial and temporal scales. We used Shapley local importance methods to evaluate how the strength of top-down drivers in a predictive modeling framework can mask potential finer scale controls on fire severity. These methods allowed for closer inspection of the circumstances where bottom-up controls reduced fire severity and characterized the conditions where they are most influential. Finally, we provide insights for land managers concerning fuel treatment effectiveness and cross-scale strategies for re-establishing landscape resilience to wildfire.

Methods

Study area

We examined 17 large wildfires that burned in north-central Washington during 2014 and 2015 (Fig. 1). Regional climate is continental with warm to hot, dry summers, and cold winters with most precipitation falling as snow. Vegetation in the lowest elevations is shrub steppe, historically dominated by bunchgrasses, bitterbrush (*Purshia tridentata*), and sagebrush (*Artemisia* spp.) but increasingly invaded by nonnative grasses including cheatgrass (*Bromas tectorum*) and bulbous bluegrass (*Poa bulbosa*). Outside of riparian areas, lower and mid montane elevation zones support dry, mixed-conifer forests of ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*). Upper montane and subalpine forests are codominated by lodgepole pine (*P. contorta*), Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*). Moist riparian areas and floodplains support mixed assemblages of aspen (*Populus tremuloides*), black cottonwood (*P. trichocarpa*), maples (*Acer* spp.), and willows (*Salix* spp.) often intermixed with conifers after long periods of fire exclusion. Topography is highly dissected with steep elevation and aspect gradients. South-facing aspects and ridges tend to be dominated by open-canopy seasonally dry forests, and denser, often closed canopy forests are found on northerly aspects and in valley bottoms.

The 2014 and 2015 wildfire seasons were influenced by a multi-year regional drought (Marlier et al 2017; Engel et al. 2019). The 2014 summer wildfire season was preceded by a warm and wet autumn period followed by low winter snowfall, early spring snowmelt, and rapid runoff. A subsequent early summer heat wave was followed by a mid-July lightning storm, which ignited several small fires in the Methow Valley, Washington. A major wind event

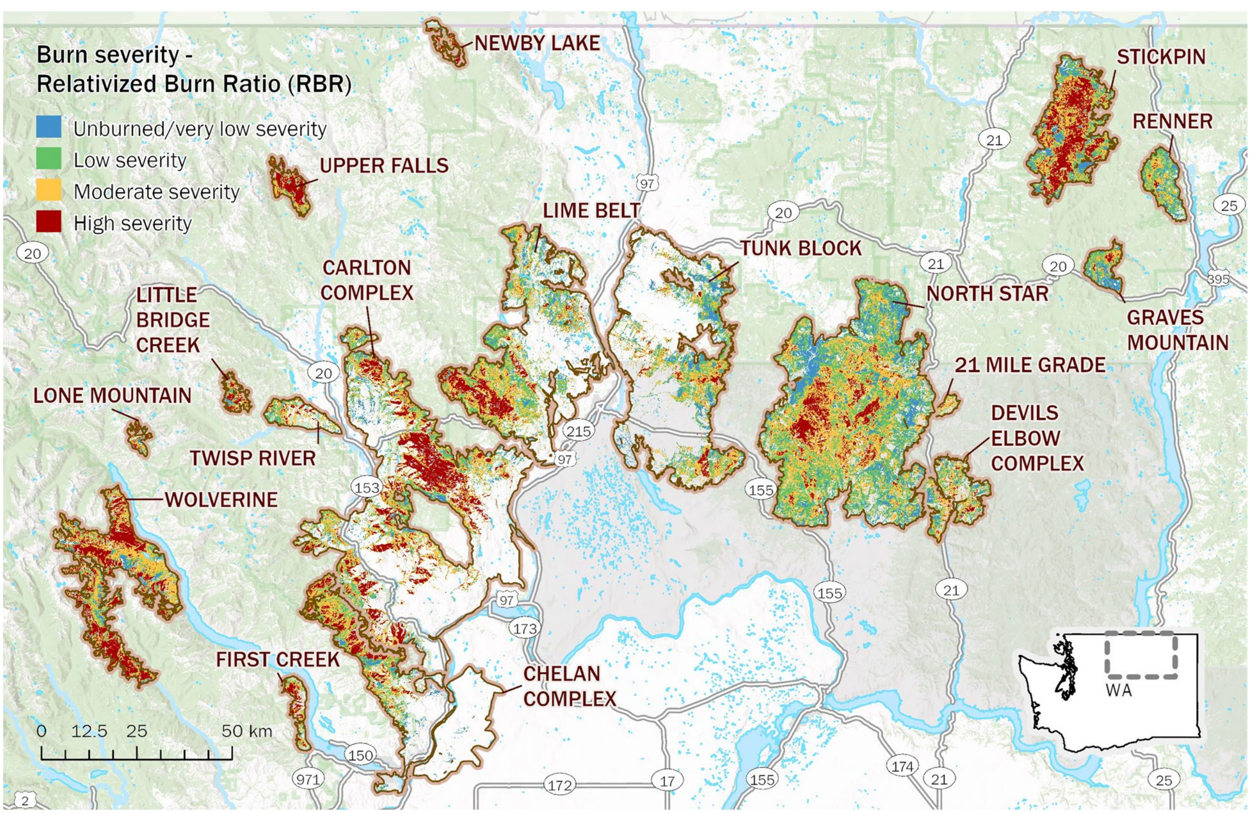

Fig. 1 Study area showing the extent and severity (forested areas only) of 17 wildfires that burned during the summers of 2014 and 2015 in north-central Washington State, USA. Fire severity was quantified using the relative burn ratio with unburned, low, moderate, and high severity classification cutoffs following Parks et al. (2014b)

followed with sustained winds over 48 km h^{-1} caused fires to erupt into events that burned over 64,000 ha in a single burn period on July 17 th, 2014. Over the next 2 days, the 2014 Carlton Complex Fires grew to 102,000 ha. A rainfall event of >5 cm on July 23rd dampened fire behavior and contributed to containment.

With continuing regional drought conditions, the 2015 wildfire season closely resembled that of 2014. By early July 2015, live and dead fuel moistures of low elevation forests and shrub steppe lands were low, and fuels were receptive to burning. A series of large wildfires ignited by dry lightning and humans quickly spread under hot, dry, and windy conditions, burning a total of 289,211 ha from July to September 2015 (Table 1).

Burn severity analysis

To quantify burn severity within 17 study area wildfires, we used the Landsat-based Relativized Burn Ratio (RBR). Compared to other related indices, RBR showed a slightly higher correspondence with field measures of burn severity within our study area (Parks et al. 2014b; Prichard et al. 2020). We calculated RBR using Landsat imagery via Google Earth Engine, following Parks et al. (2018a). The Parks et al. (2018a) method creates 30-m mean composite images from a set of pre- and post-fire scenes to provide a more complete assessment of burn severity than an a priori selection of individual pairs of pre- and post-fire scenes. To span the date range of fires, we selected LANDSAT 8 Tier 1 datasets, which are adjusted for cloud, shadow, water, and snow interference. We calculated RBR using dNBR with the offset described in Parks et al. (2014b).

Descriptive statistics

We characterized the size and severity patterns of the 2014–2015 wildfires using several summary statistics. To do so, we first separated forest and non-forest areas in our analysis because the ecological effects of fires of a given severity differ from those of grassland and shrubland types. We calculated the stand-replacing decay coefficient (SDC) metric following methods of Collins et al. (2017) and Stevens et al. (2017) for all high-severity forest patches as an indicator of the scale of potential ecological impacts across forested landscapes. Smaller SDC values indicate that larger patches of high severity are most influential, and larger SDC values indicate greater influence of smaller patches. For each fire, we calculated SDC metrics for all high-severity patches and for forested high-severity patches. We then compared our results to those of Stevens et al. (2017) for a set of 477 fires that burned between 1984 and 2015 in semi-arid forests of California.

Table 1 Summary statistics of major wildfires in north central Washington during the 2014 and 2015 wildfire seasons, including total burned area, percentage of forested area, and percentage of forest area burned at high (H), moderate (M), low (L) and unburned/very low (U) severity

Wildfire name	Total area (ha)	Forested area (%)	Percentage of forested area burned by severity class (%)
2014 Wildfires			
Carlton Complex	96,468	33	H 44, M 34, L 18, U 3%
Devil's Elbow Complex	7796	72	H 12, M 43, L 38, U 7%
2015 Wildfires			
21 Mile Grade	654	59	H 13, M 70, L 17, U 0
Chelan Complex	36,114	35	H 26, M 36, L 26, U 11
First Creek	2024	53	H 49, M 34, L 16, U 1
Graves Mountain	2823	93	H 10, M 30, L 47, U 14
Lime Belt	48,663	48	H 10, M 41, L 41, U 8
Little Bridge Creek	1193	87	H 44, M 37, L 16, U 3
Lone Mountain 1	607	84	H 31, M 45, L 19, U 5
Newby Lake	764	84	H 62, M 26, L 9, U 3
North Star	83,834	83	H 10, M 36, L 47, U 7
Renner	4756	89	H 4, M 37, L 53, U 6
Stickpin	18,740	96	H 45, M 32, L 19, U 5
Tunk Block	61,501	31	H 21, M 42, L 30, U 6
Twisp River	3837	34	H 27, M 38, L 35, U 1
Upper Falls	2448	91	H 64, M 27, L 9, U 1
Wolverine	21,253	84	H 46, M 38, L 12, U 3

Random forest modeling

We developed RF models to compare drivers of fire severity across fires and between first-entry fires and reburns. First-entry fires were those that burned in long unburned areas (burned prior to 1960), and reburns included areas that burned two or more times (initial burn ≥1960). Final models were run using the R package *ranger* v0.12.1 (Wright and Ziegler 2017). Model outputs included global model predictions and errors, linear and non-linear relationships among predictors and the response variable, variable importance, and spatial maps of local predictor variable importance.

We defined forested cells as those 30-m cells with >10% tree cover based on the LANDFIRE 30-m Existing Vegetation Cover map (LANDFIRE 2014). In using this broad definition of forestland, we included a range of forested vegetation types from low-elevation pine savannas to high elevation conifer forest.

To limit effects of spatially autocorrelated data on the predictions, we selected a subset of pixels on a 270-m grid (Povak et al. 2020a). We excluded cells that fell within a 100-m interior buffer of fire perimeters to reduce edge effects as fire severity in these cells are likely driven largely by firefighting efforts, which are not the focus of the current effort. All analyses were conducted with the statistical software R package (R Core Team 2023).

A total of 80 candidate predictor variables were evaluated across six predictor groups, including (1) climate, (2) day-of-burn fire weather, (3) topography, (4) forest management and fire history, (5) live and dead fuels, and (6) spatial autocorrelation variables. We performed variable reduction to balance model complexity with parsimony. We first partitioned each predictor variable into a predictor group. Within each predictor group, variables were removed where pair-wise correlations exceeded 0.75, using the *Caret* package *findCorrelation* function (Kuhn 2020). We then removed individual variables from each predictor group that had low variable importance in initial RF model runs. Final predictor variables are shown in Table 2.

Random forest modeling—predictor variables

Climate variables

Thirty-year (1981–2010) climate normals (90-m resolution) for actual evapotranspiration (AET) and climatic water deficit (Deficit) were obtained from a previous study by Cansler et al. (2022) in this area. Data were calculated using the Priestley-Taylor equation (Priestley and Taylor 1972), following methods of Dobrowski et al. (2013). Full details on data development can be found in Cansler et al. (2022).

Day-of-burn fire weather variables

Day of burn weather variables were assigned by fire progression interval. Daily maximum temperature and maximum relative humidity values were obtained from gridMET (Abatzoglou 2013) at 4-km resolution for each burn day. Although minimum relative humidity has been used as a significant predictor of fire severity in previous studies (e.g., Prichard et al. 2020), we used maximum relative humidity because it had higher variable importance in preliminary RF modeling. We acquired wind variables, including wind gust speed and direction of maximum gust, from Remote Automatic Weather Stations (RAWS), for each burn day. The most appropriate RAWS station was assigned to each fire based on proximity; if a fire contained multiple RAWS stations, we assigned a station based upon RF modeling of RBR using RAWS station windspeed and direction. For each progression day, we assigned the mean gust speed and direction as measured at the respective RAWS station to cells that burned on that progression day. Because these variables were assigned by progression interval, they were not applicable to individual fire progression RF models.

Topographic variables

Topographic variables, including slope gradient and topographic position index (TPI), were derived from a 10-m DEM. We calculated TPI at fine (100-m), moderate (600-m), and coarse scales (1200-m) using a method introduced by Weiss (2001), which compares the elevation of each DEM pixel with the mean elevation within the defined neighborhood of each pixel. Valley positions were classified as negative TPI (− 2 to 0), and ridge positions as positive values (0 to 2).

Management and fire history variables

We obtained records from the US Forest Service *For*est *Act*ivities (FACTS) database for past harvests and prescribed burns from 1995 to present. When comparing treatment polygons with pre-wildfire orthorectified imagery (NAIP images from pre- 2014) in a GIS, we determined that many treatment polygons required geospatial re-alignment due to digitization and projection errors. For fires occurring on the Methow Valley and Tonasket Ranger Districts, we validated the FACTS treatment layer with local harvest and burning records. We then obtained additional treatment layers from the Washington State Department of Natural Resources, Washington Department of Fish and Wildlife, and the Colville Indian Reservation. Each layer was compared with pre-burn NAIP imagery before compiling a master file geodatabase, which in many cases required re-digitizing treatment polygons. Treatment records were then condensed into 8 classes: clearcut (CC), clearcut and

Table 2 Final variables used in the random forest models of all the 2014 and 2015 wildfires

Dataset	Variable name	Description
Climate		
- 30-year climatic water deficit normal	Deficit	1980–2010 (mm) Cansler et al. (2022)
Fire weather		
- Maximum daily temperature	MaxTemp	Maximum daily temperature (°C) gridMET. Abatzoglou et al. (2013)
- Maximum relative humidity	MaxRH	Maximum relative humidity (%) gridMET. Abatzoglou et al. (2013)
- Maximum gust speed	MaxGust	Maximum wind gust (m s^{-1}) Nearest RAWS station was used to summarize hourly data over the progression interval
- Maximum gust direction	MaxGustDir	Wind direction of maximum gust speed, transformed to linear variable between 0 and 2. Beers et al. (1966) Nearest RAWS station was used to summarize hourly data over the progression interval
Topography		
- Slope	Slope	Slope gradient (%)
- TPI_Ridge_1200	Ridge	Ridge-like classification of TPI at 1200-m neighborhood. 100 (ridge) to 0 (not ridge)
- TPI_Valley_1200	Valley	Valley-like classification of TPI at 1200-m neighborhood. 100 (valley) to 0 (not valley)
Management and fire history		
- Distance to past fire[a]	DistFire_20 yr	Distance from past fire edge (m) of wildfires within past 20 years
- Time since wildfire[a]	TSWildfire	Time since last wildfire (year)
- Treatment type[b]	Treat	Clearcut (CC), clearcut and broadcast burn (CC_BB), shelterwood and underburn (SW_UB), thin-only harvest (Thin), Thin and mastication or thin and piled (ThinPileMast), thin and prescribed under burn (ThinUB), thin and pile burn (ThinPB), landscape burn (UB), no treatment (none)
- Past prescribed burn[b]	RxBurn	Presence/absence of historical prescribed burn
- Max Past Severity[a]	RdNBR	Maximum past RdNBR severity class
- Time since prescribed burn[b]	TSRx	Time since last prescribed burn (year)
- Time since harvest[b]	TSH	Time since last harvest (year)
- Time since treatment[b]	TSTreat	Time since last treatment including harvests and prescribed burns (year)
Live and dead fuels		
- Canopy base height	CBH	Canopy base height (m, LANDFIRE 2014)
- 100-h fuel moisture	FM100	100-h dead wood (%)
- Cover Type	CovType	Reclassification based on Existing Vegetation Type (LANDFIRE 2014) including: dry mixed conifer, riparian forest or woodland, moist mixed conifer, Douglas-fir, subalpine forest, lodgepole pine, Engelmann spruce- subalpine forest, ponderosa pine
- Normalized Difference Moisture Index	NDMI	Calculated as (NIR – SWIR)/(NIR + SWIR) used as an index of live fuel amount and moisture. Composites of one year pre-fire imagery from GEE. Parks et al. (2018a)
- Normalized Difference Vegetation Index of non-forest	NDVI_NF_750	Mean NDVI of all non-forested cells within 750-m moving window around forested cells. Composites of 1 year pre-fire imagery from GEE. Parks et al. (2018a)

[a] Only for the reburn models

[b] Only for first-entry fire model

broadcast burned (CC_BB), pile burned (PB), thinned, pile burned, and masticated (Thin_Pile_Mast), thinned only (Thin), thinned and pile burned (Thin_PB), thinned and underburned (Thin_UB), and underburned only (UB).

We characterized past wildfires using three variables: time since the last wildfire (years), the maximum RdNBR of all previous wildfires, and distance (m) from pixel to edge of past wildfire (1984–2015) within a 2-km buffer. To be used, past wildfires had to be a minimum of 400 ha (MTBS minimum size threshold) and have occurred between 1984 and 2015. Burn severity and fire perimeter data were acquired from the MTBS database (Eidenshink et al. 2007; www.mtbs.gov).

For the distance to previous fire perimeter variable, a negative distance was recorded in cases where a pixel burned within the boundaries of a recent burn. If a burned pixel fell outside of a recent burn, it was recorded as a positive distance.

Live and dead vegetation variables

We used LANDFIRE for live and dead vegetation and fuel predictor variables. For 2014 wildfires, we used 2012 layers because the 2014 dataset potentially represented post-fire vegetation conditions. For 2015 wildfires, we used the 2014 layers to represent the most current fuel and topography layers. Canopy base height (CBH), 100-h fuels (from the 40 Scott and Burgan (2005) Fire Behavior Fuel Models, FBFMs), and cover type (Existing Vegetation Type) were derived from LANDFIRE layers (www.landfire.gov). We then reclassified the LANDFIRE Existing Vegetation Type layer (EVT) from the original 640 vegetation types into eight broad cover type classes that represent major forest types within the study area (Table 2). Of these forest types, dry mixed conifer, moist mixed conifer, Douglas-fir, and ponderosa pine types are considered fire tolerant compared to cold forest types with species that have few adaptations to survive fire (subalpine forest, lodgepole pine, Engelmann spruce-subalpine forest, and riparian forest or woodland).

We also characterized live fuels 1 year prior to the 2014 and 2015 wildfire seasons directly from LANDSAT- 8 imagery. To do so, we calculated the Normalized Difference Moisture Index (NDMI) and Normalized Difference Vegetation Index (NDVI) in nonforest pixels within a 750-m moving window (NDVI_NF_750) using LANDSAT imagery obtained via Google Earth Engine, following the methods of Parks et al. (2018a). NDMI measures moisture content of vegetation and is used as a proxy for live fuels with high values representing high biomass and/or high moisture content in leaves and low values representing low biomass and/or low moisture content (Wang et al. 2013; Antognelli 2018; Costa-Saura et al. 2021). NDVI_NF_750 represented the mean NDVI of all nonforested cells, within a 750-m moving window. Although we focused on burn severity of forested areas, nonforested areas play an important role in facilitating nearby fire spread (Povak et al. 2023; Hessburg et al. 2016, 2019), which were represented by this variable.

Spatial autocorrelation variables

We applied a 270-m spacing among sampled raster cells to reduce the impact of spatial autocorrelation on model results. Variability of fire severity at scales larger than the 270-m neighborhood still existed and could be explained through the inclusion of spatial autocorrelation variables within the RF models. Following Povak et al. (2020a), we used principal components of neighborhood matrices (PCNM) analysis, a special case of spatial eigenvector maps (Borcard and Legendre 2002), to evaluate spatial autocorrelation and its scale. PCNM applies principal coordinates analysis to a matrix of neighboring points, producing eigenvectors that maximize Moran's index of autocorrelation. High-order vectors represent local-scale spatial autocorrelation, while low-order vectors represent larger-scale spatial autocorrelation (Borcard and Legendre 2002). Similar methods were successfully adopted by Pascolini-Campbell et al. (2022).

We used truncated distance matrices with a threshold distance of 10,000 m to calculate lower-ordered (1–10) PCNM vectors and included the first six eigenvectors as predictors. PCNM eigenvectors were calculated in R using the *vegan* (Oksanen et al. 2018) and *RSpectra* packages (Qiu and Mei 2022). See Povak et al. (2020a) for a full discussion of PCNM predictors.

Random forest modeling—Shapley local importance

Local predictor variable importance methods are often applied to better understand why a model made a certain prediction at a particular location. The Shapley methodology, a variable importance method, is widely used in machine learning applications. It provides an assessment of the average marginal contribution of any given predictor on the modeled response when compared with the average prediction (Lundberg and Lee 2017; Molnar 2020; Sutera et al. 2021). Shapley methods are based on game theory, where each predictor is likened to a "player" in a game and the goal is to fairly distribute the "payout" among the players. The payout in our application was the difference between a cell's predicted fire severity and the average predicted fire severity across all cells. Shapley methods apply a permutation approach to account for combinations of predictor variables such that one may isolate the contribution of a single predictor at a given location.

Shapley values were estimated using the R *treeshap* package v0.0.1 (Komisarczyk et al. 2021), which employs an algorithm optimized for tree-based machine learning applications to reduce computational time (Lundberg et al. 2018). This was done separately for the global first-entry fire model and the global reburn model. Each of these models used all 270-m spaced sample points across all fires and progression days, and Shapley values were calculated for each predictor variable included in the models (Table 2). We further simplified outputs by aggregating across predictor variable groups rather than presenting results for individual predictors. This was done by taking the Shapley value with the highest magnitude, positive or negative, within each predictor group, and mapping these values by predictor group, across each fire. As defined earlier, predictor groups included climate, fire weather, topography, fuels/vegetation, and management history (first-entry fires) or fire history (reburns).

Finally, we identified approximate rulesets associated with the dominant drivers of fire severity patterns using the Shapley local importance outputs to answer two questions: (1) under what set of conditions were top-down drivers dominant and (2) under what conditions did bottom-up drivers exhibit significant spatial control? To do so, we first classified each raster cell into one of five classes representing the predictor variable group with the highest absolute Shapley value. Classes were as follows: (1) climate, (2) fire weather, (3) vegetation/fuels, (4) topography, and (5) management (first entry models) or fire history (reburn model). Shapley classes were used as the response variable in a classification tree along with the set of predictor variables used in the original RF modeling (rpart v4.1.23, Therneau and Atkinson 2023). Several considerations were made when parameterizing these models: response variable class imbalances, model complexity, Shapley class representation, and model accuracy (see Table S1). Class imbalances were addressed using class weights to increase the influence of lesser represented classes. Several weighting schemes were tested, and resultant trees generally varied in the order of predictor variable importance and model accuracy. For example, increasing the weights of lesser represented classes generally increased the importance of predictor variables associated with that class but at the cost of reducing model accuracy. By means of this approach, we developed three models for (1) first-entry fire, (2) reburns, and (3) first-entry fires with recent fuel treatments.

Results

2014–2015 North-Central Washington (NCW) wildfire patterns

During the 2014 and 2015 fire seasons, 17 major wildfires burned a total of 393,475 ha across ncWA (Table 1). Forests comprised approximately half of all burned area, which varied between 31 and 96% among individual fires. The 2014 Carlton Complex burned the largest area (96,469 ha), but less than a third of that area (31,833 ha) was forested. In contrast, the 2015 North Star fire was the second largest fire (83,834 ha), and over 80% of the area burned was mid-montane to high elevation conifer forest. Most fires burned as a first-entry fire, with no record of past burning since 1960. Reburns accounted for only 8.4% of the forested area burned, and reburns occurred within 8–14 years of the most recent fire.

Among the forested areas that burned, the distribution of fire severity was relatively even among severity classes (high: 24.3%, moderate: 36.8%, low: 32.8%, unburned: 6.0%, Table 1). High-severity patch sizes were generally large (> 100 ha), with ~70% of the area that burned at high-severity occurring in patches >100 ha (Fig. 2). Accordingly, stand-replacing decay coefficient (SDC) values were generally low (i.e., ≤ -5.0), indicating that large high-severity patches were prevalent across most fires (Fig. S1). No clear relationship was found among SDC and percent forested area or fire size. Hence, while high-severity burned area was not always dominant within fire perimeters, it generally occurred in large patches.

Across all 17 fires, fuel treatments were implemented on only 9% of the 211,975 ha combined forested area within 20 years prior to the 2014 and 2015 wildfire events. The most common fuel treatments included forest underburning (7816 ha), thinning only (4381 ha), thinning followed by underburning (2823 ha), clearcutting only (1247 ha), clearcutting followed by broadcast burning (1138 ha), pile burning (1120 ha), thinning with subsequent pile burning (500 ha), and thinning followed by piling and mastication (400 ha).

Global drivers of fire severity—first-entry fires

The global RF model for first-entry fires (sample size =24,969) had an $R^2{}_{OOB}$ of 0.554. Across the study area, there was consistency among drivers of fire severity. Top-down climate and fire weather drivers exhibited the highest predictor variable importance values in the global models (Fig. 3, column 1), and there was a strong negative relationship between climatic water deficit (CWD) and fire severity, reflecting that high-severity fire often occurred in cold and moist, higher elevation, mixed-conifer forests. This result was also found within individual RF models for four of the five largest fires (Carlton, Lime Belt, North Star, Stickpin, Fig. 3, columns 2-5). Conversely in the Tunk Block fire, fire severity was highest in dry, low elevation, ponderosa pine-Douglas-fir forests (Fig. 3, column 6). Variables associated with extreme fire weather, including MaxTemp, MaxGustSpd, and MaxGustDir, were associated with increased fire severity in the global model and in most individual fire models.

Bottom-up drivers of first-entry fires exhibited weaker relationships than top-down climate and fire weather variables in the global models. Severity was greater in valley bottom and steeply dissected mountain valley pixels (TPI_Valley_1200 m), and on steeper slopes (Slope). Severity was also higher with increasing live fuel loads (NDMI) and where nonforest vegetation surrounding a burned pixel was prevalent (NDVI NF 750). Dead fuel moisture (100-h FM) and canopy base height (CBH) were also important drivers, with high fuel moistures and high CBH negatively correlated with burn severity. Cover type was strongly related to burn severity; fire-tolerant types were less severely burned, while fire-intolerant types were more severely burned.

Global drivers of fire severity—reburns

The global RF reburn model had a $R^2{}_{OOB} = 0.497$, which was slightly lower than the global first-entry fire model. When compared with first-entry fire RF models, vegetation and fuels had higher variable importance in reburn

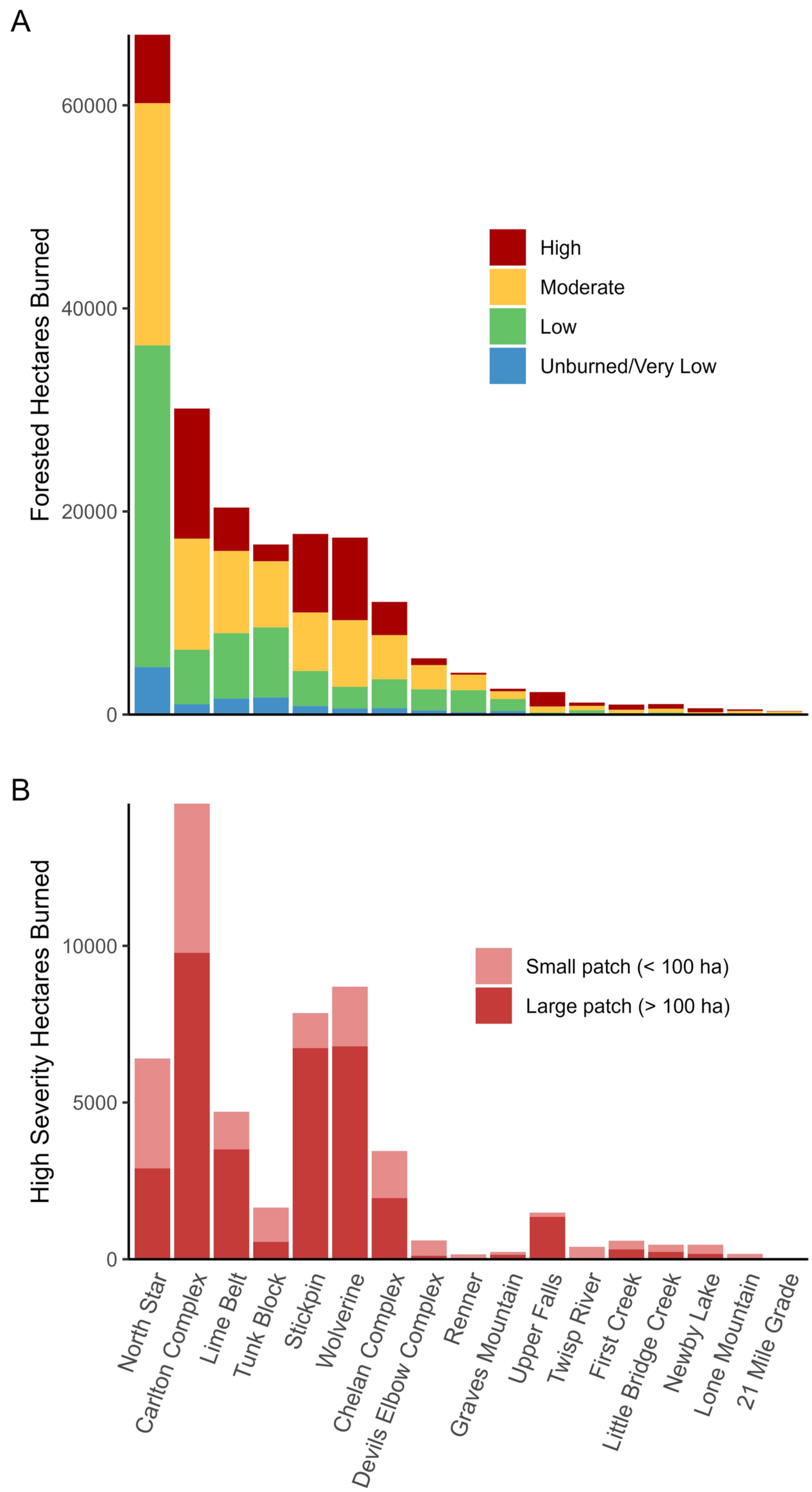

Fig. 2 Histogram distributions of classified forest fire severity in (**A**) categories of unburned/low, low, moderate, and high fire severity, (**B**) forested area (hectares) of high severity in small (< 100 ha) and large (> 100 ha) patch sizes across 17 study area fires

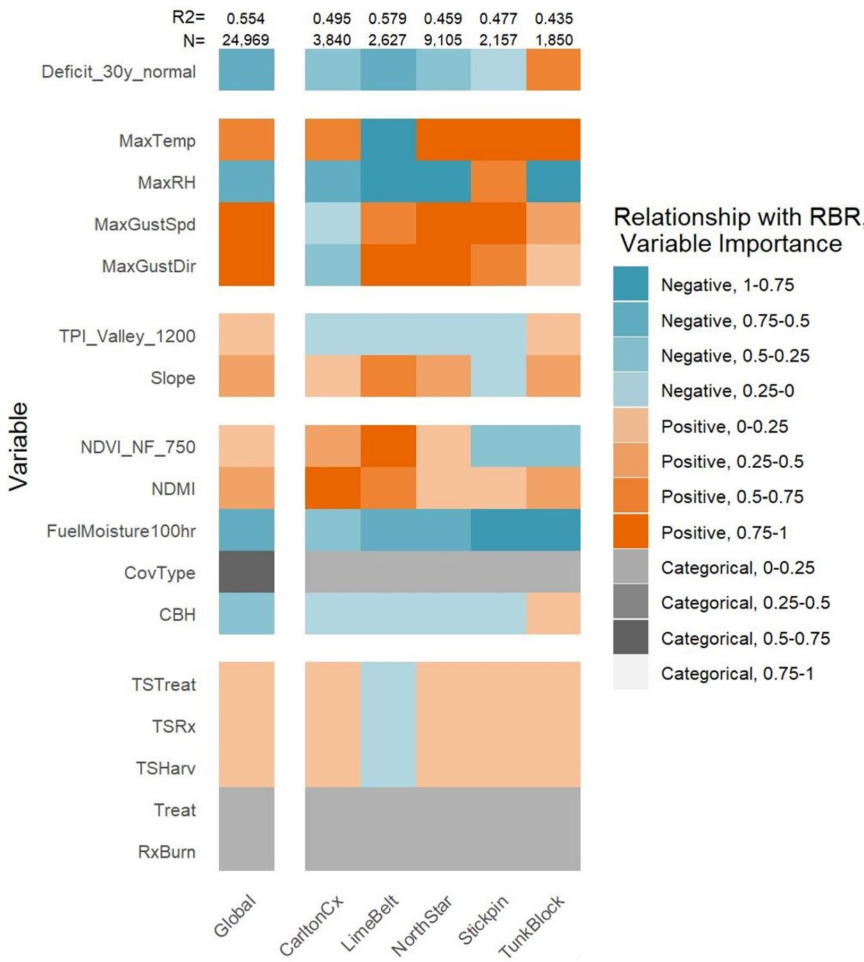

Fig. 3 Heat map showing the relative strength of predictors of the relative burn ratio (RBR) for first-entry burned pixels after a long period of fire exclusion. Refer to Table 2 for variable definitions. Blue cells indicate a negative relationship between the variable and fire severity, while red cells indicate a positive relationship. Categorical variables are represented in a gray shading as they have no inherent sign

RF models while fire weather and fuel moisture had lower variable importance (Fig. 4).

Local drivers of fire severity

Mapped Shapley importance values, representing the unique influence of predictor variables at the cell level, revealed a diversity of local drivers of fire severity and illustrated the place-based conditions that contribute to fire severity patterns (see Figs. 5, 6, and 7 for examples from the Lime Belt, Stickpin and North Star fires, respectively). Patches of high-severity fire were largely driven by top-down climate and fire weather variables, but elsewhere, a combination of topography, fuels, fire history, and management history exerted local controls on fire severity. For example, fire severity was significantly higher on steep slopes, in valley bottoms, and within steeply dissected mountain valleys across most fire areas, but lower on more gently sloped terrains. Moreover, low fuel moisture (represented by 100-h fuel moistures), abundant live fuel (NDMI), and low canopy base heights (CBH) were often associated with presence of high-severity fire patches and high spatial autocorrelation of high fire severity area. Mapped Shapley values for three additional fires are included in the Supplementary materials (Fig. S2, 2014 Carlton complex; Fig. S3, 2015 Chelan complex; and Fig. S4, 2015 Wolverine fire).

In the Lime Belt fire (Fig. 5), fuels were more dominant than fire weather in the largest high-severity fire patch located in the southwestern corner of the fire. Similarly, within the Stickpin Fire (Fig. 6), which burned mostly within mid- to high-elevation forests, a combination of climate, fire weather, topography, fuels, and vegetation contributed to the largest high-severity fire patch, which comprised much of the fire footprint. Fire weather was the dominant variable within the center of the North Star fire, representing an early, wind-driven, fast-moving fire

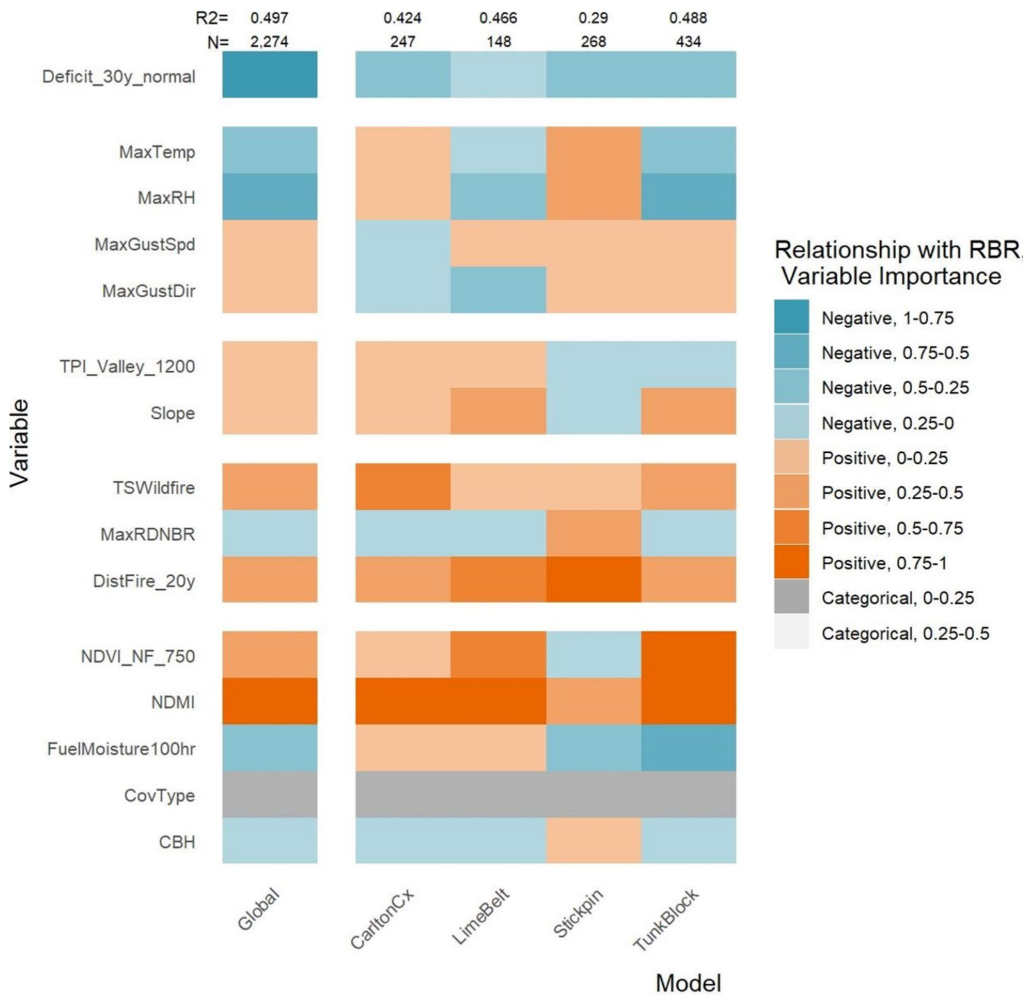

Fig. 4 Heat map showing the relative strength of predictors of the relative burn ratio (RBR) for reburned pixels that had a recent prescribed or wildland fire prior to the 2014 and 2015 wildfires. Variable definitions are provided in Table 2. Categorical variables are represented in a gray shading as they have no inherent sign. Columns differ between Figs. 3 and 4 because of fewer reburn pixel counts and significant results

progression (Fig. 7). However, a combination of fuels, topography, past fires, and past management influenced patterns of fire severity elsewhere.

Shapley local importance values also demonstrated how past fires and fuel management exerted strong local controls on fire severity. Past treatment areas within all three fires (Lime Belt, Stickpin, and North Star) represented a small fraction of the total area burned, but cells within treated areas were generally associated with lower fire severity. For example, a pronounced difference between high and low severity fire is notable within a past fire within the Stickpin fire (Fig. 6).

Classification tree analysis using the Shapley importance values provided insight into the conditions under which local spatial controls on fire severity were strongest for first-entry fires (Fig. 8), reburns (Fig. 9), and treated areas (Fig. S5). As a reminder, the response variable for these models was a categorical variable representing the predictor variable group with the largest absolute Shapley value, and predictor variables were those from the original RF models.

For first-entry fires, climate was the main determinant of fire severity, where cooler, moister sites (Deficit < 157 mm) were associated with higher severity fire (Fig. 8). For drier sites in low and mid-montane environments, a combination of fuels, topography, and wind variables determined severity. The highest severity burns occurred on steep ($\geq 24\%$) slopes or where wind gusts were ≥ 16 m·s^{-1}. The lowest severity within first-entry patches occurred where live fuel loads were low (NDMI < 0.039) and on shallow slopes with low wind gust speeds (< 10 m·s^{-1}; Fig. 8). Interestingly, under moderate windspeeds (10–16 m·s^{-1}), areas that were managed tended to have lower severities.

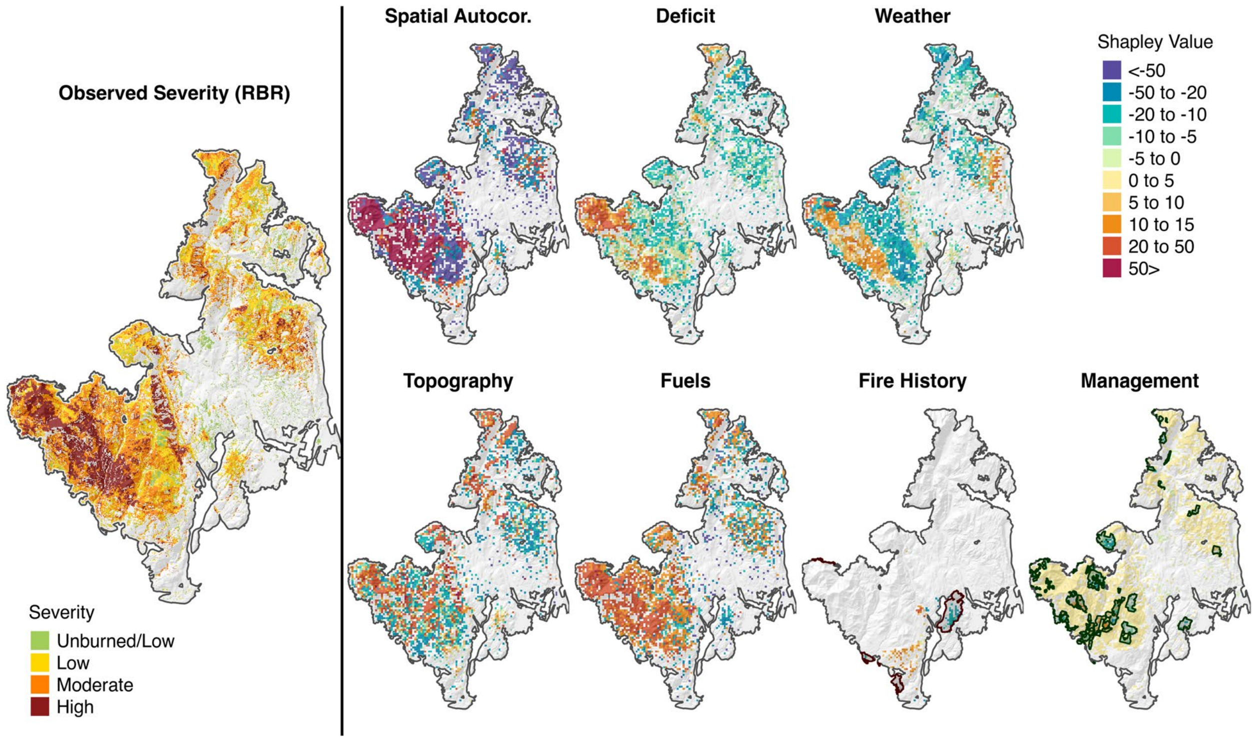

Fig. 5 Spatial distribution of local importance values for the 2015 Lime Belt fire, WA State, for the predictor variables groups: climate deficit, weather, spatial autocorrelation, topography, live and dead fuels, fire history, and management. Classified fire severity based on RBR is presented in the left-most panel; light grey pixels represent either non-forest that was not included in this analysis or areas that do not apply for a given predictor group (e.g., fire history variables were only relevant within past fire footprints)

For reburns, the first division of the classification tree was driven by distance to previous fire edge, where cells well within the interior of a past fire (> 699 m[1] from the previous fire edge) generally had lower subsequent fire severity (Fig. 9). Within fire interiors, areas with low live fuel load (NDMI < − 0.01) showed lower severity burn patches. Closer to the previous fire boundary, cells on shallow slopes (< 7%) or with low live fuel loads (NDMI < − 0.015) also had lower severities. Higher severities were associated with high live fuel loads, lower relative humidity during the progression, and where the previous fire occurred > 3 years prior to the burn.

Management effects on fire severity

Treatment effects varied in magnitude and direction (positive or negative sign) among treatment types (Fig. 10). Prescribed fires, including prescribed underburns and mechanical thinning followed by prescribed underburns, were among the most abundant treatments and had lower subsequent fire severity in 80 and 92% of treated cells, respectively. Thinning treatments that did not include understory burning had mixed effects on subsequent fire severity. Thinning alone reduced severity only half of the time, and reductions in severity were generally minor. Clearcutting with and without broadcast burning was mostly associated with higher severity (87 and 70% of treated cells, respectively), and the magnitude of the effect was often large.

Classification tree results taken from Shapley importance values for treated first-entry cells suggested that canopy base heights (CBH) ≥ 1.3 m led to the largest reductions in fire severity (Fig. S5). Elevated CBHs are often associated with fire-tolerant species that naturally undergo lower branch pruning, and/or as a consequence of prior low and moderate-severity fire disturbances. Where CBHs were closer to the ground, severities were generally higher, particularly under windy conditions (gust speeds ≥ 17 $m \cdot s^{-1}$) and on steep slopes (≥ 21%). However, even under high winds and low CBHs, areas with lower live fuel loads resulted in lower fire severities.

[1] Distances reported as negative numbers indicate a given cell was within the past fire footprint, whereas positive numbers indicate the cell was outside a past fire footprint. The more negative the distance, the further the cell was from the edge of the past fire.

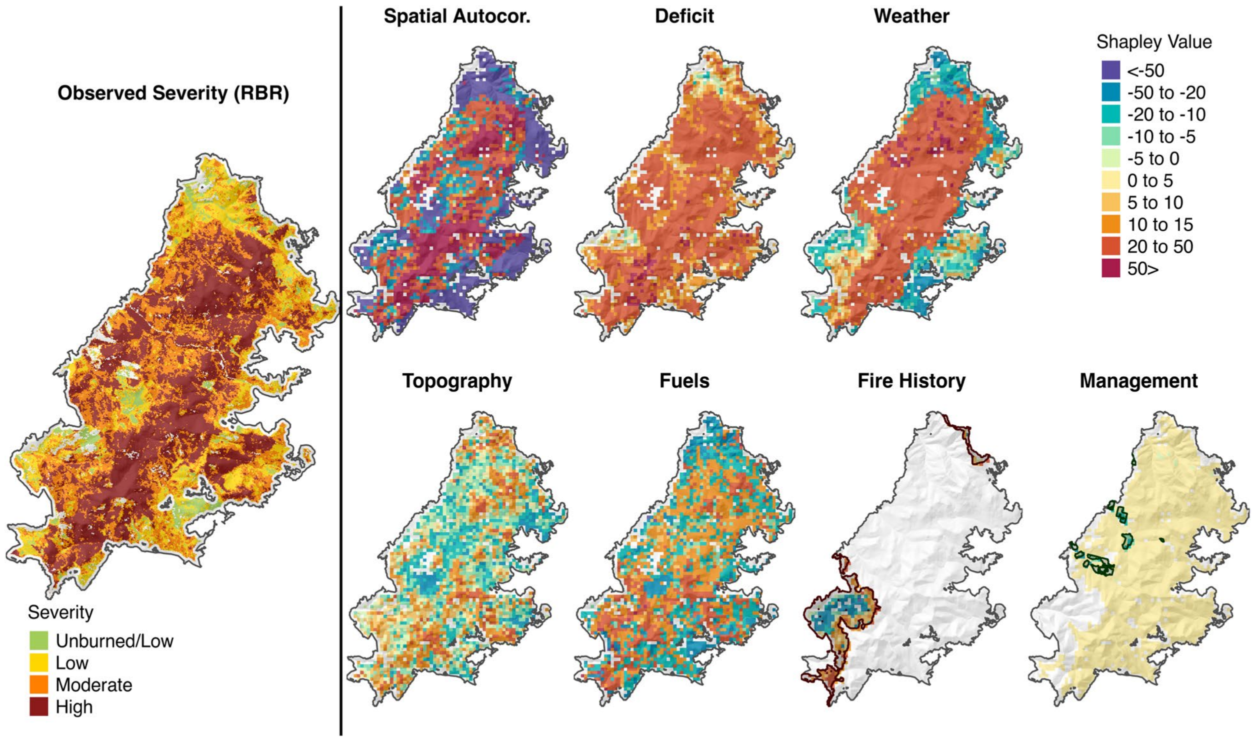

Fig. 6 Spatial distribution of local importance values for the 2015 Stickpin fire, WA State, for the predictor variables groups: climate deficit, weather, spatial autocorrelation, topography, live and dead fuels, fire history, and management. Classified fire severity is presented in the left-most panel; light grey pixels represent either non-forest that was not included in this analysis or areas that do not apply for a given predictor group (e.g., fire history variables were only relevant within past fire footprints)

Discussion

With the increasing prevalence of wildfires across wNA, forest and fire managers seek to leverage the positive influences of wildfires, cultural and prescribed burning, and mechanical fuel treatments on forest resilience and the return of active fire regimes (Hessburg et al. 2021; Parks et al. 2016; Stephens et al. 2012; van Wagtendonk 2007). Managed wildfires are increasingly recognized for their potential to help meet landscape-scale restoration goals (Prichard et al. 2021; Bean and Evans 2023; North et al. 2024). To do so, managers must balance the capacity for wildfires to achieve restoration goals while minimizing, to a practical extent, adverse effects to highly valued resources and socially- and/or ecologically valued conditions, including impacts on neighboring communities (Ager et al. 2017; Timberlake et al. 2020; Davis et al. 2022). Improved understanding of the conditions where beneficial effects of burning can be achieved will increase opportunities to allow wildfires to burn at low- or moderate-severities outside of the wildland-urban interface (North et al. 2024).

By studying large regional fire years, we were able to characterize resulting fire severity patterns and identify conditions where bottom-up controls can mitigate fire severity, even across areas where top-down forcings are primary. The main findings from our study were:

(1) Most forested area burned after a long period of fire exclusion (first-entry fires), and large burn patches were primarily driven by top-down climate and fire weather. In these situations, fuel contagion was high and did not mitigate the spread of high-intensity fire.
(2) Reburned areas experienced lower fire severity than those burned by first-entry fires.
(3) Where patches of high-severity fire occurred, they were large (> 100 ha) and played an outsized role with consequences for forest recovery (Coop et al. 2020).
(4) Bottom-up factors moderated fire severity, particularly in reburns, but also where forest cover was open, fuels were limited, slopes were shallow, and wind speeds were moderate.
(5) Across 17 large wildfires, ~40% of the forested area burned at no or low severity, showing that even "severe" wildfire seasons can contribute to resilient landscape conditions.

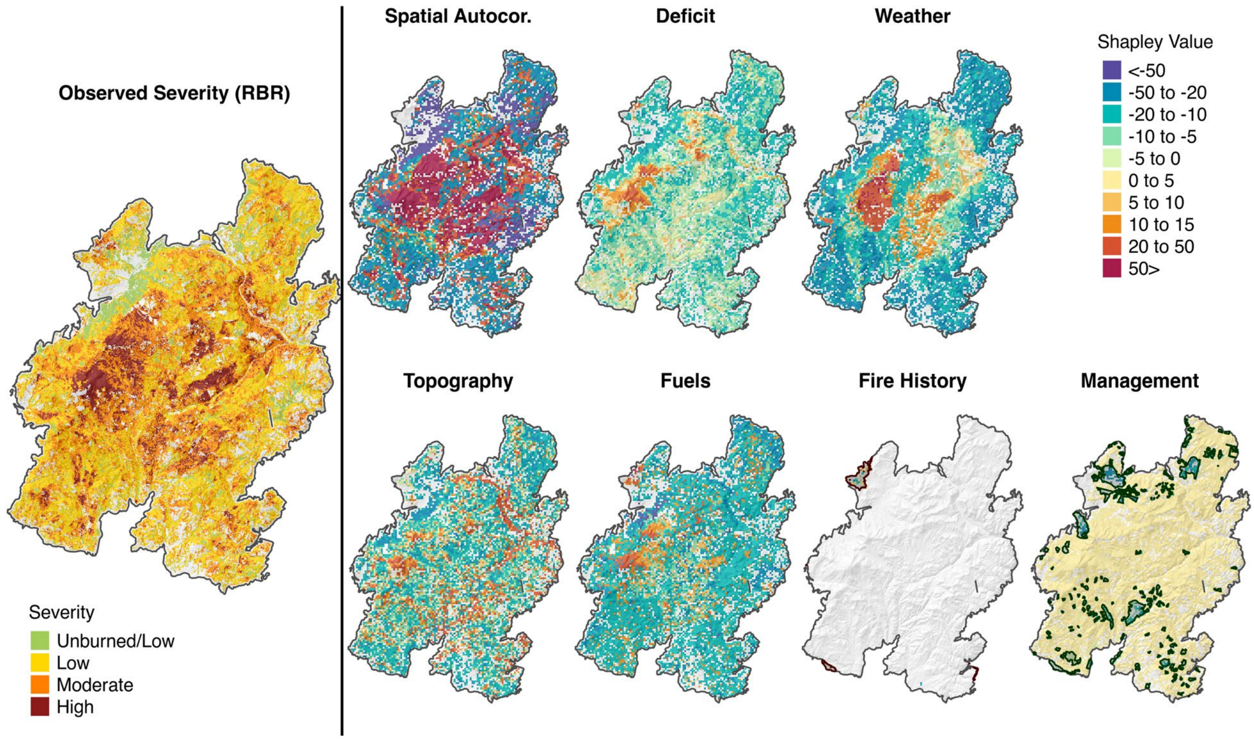

Fig. 7 Spatial distribution of Shapley local importance values for the 2015 North Star fire, WA State, for the predictor variables groups: climate deficit, weather, spatial autocorrelation, topography, live and dead fuels, fire history, and management. Classified fire severity is presented in the left panel; light grey pixels represent either non-forest that was not included in this analysis or areas that do not apply for a given predictor group (e.g., fire history variables were only relevant within past fire footprints)

(6) Management effectively reduced fire severity, particularly after combined thinning and underburn treatments, and where canopy base heights were elevated above 1.3 m.

Spatial patterns of fire severity

Our study shows a substantial opportunity for wildfires to contribute towards landscape restoration objectives, despite the occurrence of large high-severity fire patches. Current wildfires are treating more area within the western USA than forest restoration treatments (North et al. 2015, 2024; Hessburg et al. 2021). Used strategically, managed wildfire, or resource benefit fires, can accelerate the return of active fire regimes and their beneficial effects (North et al. 2021, 2024; Bean and Evans 2023; Greenler et al. 2023). In this context, improved understanding of reburn dynamics and their drivers can be important to determining the future role that wildfires and management can play in invoking positive changes on the landscape (Parks et al. 2015; Povak et al. 2023; Hessburg et al. 2021).

Where high-severity fire occurred, patches were large and generally associated with future challenges to forest recovery, carbon storage, and re-establishment of forest-dependent wildlife habitat (Stephens et al. 2016; Stevens-Rumann and Morgan 2019; Jones et al. 2021; Lyons et al. 2023). Historically, these patches were relatively rare on the landscape but are an increasingly common feature of twenty-first century fires (Hagmann et al. 2021). For example, in the 2020 Creek Fire, Cova et al. (2023) found that some high-severity patches were >20,000 ha in size. Safford et al. (2022) found that the occurrence of these largest patches in California were driven by interactions among extreme fire weather, high densities of fire-excluded mature trees, and high surface fuel loads stemming from combined drought and bark beetle mortality. Similar patterns were found in the 2021 Dixie Fire (Taylor et al. 2022), and the authors reported that severity was moderated by past low- and moderate-severity fires and mechanical treatments, despite plume-dominated fire spread.

We were unable to directly validate plume-dominated fire spread in our study, but wind gust speeds $\geq 16\ \mathrm{m{\cdot}s^{-1}}$ (~ 36 mph, 58 kph) were associated with severe fire. For first-entry fires, this effect was apparent only for moderate to high fuel loads (NDMI >0), suggesting that the effect of wind in promoting high-severity fire was limited by fuel availability. Maps of local importance showed that

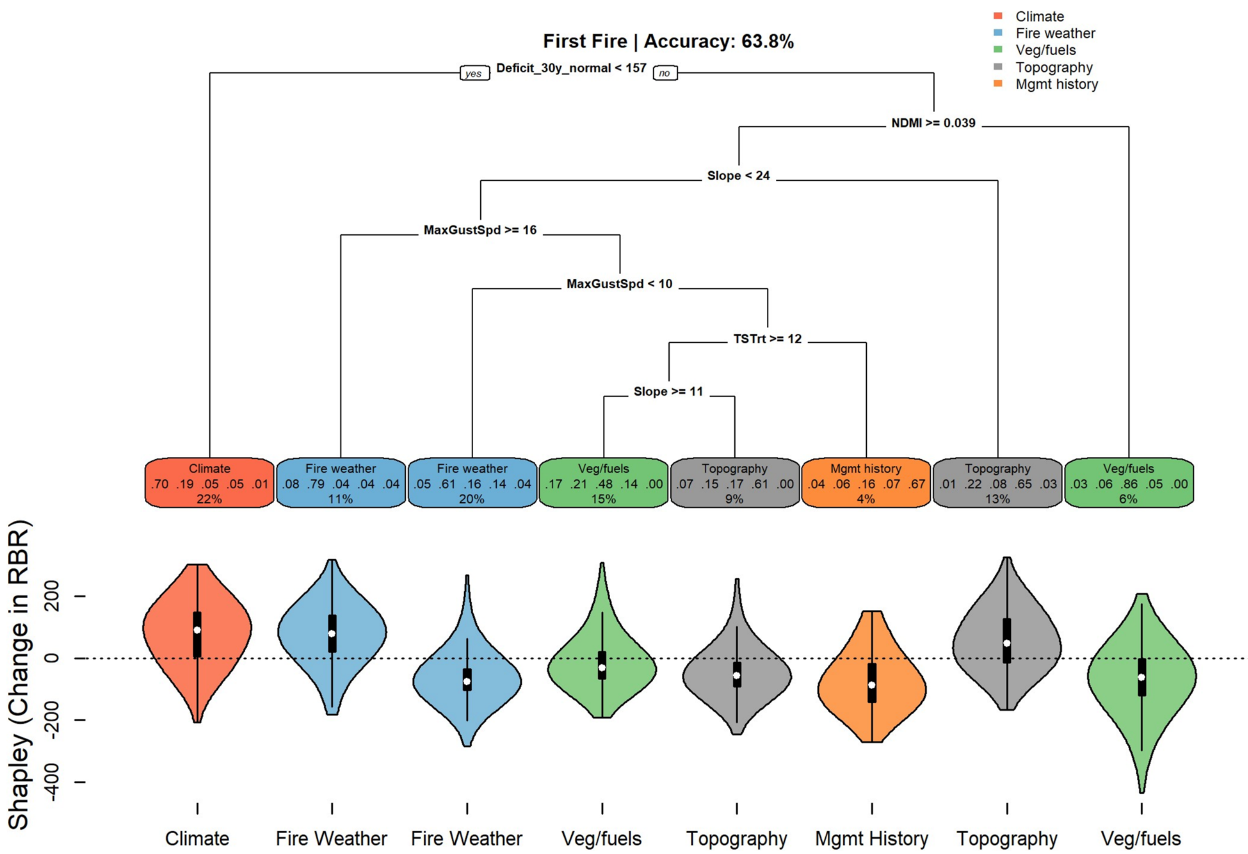

Fig. 8 Classification tree model for first-entry fires, characterizing conditions associated with the local influence (Shapley value) of predictor variable groups on fire severity. Predictor variables were assigned to one of five predictor variable groups: climate, vegetation and fuels (Veg/fuels), fire weather, topography, and management history. The variable group with the Shapley value of highest absolute magnitude was assigned to each raster cell. Proportions displayed in each box represent the modeled probability of each Shapley variable class in the order defined above. The percentage values within each box indicate percentage of observations in the node. Positive Shapley values in the violin plot indicate that a given variable was associated with an increase in fire severity, while negative values indicate a reduction in severity. For example, burned cells that experienced climatic water deficit (CMD ≥ 157 mm) and low live fuel levels (NDMI < 0.039) were strongly associated with vegetation and fuels variables, which in general led to lower fire severity (i.e., mean Shapley values < 0). Units for each predictor variable can be found in Table 1

large, high-severity burn patches also corresponded with spatial autocorrelation variables, suggesting that patterns of high-severity were best explained by proximity to other high-severity cells.

Reburns vs. first-entry fires

With much of the western USA currently in a fire deficit (Parks et al. 2015, Haugo et al. 2019) wildfires are returning to the landscape in areas that have exceeded their historical return intervals by many decades (Safford and Van De Water 2014). While first-entry fires are generally interpreted as a lack of resilience to fire in these landscapes, evidence suggests that even with the recent influx of area burned in recent decades, annual burned area is still much lower than historical levels (Donato et al. 2023; Halofsky et al. 2024). This suggests that as burned area increases across wNA landscapes, first-entry wildfires will be a dominant feature in the near term.

Others have found similarly that first-entry fires can impart resilience to these landscapes where they burn with a mixture of severities. For example, Kane et al. (2019) found that first-entry burns within the footprint of two fires in the Sierras exhibited post-fire structural characteristics similar to contemporary reference sites that had experienced multiple fires, suggesting a resultant increase in resilience. However, Churchill et al. (2022) describe wildfire as a "blunt tool" for improving ecological conditions in fire-excluded landscapes. The authors found that low- and moderate-severity fires pushed post-fire landscapes within historical (HRV) and future (FRV) ranges of variability, but large patches of high severity tended to homogenize the landscape and move them outside of desired ranges. Their findings highlight the capacity for wildfires to achieve restoration goals, potentially across large landscapes, but, where fire has remained out of the system for decades or longer, the resultant build

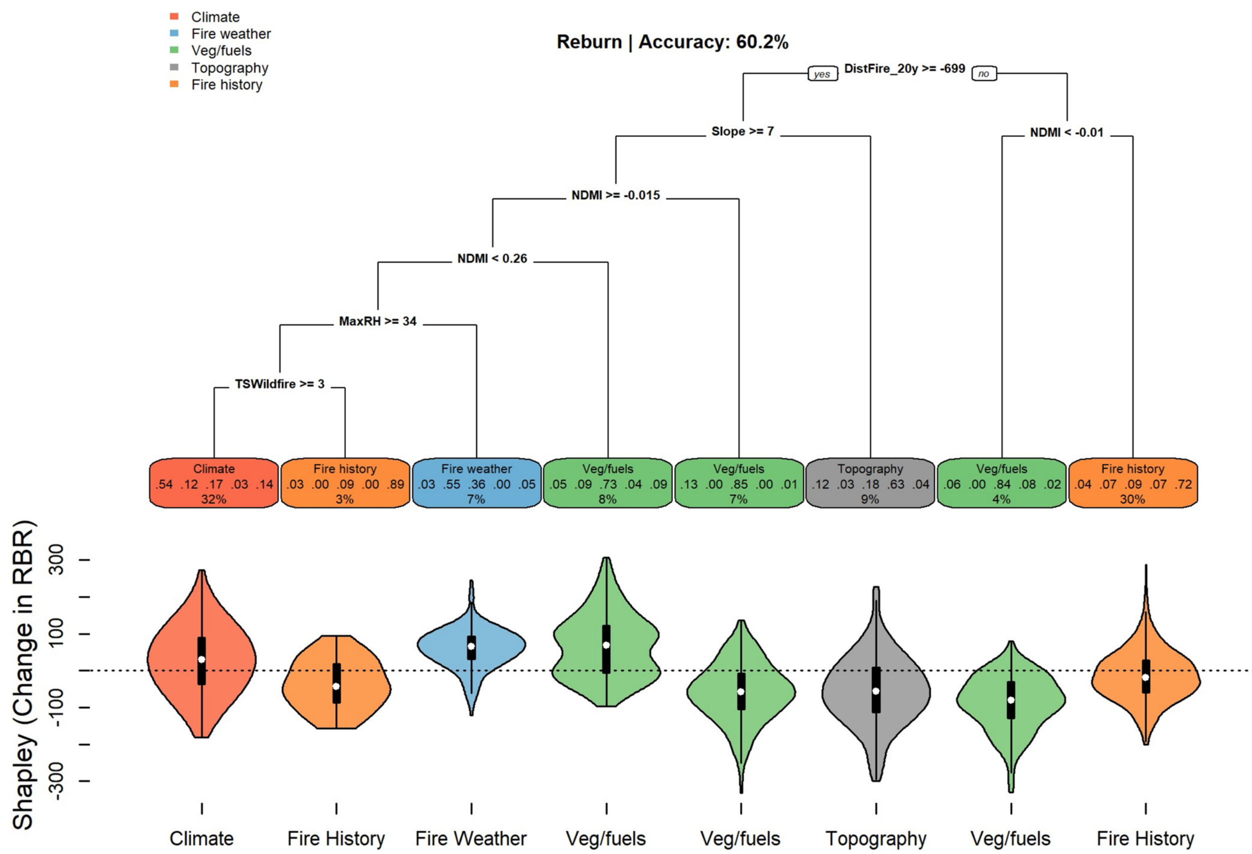

Fig. 9 Classification tree model for reburns, characterizing environmental conditions associated with the local influence (Shapley value) of predictor variable groups on increasing or decreasing fire severity. Predictor variables were assigned to one five predictor variable groups: climate, vegetation and fuels, fire weather, topography, and fire history. The variable group with the Shapley value of highest absolute magnitude was assigned to each cell. Proportions displayed in each box represent the modeled probability of each Shapley variable class in the order defined above. The percentage values within each box indicate percentage of observations in the node. Positive Shapley values in the violin plot indicate that a given variable was associated with an increase in fire severity, while negative values indicate a reduction in severity. For example, reburned cells that were far from the edge of a previously burned patch, and that had low live fuel loads (NDMI < – 0.01) were strongly associated with vegetation and fuels variables, and generally experienced lower fire severity (i.e., mean Shapley values < 0). Units for each predictor variable can be found in Table 1

up and contagion of fuels may supersede other potential controls on fire spread and severity leading to negative outcomes.

In this study, we found marked differences between the severity and environmental drivers of first-entry fires and reburns. First-entry fires were strongly driven by top-down factors, including temperature, wind gust speed, and relative humidity. Where landscape fuel loads and connectivity were high, first-entry fires generally supported contagious spread of crown fires. However, these variables were much less important in reburned areas, demonstrating that heterogenous patterns of forest density and surface fuel conditions can buffer the effects of local or synoptic weather conditions (see Taylor et al. 2016, Swetnam et al. 2016, and Roos et al. 2022). For example, wind speeds across our 17 wildfires were generally higher in reburned patches compared to first-entry fire patches, yet fire severity was lower. Povak et al. (2020a) found comparable results when evaluating drivers of severity across the 2013 Rim Fire in Yosemite National Park. There, plume-driven spread was dampened once the fire reached the Park, which had experienced recent wildfires and much prescribed burning. Taken together, the strength of bottom-up controls within reburned patches can reduce the importance of other key variables associated with severe fire behavior and are outside the control of suppression crews (e.g., fire weather), and this effect can operate across multiple scales.

Within reburned areas, the strongest spatial controls were provided by large recently reburned patches (< 3 years' time since fire). Within our study area, Cansler et al. (2022) also found that prior fires moderated subsequent fire severity for up to 16 years, and that the

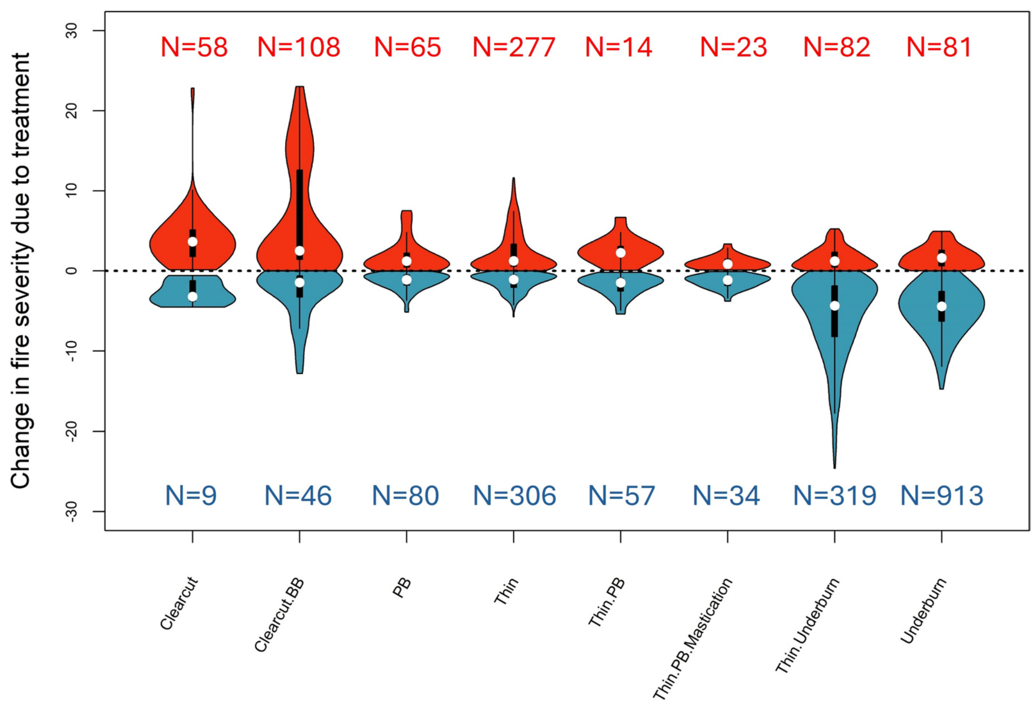

Fig. 10 Violin plots representing the relative change in fire severity, as depicted by the relative burn ratio by fuel treatment type, ordered L to R by increased treatment severity from intensive clearcut treatments to thinned and underburned treatments. Violin plots were developed separately for cells that exhibited increases in fire severity related to treatments (red plots) and those that exhibited reductions in fire severity (blue plots). Cell counts that contributed to higher or lower severity are presented at the top and bottom of each plot. Acronyms are: BB—broadcast burn, and PB—pile burn

probability of future high-severity fire was negatively correlated with the severity of a prior fire. Similarly, Prichard et al. (2020) found that past wildfires and prescribed burns mitigated fire severity even within extreme fire weather progression days in the 2014 Carlton Complex fire. However, the strength of feedbacks provided by prior burns varies greatly across regions and over time (Taylor et al. 2022; Lydersen et al. 2014; Povak et al. 2020a; Parks et al. 2014a; Harvey et al. 2016; Prichard et al. 2020; Davis et al. 2024). Examples of positive feedbacks (i.e., high severity begets subsequent high severity) were prevalent in large burns in the central Sierra Nevada Mountains in California due to either the re-accumulation of surface fuel loads or the dominance of shrublands in the post-fire landscape (Povak et al. 2020a; Taylor et al. 2022; Davis et al. 2024). However, some burned areas constrained fire spread where previous burns were more recent (< 10 year), and where fire weather was moderate (Collins et al. 2009). Harvey et al. (2016) also reported a negative feedback to severe fire among recent burns in low- and mid-elevation forests of the US Northern Rocky Mountains, but as intervals increased between fires (> 10–12 year), a positive feedback emerged. Similar results have been reported elsewhere around the western US (Buma et al. 2020).

Parks et al. (2018b) used NDMI as a surrogate for live fuel loads and found that along with NDVI and EVT, fuels were the main determinant of high-severity fire across most regions in the western USA. In our study, whether a first-entry fire or a reburn, the level and connectivity of fuels provided consistent spatial control on fire severity. We used NDMI as a measure of both vegetation moisture stress and live fuel abundance (McDonald et al. 1998). Our results corroborate those of Parks et al. (2018b), and we further illustrate the primacy of fuel load spatial controls on fire severity for the eastern Cascade Mountain region. NDMI was significantly lower in reburns (mean: 0.093 ± 0.16), compared with first-entry fires (mean: 0.239 ± 0.13) and severity was consistently lower for areas where NDMI was < 0.

Local importance of predictor variables

RF models of fire severity can accommodate complex relations among covariates. However, past research shows that reliance on global variable importance can obscure the influence of fine- to meso-scale bottom-up controls on fires (Povak et al. 2020a; Prichard et al. 2021; Moritz et al. 2011). This is particularly true where bottom-up controls exist with low representation on the landscape. The local Shapley importance measures derived from the global first-entry and reburn models were effective at showing the influence of each predictor variable on fire severity at fine spatial scales.

Classification tree analysis provided insight into the conditions that were associated with fire-severity patterns, which were illustrated by the local importance maps. In first-entry fires in mid- and high-elevation mixed-conifer forests (i.e., low moisture deficit), fires tended to burn at high-severity due to their species composition (owing to thin-barked tree species and relative lack of fire resistance), high canopy density conditions, and multi-layered canopies. However, in dry and moist mixed-conifer environments, the Shapley local importance results suggested that strong bottom-up controls were provided by topography, fuel loads, and their connectivity. Among the biophysical controls, only the highest wind gust speeds (> 15 $m \cdot s^{-1}$) and steepest slopes (> 25%) were consistently associated with higher fire severity. These results suggest a key role for fuels driving severity patterns, particularly in mid- to low-elevation conifer forests.

Reburns are an essential component of returning the active role of fire to these landscapes (Povak et al. 2023); however, the interval between fires is a main determinant of ecological outcomes. Some short-interval fires can cause undesired transitions to alternative states or compositions depending on the post-fire fuel and vegetation successional trajectory (Harvey et al. 2016; Hayes and Buma 2021; Povak et al. 2023). Prolonged periods between fires often allow for the accumulation of surface and canopy fuels as the impress of prior fires wanes on the landscape. In our study, high fuel loads (NDMI ≥ 0.26) in reburns were associated with some of the highest subsequent fire severities. Interestingly, the median time-since-fire for these cells was 14 years, which corresponds well with the longevity of past reburns found by Cansler et al. (2022) and Davis et al. (2024). Their results and ours show that biomass accumulation over this period steadily increases, as does the rising likelihood of high-severity fire, and suggest a "shelf life" for treatments in this region. Similarly in our study, when only treated areas were analyzed, those treated < 10 years prior to the fire exhibited relatively low fire severity compared to areas experiencing a greater lag since treatment (Fig. S5).

Along with frequency, the size of reburn patches was also a strong determinant of fire severity. Distance to reburn edge was the strongest predictor of fire severity in our study; larger reburn patches contributed more bottom-up spatial control than smaller patches, indicating that treatments with large interior core area were more effective at mitigating fire severity. However, a balance is needed between the size of most wildfire and treatment patches and their severity (Harvey et al. 2023; Steel et al. 2022). Large high severity patches may prolong conifer forest recovery due to the protracted distances conifer seeds must travel to naturally regenerate (Littlefield 2019; Haffey et al. 2018; Povak et al. 2020b; Davis et al. 2023).

Topography can act as a direct influence on the spread and severity of wildfires (e.g., convective heating on steep slopes, Povak et al. 2018), and an indirect influence (e.g., variability in vegetation types and fuel loads on north vs south aspects, Parks et al. 2018b). Slope steepness was the only topographic variable selected in classification trees of fire severity drivers. Other studies have found strong controls provided by topography, but as Parks et al. (2018b) discuss, many of those studies did not directly incorporate fuel variables, and therefore topography may have acted as a proxy for the spatial variability in fuel loads across topographic gradients.

Management implications

The strong dependence of fire severity on the amount and contagion of fuels suggests that evidence-based fuel treatments and wildland fire management can play an important role in reducing the spread and severity of future wildfires. These findings are also supported by a growing body of literature on repeat fires and vegetation dynamics (Prichard et al. 2017; Parks et al. 2018b; Povak et al. 2023; Urza et al. 2023). In our work, we found that forest thinning followed by underburning reduced fire severity even during extreme progression days. Within treatment areas, the lowest severities occurred where live fuels were less abundant and moisture stress was low, and where canopy base heights (CBH) were ≥ 1.3 m. This suggests that fire severity was not only influenced by the quantity of live fuels, but also by their horizontal and vertical distribution.

Our results corroborate the findings of Cansler et al. (2022), who found that forest fuel treatments that included prescribed burning were most effective at mitigating future fire severity relative to thinning alone. In addition, we found that clearcutting generally led to higher subsequent fire severity. These results suggest that slash concentrations were inadequately reduced by broadcast burning after harvests. Where clearcut treatments with or without broadcast burning were located within large, high-severity burn progressions, they were less effective at reducing fire severity. For example, within the 2015 Lime Belt fire, a large network of past management treatments was located within a patch of high-severity fire (Fig. 5, SW portion).

Conclusions

We used machine learning with local variable importance measures to identify the influence of top-down and bottom-up drivers of fire severity for 17 large fires that burned across two consecutive region-wide fire years in the eastern Cascade Mountains and Okanogan Highlands of Washington State. Our results provide strong evidence to counter two emerging narratives regarding wildfire in wNA. First, although top-down effects were important, climatic gradients and fire weather were not always the primary influence on wildfire behavior. Models that incorporated the local importance of predictor variables identified conditions under which bottom-up factors were influential in regulating fire severity. Results showed that fuels were a central factor driving fire severity patterns—a result that can be obscured by looking solely at global statistics of variable importance. While severe wind speeds and fire weather conditions increased severity, actual fire severity was dependent on bottom-up factors that influenced available fuels for burning. Second, our study provides empirical support for the efficacy of ecological forest management for restoring resilience and building climate-adapted forested landscapes in the interior Pacific Northwest. Treatments were most effective where they reduced the amount, distribution, and connectivity of surface and canopy fuels. In particular, those that included mechanical thinning followed by prescribed burning appeared to be most effective, even under extreme fire progression days. As with other studies (see Kalies and Kent 2016, Prichard et al. 2021, and McKinney et al. 2022 for reviews), we showed that fuel reduction treatments were effective at mitigating fire spread and severity, and our results support their broader use to meet fire and forest management goals.

Supplementary Information

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Supplementary Material 1.

Authors' contributions

NAP—conception, data development, analysis, writing, editing; SJP – conception, data development, writing, editing; PFH—conception, writing, editing; VG—analysis, figures, data development; RBS—data development; TJF—graphics, analysis; GC—analysis; RWG—conception.

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Data availability

Relevant code and data are provided as private-for-peer review via the following link: https://osf.io/hprwz/

Declarations

Ethics approval and consent to participate

Not applicable. The findings and conclusions in this publication are those of the author(s) and should not be construed to represent any official USDA or U.S. Government determination or policy.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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