

An interpretable remote sensing–machine learning framework for wildfire soil burn severity prediction in the northwestern United States

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Received: 30 December 2025

Accepted: 14 June 2026

Published: 4 August 2026

Cite this: Das S *et al.* (2026) An interpretable remote sensing–machine learning framework for wildfire soil burn severity prediction in the northwestern United States. *International Journal of Wildland Fire* **35**, WF25295. doi:10.1071/WF25295

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ABSTRACT

Background. Although soil burn severity (SBS) is traditionally mapped post-fire, pre-fire predictive approaches remain limited despite their potential to identify areas at risk of soil degradation, runoff and erosion. **Aim.** To develop a large-scale model for predicting post-fire SBS from pre-fire conditions at ~30 m spatial resolution. **Methods.** A harmonized dataset of 62 wildfires (2018–2024) was used to build machine learning (ML) frameworks based on Random Forest, eXtreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM), using pre-fire vegetation, climate, soil–terrain and anthropogenic predictors. Performance was evaluated using five-fold cross-validation (CV), leave-one-fire-out (LOFO) validation and independent testing on 2025 fires. **Key Results.** All models showed similar CV overall accuracy (OA ~0.58), but LOFO performance varied. LightGBM maintained more consistent OA (0.51–0.58) across fire size classes, whereas XGBoost and Random Forest exhibited comparable performance. Key predictors included vegetation biomass (Normalized Difference Moisture Index, Enhanced Vegetation Index), fuel stress (Evaporative Stress Index, Evapotranspiration), elevation and soil moisture. High SBS was associated with dry conditions and high biomass availability, with region-specific controls modulating these patterns. **Conclusion.** ML models using pre-fire environmental data enable proactive SBS prediction. **Implications.** This framework supports fuel management planning, potential post-fire hydrological impact assessment and the prediction of SBS from pre-fire conditions.

Keywords: Landsat, LightGBM, machine learning, proactive fire prevention, pre-fire environmental conditions, remote sensing, soil burn severity prediction, U.S. Pacific Northwest, wildfire risk assessment.

Introduction

Wildfires are one of the most pervasive natural disturbances globally, burning an estimated 350–450 million ha annually, and increasingly reshaping ecosystems, carbon cycles and human livelihoods (Bowd *et al.* 2019; Jones *et al.* 2022; Gajendiran *et al.* 2024). Fire regimes have intensified under climate change, with rising temperatures, prolonged droughts and shifting land-use patterns driving more frequent, larger and more severe fires (Dennison *et al.* 2014; Abatzoglou and Williams 2016; Liu *et al.* 2021; Wasserman and Mueller 2023; He *et al.* 2025).

In the US, wildfire activity has more than doubled over the past four decades, with the western US experiencing the highest increases in burned area and severity (Westerling 2016). Annual burned area increased from approximately 1.0 million ha in the 1980s to about 3.0 million ha during 2021–2025, largely driven by human-induced climate change (Wasserman 2020; National Interagency Coordination Center 2025). Even more striking, the area burned at high severity in the western US increased nearly eightfold between 1985 and 2017 (Parks and Abatzoglou 2020). The record-breaking

2020 wildfire season burned more than 4.1 million ha in US and caused damages exceeding \$20 billion (Smith 2020).

While trends in fire frequency and size are well documented, less attention has been devoted to fire severity, particularly soil burn severity (SBS), which is critical for understanding post-fire ecological and hydrological impacts (Robichaud 2000; Vieira *et al.* 2015; Parks and Abatzoglou 2020). SBS represents the degree of soil and ground surface changes caused by fire, including effects on ash loads, soil structure, organic matter consumption and water repellency (Robichaud *et al.* 2007). It is commonly classified into discrete categories (e.g. unburned, low, moderate and high), reflecting increasing levels of soil heating and ecological alteration and corresponding post-fire soil and vegetative conditions (Parsons *et al.* 2010). Low SBS is characterized by partial consumption of fine fuels, and minimal soil disturbance (Kolden 2019; Wu *et al.* 2023). Moderate SBS is characterized by 50–80% loss of organic cover, partial alteration of soil structure and potential soil water repellency, although water can still infiltrate (Girona-García *et al.* 2021). High SBS reflects prolonged heating, near-complete loss of organic layers, reduced infiltration and delayed recovery, leading to increased post-fire runoff and erosion (Moody *et al.* 2013; Vieira *et al.* 2015), ecosystem disruption (Keeley 2009; Lewis *et al.* 2017), water quality degradation (Neris *et al.* 2021; Robichaud and Padowski 2024), and risks to downstream infrastructure and human safety (Calkin *et al.* 2014).

In the US, SBS is operationally mapped by Burned Area Emergency Response (BAER) teams led by the US Forest Service (USFS), US Department of Interior and partner agencies following wildfire events. These assessments are based on initial Burned Area Reflectance Classification (BARC) products generated from pre- and post-fire multi-spectral imagery (primarily Landsat and, more recently, Sentinel-2) using satellite-derived indices such as the differenced Normalized Burn Ratio (dNBR) or its relativized form (RdNBR) (Miller and Thode 2007; Miller *et al.* 2009; Wilson and Prentice 2024). BARC maps provide a rapid, preliminary, remotely sensed estimate of burn severity, which is subsequently refined by BAER teams through field-based evaluation of soil burn indicators, including organic layer consumption, ash characteristics, soil structure alteration and water repellency, to produce final classified SBS maps following standard protocols (Parsons *et al.* 2010; Robichaud 2023). While this workflow provides spatially explicit and field-informed classified SBS maps, it remains inherently retrospective and dependent on post-fire field data availability (Hudak *et al.* 2007).

Post-fire hazard assessments, including debris-flow and soil erosion modeling, rely fundamentally on SBS because it controls key surface and hydrologic changes after wildfire (Wells *et al.* 2023). In particular, SBS is a critical input in post-fire hazard assessments, including BAER analyses,

where it helps identify areas of elevated runoff and erosion potential that are highly susceptible to debris flows and landslides (Gartner *et al.* 2014; Moody *et al.* 2016; McGuire *et al.* 2024). However, this reliance on SBS makes such assessments inherently reactive, limiting pre-fire preventative planning (Staley *et al.* 2018; Chamberlain *et al.* 2024; Rossi *et al.* 2025; Penot *et al.* 2025).

Several tools and platforms, such as FlamMap, FARSITE (Fire Area Simulator), ArcFuels and LANDFIRE, simulate fire behavior and potential burn scenarios but do not directly estimate SBS (Finney 1998, Finney 2006; Ager *et al.* 2011; Ryan and Opperman 2013; La Puma IP 2023). Similarly, datasets such as the Wildfire Hazard Potential (WHP) and hazard products available through the Fire Research and Management Exchange System (FRAMES) (Parks *et al.* 2018) provide probabilistic representations of burn severity but do not explicitly represent SBS. Prediction of SBS remains limited due to the complex, indirect, and poorly constrained relationship between pre-fire conditions and post-fire responses (Jian *et al.* 2018).

The increasing availability of machine learning (ML), along with advances in remote sensing and computational capacity, offers significant potential to overcome aforementioned limitations through two pathways: (i) improving post-fire SBS mapping using satellite-derived indices and ML trained on limited field data, reducing reliance on extensive field validation and manual refinement, and (ii) enabling direct prediction of SBS from pre-fire conditions, supporting pre-fire assessment of potential burn severity (Fernández-Alonso *et al.* 2019). Most existing approaches focus on the first pathway, where ML models are trained using satellite-derived indices such as dNBR, RdNBR and Blue Normalized Difference Vegetation Index (BNDVI), along with reference SBS data from field observations or BAER-mapped products, to learn relationships with SBS and subsequently generate spatially continuous SBS maps (Wilson and Prentice 2024; Esposito and Famiani 2025; Novo *et al.* 2025). These data-driven ML models effectively capture complex, nonlinear relationships between spectral responses and SBS, thereby improving spatial prediction with limited dataset (Seydi *et al.* 2024).

In contrast, only a limited number of studies have explored the direct prediction of SBS from pre-fire environmental conditions that can provide critical information prior to wildfire occurrence to improve understanding of hydrological responses, support proactive post-fire hazard assessments and inform ecologically sustainable fuel management (Dobre *et al.* 2017; Miller *et al.* 2024). Pre-fire environmental conditions, including climatic conditions, vegetation and fuel characteristics, topographic attributes, soil properties and anthropogenic influences, affect fuel moisture, fuel availability, fire behavior and soil heating processes, thereby influencing burn severity outcomes (Holden and Jolly 2011). ML models have demonstrated strong performance in burn severity prediction (e.g.

BARC classes or dNBR-based metrics) by integrating satellite-derived pre-fire indices with environmental conditions (Estabrook *et al.* 2025; Klimas *et al.* 2025; Pascolini-Campbell *et al.* 2025; Penot *et al.* 2025), yet their application for direct SBS prediction from pre-fire conditions remains limited.

To address these gaps, this study develops a scalable, data-driven framework for predicting SBS directly from pre-fire conditions across the US Pacific Northwest. Leveraging a dataset of 62 historical wildfires (2018–2024) and ML models (Random Forest, eXtreme Gradient Boosting and Light Gradient Boosting Machine), we present one of the first large-scale efforts to proactively predict SBS under existing fuel and climatic conditions, bridging the gap between post-fire mapping and forward-looking risk assessment. The specific objectives are to: (1) develop models to predict SBS from pre-fire environmental conditions; (2) evaluate the ability of ML models to perform on independent fire events not used in training and across different landscapes and environmental conditions; and (3) interpret the relationships between SBS and pre-fire environmental conditions across the region.

Study area

This study focuses on wildfire-prone landscapes of the US Pacific Northwest, specifically Washington and Oregon, encompassing the Cascade Range and adjacent ecoregions (Environmental Protection Agency Level III) (Wiken *et al.* 2011) (Fig. 1). Climate in this region follows a pronounced west–east orographic gradient, where cool and wet maritime conditions west of the Cascade crest transition to warmer, drier interiors to the east. In Köppen–Geiger terms, the west side is predominantly Csb/Cfb (warm-summer Mediterranean/marine temperate), Montana belts are Dsb/Dfb (dry-summer continental), the interior plateaus and basins are largely BSk (cold semi-arid) and the highest elevations grade into Dfc/ET (subalpine/alpine) (Beck *et al.* 2018). Elevation ranges from sea level in the coastal lowlands to nearly 4300 m at Cascade summits, with foothills at approximately 300–1200 m. Vegetation ranges from wet, west-side conifer forests (Douglas-fir *Pseudotsuga menziesii*, western hemlock *Tsuga heterophylla*) to drier, east-side forests (ponderosa pine *Pinus ponderosa*, mixed conifer) and large areas of sagebrush and grassland; high elevations are predominately subalpine fir (*Abies lasiocarpa*) and alpine meadows, as mapped by LANDFIRE (Rollins 2009). Geologically, the Cascade Range includes young Quaternary volcanic rocks with extensive tephra and pumice near the major volcanic peaks, while the lower and western parts of the range are underlain by older, more deeply weathered volcanic and volcanoclastic formations. East of the crest, the terrain transitions to thick Miocene Columbia River Basalt flows locally mantled by wind-blown loess, whereas

the west-side lowlands and the Coast Range consist mainly of marine sandstones, siltstones, and Quaternary alluvial and glacial deposits (Hammond 1979; Wells *et al.* 2009).

Data and methods

Data sources

The list of datasets and variables used in this study for SBS prediction is summarized in Table 1. USFS-BAER teams produce SBS maps, often using 20 m Sentinel-2 or 30 m Landsat imagery, to categorize fire impacts. These classified maps (often derived from field-adjusted BARC maps) map severity into four classes: unburned, low, moderate and high. SBS maps for 62 wildfires in the US Pacific Northwest (2018–2024) were used for model development (training and testing), while four wildfires from 2025 were used for independent model testing. All maps were obtained from the USFS-BAER archive (see Table S1 in the Supplementary Material for official fire names). Pixels corresponding to the low, moderate and high severity classes (2–4) were used as the response variable (see Supplementary Material).

Pre-fire vegetation and surface-condition information were derived from US Geological Survey (USGS) Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) Collection 2 Level-2 30 m surface reflectance data (EROS 2013), including spectral indices and snow indicators. Additional soil moisture and energy-related variables were obtained from ECOSystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS L4; 70 m) products. Land-cover data was acquired from USFS Landscape Change Monitoring System (LCMS version 2024.10; 30 m; Google Earth Engine asset: USFS/GTAC/LCMS/v2024-10) for contiguous US (CONUS) by extracting land-cover classes and a one-year pre-fire land-cover change indicator to capture recent disturbance.

Topographic variables were derived from the USGS Shuttle Radar Topography Mission (SRTM) 1-arc-second Digital Elevation Model (DEM), and soil physical and hydraulic properties were obtained from the 30 m POLARIS (Probabilistic Remapping of Soil Survey Geographic Database (SSURGO); Chaney *et al.* 2016) database. Climate data combined event-scale pre-fire meteorological information from Gridded Surface Meteorological Dataset (GridMET; ~4 km; 1979–present; Abatzoglou 2013) with longer-term pre-fire climatology from the Daily Surface Weather and Climatological Summaries (Daymet v4; ~1 km; Thornton *et al.* 2022), complemented by 30 m spatial-resolution pre-fire wind fields generated using WindNinja simulations (Forthofer *et al.* 2014). Notably, wind speed and direction for the week preceding each fire were simulated in WindNinja using data from the nearest available weather station within the software.

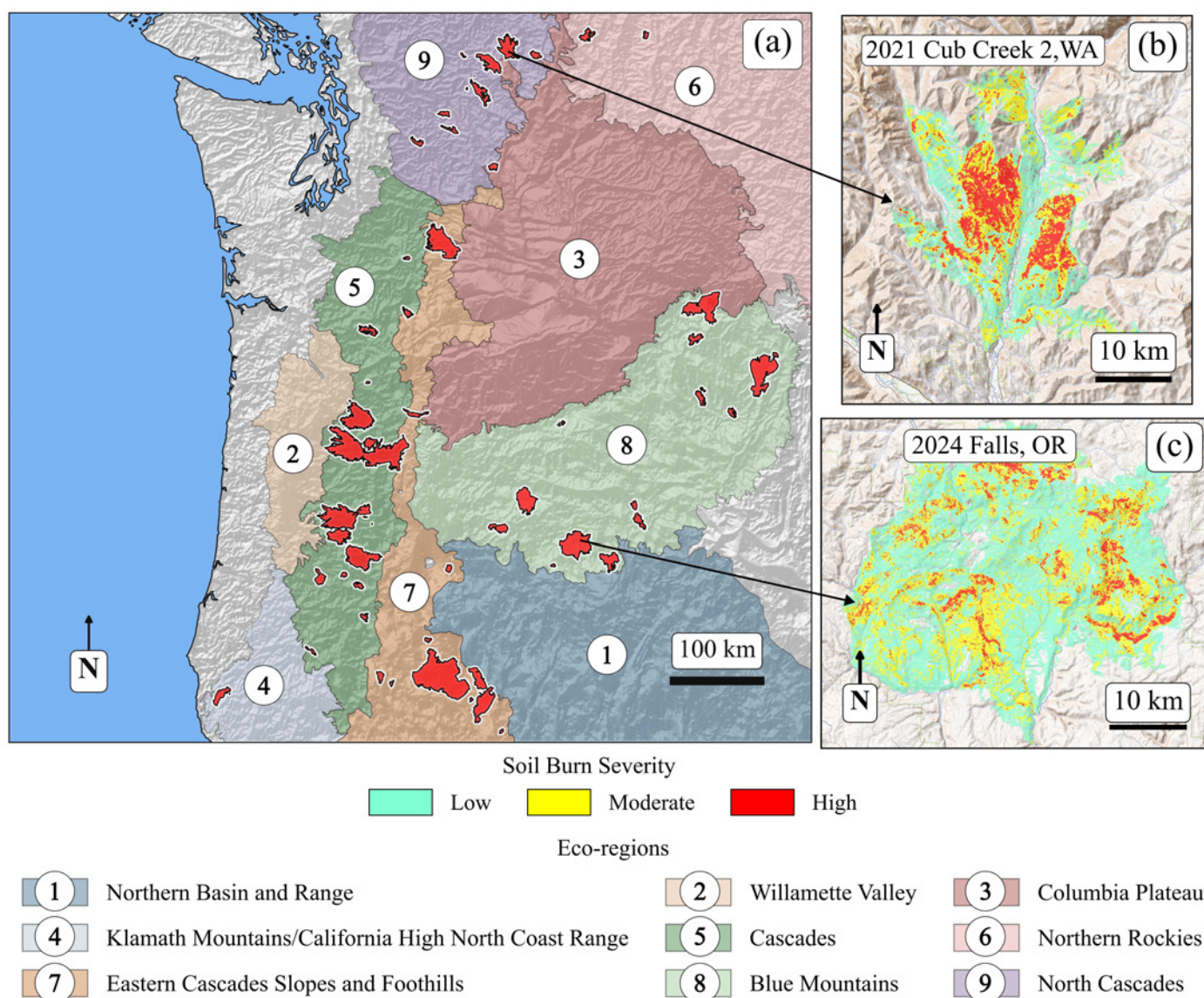


Fig. 1. (a) Location of the study area and fire boundaries of the 62 selected historical fires (red fill with black perimeters). Two soil burn severity (SBS) classified maps are also shown as examples: (b) the 2021 Club Creek 2 Fire in Washington (WA) and (c) the 2024 Falls Fire in Oregon (OR).

Anthropogenic influences were represented using Euclidean distance (m) to roads (US Census Bureau 2019), streams and waterbodies (National Hydrography Dataset; US Geological Survey 2019), populated localities (Dewitz 2024) and ignition points or lightning strikes (IRWIN; accessed 12 September 2025). These distance-based variables serve as proxies for human activity and infrastructure, influencing ignition and fire behavior, and thus wildfire occurrence and the resulting SBS (Ghorbanzadeh et al. 2019; He et al. 2022; Horn et al. 2025). Prior burn history was derived from Monitoring Trends in Burn

Severity (MTBS) mosaics, considering any burn class (2–4) between 1984 and the year preceding ignition (MTBS 2025); approximately 13% of the analyzed burned area had experienced prior burning.

All datasets underwent quality screening to remove no-data pixels, including cloud and shadow masking for remote sensing products, reprojection to a common coordinate reference system (NAD83/Conus Albers Equal Area; EPSG:5070), spatial harmonization to a 30 m grid and clipping to individual fire perimeters. Detailed descriptions of preprocessing, pre-fire composite construction, variable

Table 1. List of compiled datasets and variables used in the study for soil burn severity (SBS) prediction.

Dataset	Primary variable	Derived variable/metrics	Spatial resolution	Data source
Burned Area Emergency Response (BAER) imagery support data	SBS classes (high, moderate, low)	–	20–30 m (resampled to 30 m)	https://burnseverity.cr.usgs.gov/baer/
Landsat 8	NIR, blue, red, SWIR1	NDVI, EVI, NDMI (3 month) and NDSI (6 month) pre-fire composites/anomalies	30 m	https://landsat.gsfc.nasa.gov/satellites/landsat-8/
ECOSTRESS	ESI, ETa, SM	3 month pre-fire composites and anomalies	70 m (resampled to 30 m)	https://ecostress.jpl.nasa.gov
Landscape change monitoring system	Land cover types, land cover change	One-year pre-fire land cover and disturbance/change	30 m	https://developers.google.com/earth-engine/datasets/catalog/USFS_GTAC_LCMS_v2024-10
Shuttle Radar Topography Mission (SRTM)	Elevation	Slope, aspect, TRI and TPI	30 m	https://www.earthdata.nasa.gov/data/instruments/srtm
POLARIS	Silt, sand, clay, bd, theta_s, theta_r, Ksat, pH, OM, lambda, hb, n, alpha	Plant-available water (PAW)	30 m	http://hydrology.cee.duke.edu/POLARIS/
GridMET	Pr, rmax, rmin, tmmx, tmmn, bi, fm100, fm1000, sph, vpd	3 month pre-fire composites	~4 km (downscaled to 30 m)	https://www.climatologylab.org/gridmet.html
Daymet	Dayl, prcp, srad, tmax, tmin, vp, swe	Long-term (1994–year before fire) climatologies	~1 km (downscaled to 30 m)	https://daymet.ornl.gov
WindNinja	–	Wind speed, wind direction	30 m	https://github.com/firelab/windninja-website
Anthropogenic variables	–	Dist_roads, Dist_locality, Dist_lightning, Dist_water, Dist_streams, Fire_history	30 m	https://developers.google.com/earth-engine/datasets/catalog/TIGER_2016_Roads https://gee-community-catalog.org/projects/nhd/ https://mtbs.gov https://www.wildfire.gov/application/irwin-integrated-reporting-wildfire-information

Fire_history: binary indicator of previous fire occurrence; Dayl: day length ($s\ day^{-1}$); Dist_lightning: distance to lightning/ignition (m); Dist_locality: distance to built-up/populated locality (m); Dist_roads: distance to roads (m); Dist_streams: distance to streams/rivers (m); Dist_water: distance to waterbodies (m); ESI: Evaporative Stress Index; ETa: Evapotranspiration daily; EVI: Enhanced Vegetation Index; Ksat: saturated hydraulic conductivity; NDMI: Normalized Difference Moisture Index; NDSI: Normalized Difference Snow Index; NDVI: Normalized Difference Vegetation Index; NIR: Near-infrared reflectance; OM: organic matter; Pr: precipitation ($mm\ day^{-1}$); SM: Surface Soil Moisture; SWIR1: Shortwave infrared band 1 reflectance; TPI: Topographic Position Index; TRI: Topographic Ruggedness Index; alpha: scale parameter inversely proportional to mean pore diameter (van Genuchten); bd: bulk density; bi: burning index; fm100: 100 h dead fuel moisture (%); fm1000: 1000 h dead fuel moisture (%); hb: bubbling pressure (Brooks–Corey); lambda: pore size distribution index (Brooks–Corey); n: pore-size distribution shape parameter (van Genuchten); pH: soil pH in H_2O ; prcp: precipitation ($mm\ day^{-1}$); rmax: maximum relative humidity (%); rmin: minimum relative humidity (%); sph: specific humidity; srad: shortwave radiation ($W\ m^{-2}$); swe: snow water equivalent ($kg\ m^{-2}$); theta_r: residual volumetric water content; theta_s: saturated volumetric water content; tmax: daily maximum air temperature ($^{\circ}C$); tmin: daily minimum air temperature ($^{\circ}C$); tmmn: daily minimum air temperature ($^{\circ}C$); tmmx: daily maximum air temperature ($^{\circ}C$); vp: vapor pressure (Pa); vpd: vapor pressure deficit (kPa).

derivation, temporal aggregation, anomaly calculation and downscaling are provided in the Supplementary Material.

Machine learning (ML) models

SBS predictive mapping was framed as a supervised multi-class classification problem (low, moderate, high). Predictors included vegetation/moisture indices, evapotranspiration, terrain, soil, climate and anthropogenic distances; aggregation and anomaly derivation yielded 162 variables per fire at

30 m spatial resolution. Given this high-dimensional predictor set, we implemented a combined approach of correlation analysis and recursive feature elimination (RFE) to reduce dimensionality and multicollinearity (Fig. 2) (Pham *et al.* 2022), rather than methods such as Principal Component Analysis (PCA) and Boruta, which are computationally intensive and may reduce interpretability by combining predictors into composite features (Jolliffe and Cadima 2016).

A Spearman rank correlation analysis (Spearman 1987) was first conducted to identify highly correlated

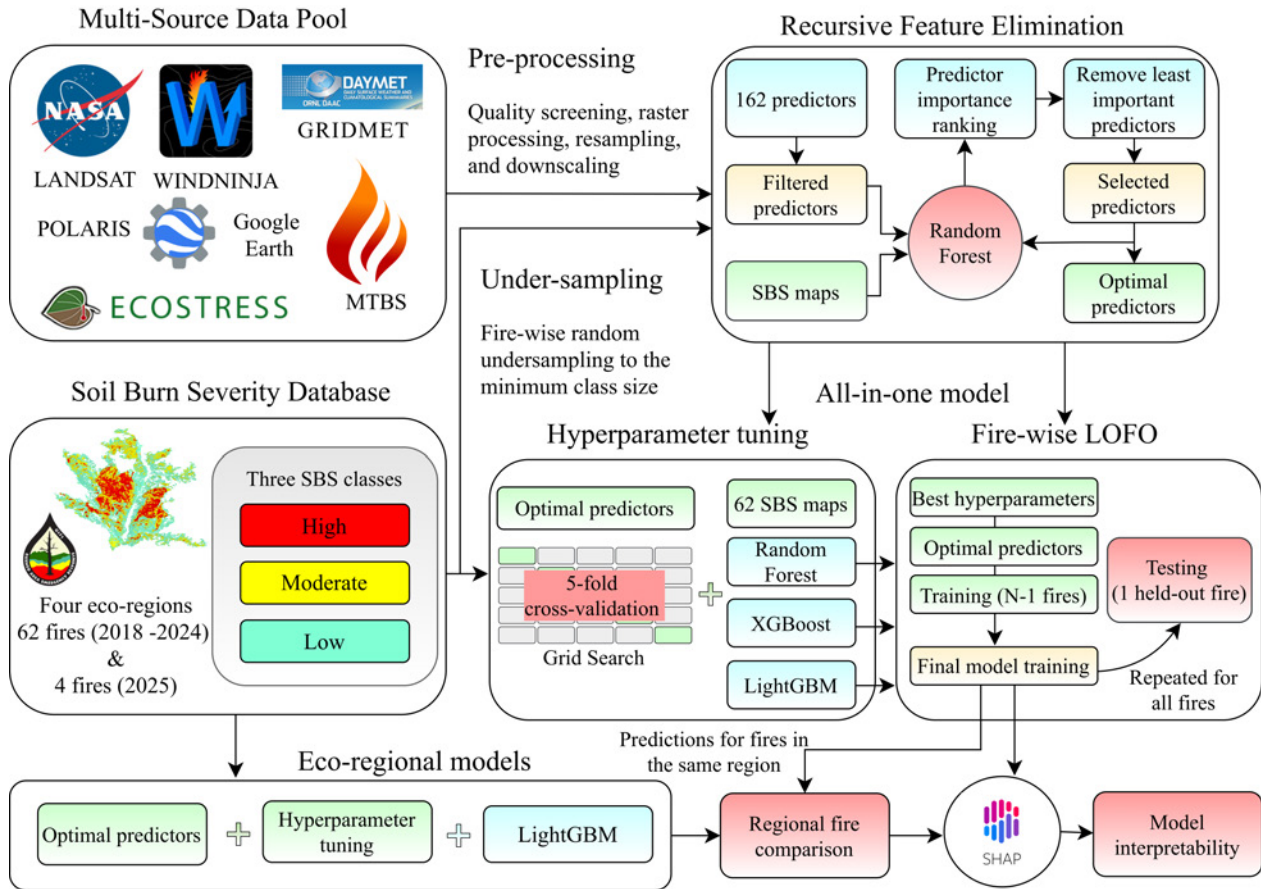


Fig. 2. Workflow used for soil burn severity (SBS) prediction and model interpretation. LOFO: leave-one-fire-out; LightGBM: Light Gradient Boosting Machine; XGBoost: eXtreme Gradient Boosting.

predictors. Variables with a correlation coefficient ($\rho > 0.85$) were considered redundant, and one representative variable from each correlated group was retained based on domain relevance and support from the literature (Dos Santos *et al.* 2023). This process reduced the predictor set to 47 quantitative variables, while three categorical variables were retained without correlation filtering and subsequently one-hot encoded (i.e. binary indicator variables representing each category) prior to model training. Subsequently, RFE was applied, removing 10% of predictors at each iteration using a Random Forest (RF) model, with variables ranked based on the importance of Gini impurity-derived feature (Strobl *et al.* 2007, see Supplementary Material). RF, a bagging-based ensemble model, constructs multiple decision trees using bootstrap sampling and aggregates their predictions to reduce variance and improve generalization (Breiman 2001; Collins *et al.* 2018). During the RFE stage, the model performance was evaluated using five-fold cross-validation (CV), with folds defined at the fire level (i.e. each fire assigned to a single fold) to avoid distributing pixels from the same fire across folds (Guyon and

Elisseff 2003). The folds were balanced to maintain comparable sample sizes; when necessary, data from multiple fires were combined within a fold to achieve this balance. An optimal fixed set of predictors was selected based on feature stability and CV performance, and this set was used for all subsequent model training and prediction.

To capture complex relationships between environmental conditions and SBS classes and to enable prediction in new regions, we implemented and compared three ensemble learning algorithms, RF, eXtreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) (Chen *et al.* 2014; Ke *et al.* 2017; see Supplementary Material). Notably, XGBoost and LightGBM are gradient boosting methods that sequentially add trees to minimize a loss function, whereas RF constructs trees independently using bootstrap aggregation. These models are well suited for SBS classification tasks due to their ability to capture complex, non-linear relationships (Novo *et al.* 2025).

During model training, class imbalance was addressed using fire-wise random under-sampling to equalize class sizes, thereby improving sensitivity to minority SBS classes (He and Garcia 2009). Using the optimal predictor set, key

hyperparameters controlling model complexity and regularization were tuned independently for each ML model via a compact grid search with five-fold CV (Probst *et al.* 2018; Ippolito 2022). Similar to the feature selection stage, CV was performed in a fire-wise manner, where each fire was treated as a single unit. Final hyperparameter configurations were selected based on average CV performance to balance bias and variance. Hyperparameter tuning was conducted independently of the leave-one-fire-out (LOFO) validation to ensure unbiased performance assessment.

The final model performance (i.e. using the optimal features and tuned hyperparameters) was evaluated using fire-wise LOFO validation, in which each fire was sequentially held out for testing, and rest were used for training. Performance metrics from all held-out fires were grouped by fire-size classes (small: <5000 ha; medium: 5000–20,000 ha; large: >20,000 ha), with median values used to assess consistency across fire extents. The best-performing (all-in-one) model was selected based on LOFO accuracy across size classes among the three ML algorithms.

To assess the reliability of this generalized approach, the selected all-in-one model was subsequently compared with region-specific LightGBM models trained independently using ecoregion-specific datasets (e.g. North Cascades, Cascades, Eastern Cascades and the Blue Mountains). These regional models were designed to account for local variability in fuels, soils and physiography. For each ecoregion, data from one fire was held out for validation and used to compare the performance of the regional and all-in-one models. The predictive performance of the all-in-one model was further evaluated using recent (2025) wildfires across the western US to assess cross-regional generalization beyond the training domain.

SHAP-based variable importance

The LightGBM classifier, trained on the pooled dataset with fire-wise class balancing, was interpreted using SHapley Additive exPlanations (SHAP; Lundberg and Lee 2017; Das *et al.* 2025). SHAP values quantify the direction and magnitude of each feature's influence, enabling both local (pixel-level) and global interpretation of model behavior. To avoid bias, SHAP values were computed on held-out fires within the LOFO framework and aggregated across folds to generate global beeswarm plots (i.e. distribution of SHAP values across samples for each feature). For computational efficiency, SHAP values were estimated on a stratified subset of samples per fire and severity class. Feature importance was quantified using the mean absolute SHAP value (details in Supplementary Material) (He *et al.* 2024; Klimas *et al.* 2025). Class-specific SHAP values were derived from the multiclass model for each SBS class (low, moderate, high), where positive values indicate an increased likelihood of a class and negative values indicate

a reduced likelihood. The same analysis was applied to region-specific ML models to assess spatial variability in predictor importance across ecoregions.

Accuracy evaluation

Model performance was evaluated at the 30 m pixel level using overall accuracy (OA), along with per-class precision, recall and F1 score. OA represents the proportion of correctly classified pixels across all classes. The F1 score (harmonic mean of precision and recall) provides a balanced measure of class-specific performance, particularly under class imbalance; precision reflects prediction accuracy, while recall reflects the ability to detect true instances (Sokolova and Lapalme 2009; Powers 2020).

To ensure fair comparison across heterogeneous fire sizes and class distributions, we summarized the performance of each fire using (i) OA and (ii) class-wise F1 scores (see Supplementary Material). Relationships between fire size and model performance were evaluated using Spearman's rank correlation. Differences among independent fire size classes were assessed using the non-parametric Kruskal–Wallis test, followed by pairwise Wilcoxon rank-sum tests with Benjamini–Hochberg correction (Kruskal and Wallis 1952; Benjamini and Hochberg 1995).

Ethics

This study did not involve human participants, animal subjects, or identifiable personal data. Therefore, ethics approval was not required.

Results and discussion

Parameter selection and model evaluation

Correlation analysis combined with RFE resulted in an optimal set of 17 predictors. RFE improved model CV performance from an OA of 0.47 (64 predictors, including quantitative and categorical variables) to 0.51 with 17 variables, while further reduction led to a decline in accuracy. The final selected variables and their correlations are available in Supplementary Fig. S1. Notably, a similar set of predictor variables has been found to be effective for SBS prediction in other studies (Seydi *et al.* 2024; Novo *et al.* 2025).

RF, XGBoost and LightGBM exhibited similar CV performance, with OA values around 0.58–0.59, using the optimal hyperparameter settings summarized in Supplementary Table S2. Under LOFO, model performance varied across fire sizes, with LightGBM showing slightly higher median OA for small (0.51) and large (0.58) fires (Table 2). Performance declined relative to CV, likely because CV used an under-sampled dataset, whereas LOFO used all pixels and evaluated all fires sequentially. RF showed the

Table 2. Comparison of machine learning models for predicting soil burn severity (SBS) classes at 30 m resolution. Hyperparameters were optimized using five-fold cross-validation (CV) on class-balanced data, and model generalization was evaluated using leave-one-fire-out (LOFO) validation across all fires and pixels. LOFO results are summarized as median performance across fire-size classes (small, medium, large) and complemented by results from selected individual wildfire events.

Evaluation scheme	Model	Overall accuracy (OA)	F1 score		
			Low	Moderate	High
Five-fold CV	RF	0.59	0.55	0.47	0.72
	XGBoost	0.58	0.56	0.44	0.70
	LightGBM	0.58	0.57	0.43	0.70
LOFO (Median of 29 small size fires)	RF	0.48	0.55	0.42	0.17
	XGBoost	0.50	0.56	0.43	0.14
	LightGBM	0.51	0.58	0.41	0.14
LOFO (Median of 20 medium size fires)	RF	0.56	0.70	0.37	0.17
	XGBoost	0.57	0.67	0.36	0.19
	LightGBM	0.55	0.65	0.38	0.23
LOFO (Median of 13 large size fires)	RF	0.56	0.60	0.47	0.31
	XGBoost	0.55	0.60	0.45	0.31
	LightGBM	0.58	0.59	0.47	0.31
2021 Cougar Peak, OR	RF	0.71	0.72	0.72	0.32
	XGBoost	0.71	0.74	0.71	0.32
	LightGBM	0.72	0.72	0.75	0.33
2021 Black Butte, OR	RF	0.68	0.82	0.21	0.34
	XGBoost	0.65	0.78	0.22	0.31
	LightGBM	0.58	0.72	0.26	0.32
2024 Pioneer, WA	RF	0.55	0.62	0.49	0.41
	XGBoost	0.57	0.66	0.46	0.41
	LightGBM	0.55	0.61	0.52	0.41
2021 Lick Creek, WA	RF	0.65	0.77	0.43	0.14
	XGBoost	0.67	0.79	0.41	0.22
	LightGBM	0.64	0.75	0.47	0.28

LightGBM: Light Gradient Boosting Machine; RF: Random Forest; XGBoost: eXtreme Gradient Boosting.

highest OA (0.57) for medium-sized fires, while LightGBM achieved the highest F1-score (0.23) for accurately predicting high-SBS pixels. Notably, all three models performed similarly in predicting high-SBS ($F1 = 0.31$) classes for large fires; however, OA varied among models.

Building on these observations, fire size emerged as an important control on model performance. OA across individual fires under LOFO showed a positive relationship with fire size (Spearman's $\rho = 0.30$, $P = 0.018$; Supplementary Figs S2 and S3). Median LOFO OA (after averaging across the three models) increased from small (0.49) to medium (0.55) and large fires (0.56), although pairwise differences were limited (Supplementary Table S3). The strongest effect was observed for high-SBS, which showed a significant increase with fire

size ($\rho = 0.43$, $P < 0.001$). Pairwise comparisons confirmed that high-SBS prediction was significantly higher in large fires compared to both small and medium fires (Supplementary Table S4). In contrast, low and moderate SBS exhibited weak or non-significant relationships with fire size, with no consistent pairwise differences among size classes.

Overall, model performance improvements with fire size were primarily driven by better prediction of high-SBS areas, likely because large fires produce more extensive and spatially coherent high-SBS patches, whereas smaller fires are more fragmented and heterogeneous. This is consistent with previous studies showing that burned area detection accuracy increases with fire and patch size, while small and fragmented fires

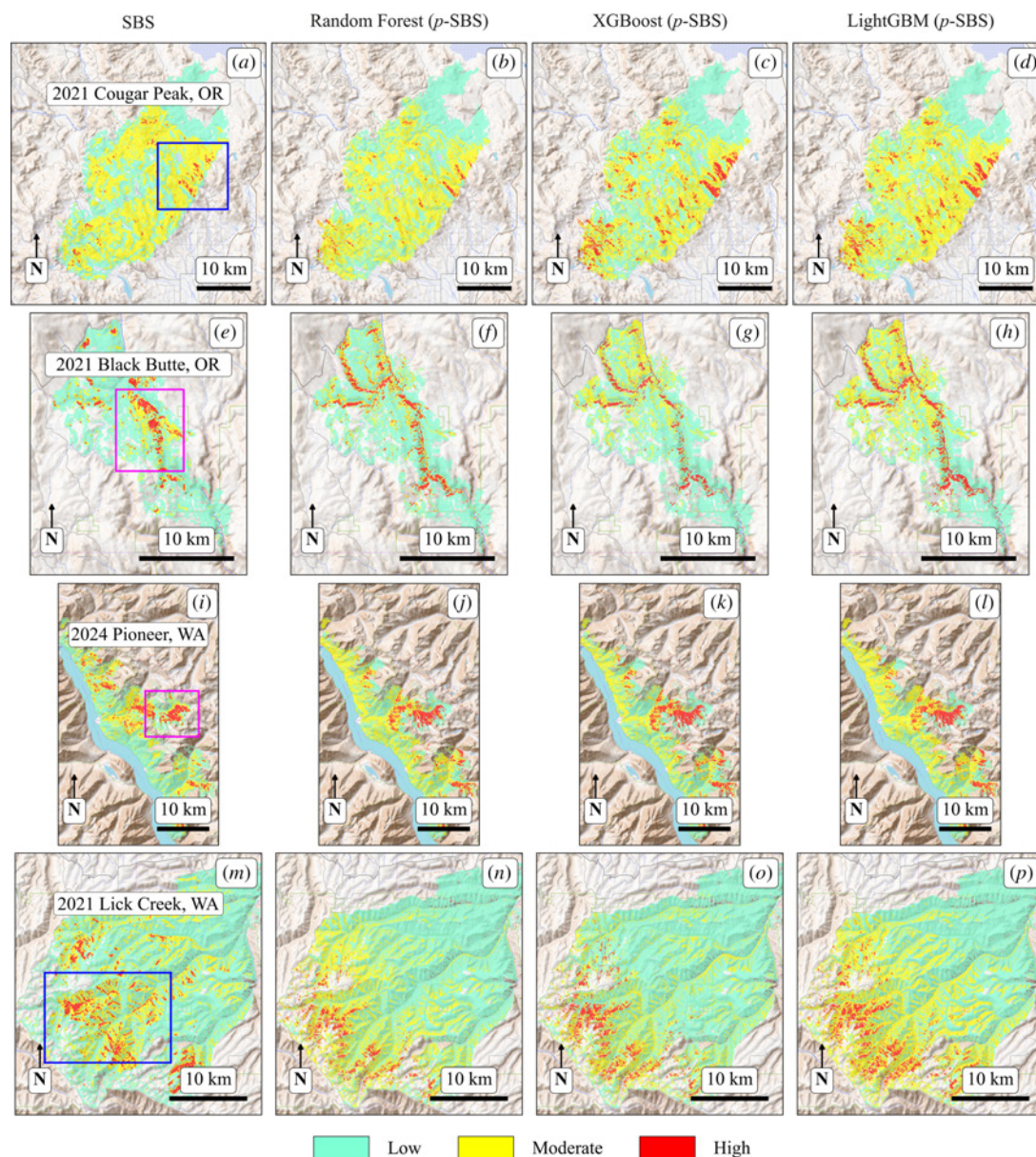


Fig. 3. Field-validated actual soil burn severity (SBS; Burned Area Emergency Response (BAER)-derived) and corresponding predictions (p -SBS) during leave-one-fire-out (LOFO) from Random Forest, eXtreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) models using pre-fire predictors. Panels (a–d) show the 2021 Cougar Peak Fire (OR), (e–h) the 2021 Black Butte Fire (OR), (i–l) the 2024 Pioneer Fire (WA), and (m–p) the 2021 Lick Creek Fire (WA). Blue boxes highlight regions where predictions differ among models and the actual SBS, whereas pink boxes indicate areas where all models consistently identify the same SBS class.

are more difficult to detect and classify (Vanderhoof *et al.* 2017; Franquesa *et al.* 2022).

To further assess model accuracy and spatial patterns, predicted SBS maps during LOFO validation from different models are presented (Fig. 3). All models reproduced broad spatial gradients of SBS across the fires, with high-SBS areas well captured in the 37,000 ha Cougar Peak, 12,000 ha Black Butte and 16,000 ha Pioneer fires, where large,

contiguous burn patches were accurately delineated and consistent with actual SBS maps. In contrast, the 33,000 ha Lick Creek Fire showed localized under- and over-estimation of high-SBS areas, reflected in low high-SBS performance (RF; $F1 = 0.14$), although LightGBM improved this prediction ($F1 = 0.28$). Despite partial reburning of the 2001 Rex Creek Complex within the 2024 Pioneer Fire, high-SBS areas were effectively captured, particularly in

previously unburned regions (Fig. 3i), consistent with its relatively balanced class performance ($F1 = 0.62\text{--}0.41$). Cougar Peak exhibited consistent performance across SBS classes ($F1 = 0.32\text{--}0.72$), while Black Butte showed strong low-SBS detection ($F1 = 0.72\text{--}0.82$) but limited ability to distinguish moderate-SBS ($F1 = 0.21\text{--}0.26$). Overall, low-SBS patterns were consistently captured across fires, while moderate and high-SBS remained more variable and fire-dependent, consistent with previous studies (Hu et al. 2023; Miller et al. 2024) reporting higher classification accuracy for low-severity classes due to their greater spatial extent and more distinct spectral and ecological characteristics.

Furthermore, the three ML models performed similarly under both CV and median LOFO across fire classes, although their performance varied among individual fires. This aligns with broader trends in the literature, where different ML models have been shown to exhibit minimal differences in burn severity classification performance (Reiner et al. 2022; Han et al. 2024). RF remains widely used for handling high-dimensional remote sensing and ecological data and producing robust models, although LightGBM showed marginal improvement (Collins et al. 2018; Potter and Alexander 2022; Seydi et al. 2024). For example, a digital soil mapping study in California reported 48% CV accuracy using RF, outperforming manual federal mapping techniques (Wilson and Prentice 2024). Likewise, the online Continuous US 'Burnsev' (Miller and Billmire 2023) uses pre-fire fuel, terrain and modeled fire behavior variables within a RF framework to predict SBS, achieving 65% overall accuracy. Although all three models showed similar overall performance, LightGBM was selected as the 'all-in-one' model due to its marginally improved accuracy for high-SBS classes.

Regional evaluation of soil burn severity predictions

Regional analysis shows (Fig. 4) both 'all-in-one' (trained across all fires within the LOFO framework) and regional-LightGBM models reproduced the general spatial patterns of actual SBS with comparable OA (Table 3). High-SBS areas were generally well captured in both models, though differences in spatial patterns were observed. The ecoregional LightGBM model for North Cascades and the all-in-one model both tended to overpredict moderate-SBS in the 29,000 ha Cub Creek 2 Fire (marked blue box in Fig. 4a). Conversely, in the 26,000 ha Falls Fire, the Blue Mountains ecoregional LightGBM model better captured localized moderate-SBS patches ($F1 = 0.48$) in the complex terrain (blue box in Fig. 4d) than the all-in-one model ($F1 = 0.27$). For the 70,000 ha Holiday Farm fire, both models successfully captured the large contiguous moderate-SBS swaths along the central valley, although the all-in-one

model slightly underpredicted high-SBS patches adjacent to moderate-SBS zones.

In the 167,000 ha Bootleg Fire, the all-in-one LightGBM model more effectively reproduced the actual moderate-SBS ($F1 = 0.66$) patterns compared to regional LightGBM model for Eastern Cascades (pink box in Fig. 4j). This suggests that models trained on larger, more diverse datasets may outperform regional models when regional training data is limited. However, the improved performance of regional models in most cases can be attributed to their ability to capture region-specific relationships between predictors and SBS, including differences in vegetation composition, fuel structure, topography and climate regimes. Previous studies have shown that accounting for spatial heterogeneity and regional stratification can enhance model accuracy and reduce bias in burn severity applications (Picotte et al. 2021; Reiner et al. 2022). Despite these advantages, both modeling approaches exhibited misclassifications in highly heterogeneous or low signal-to-noise environments, particularly in areas affected by legacy disturbances or canopy regrowth, where spectral and ecological signatures of SBS become less distinct (Miller and Thode 2007). Overall, these results suggest that regional models can provide improved representation of local SBS patterns, whereas all-in-one models offer greater robustness and generalizability across diverse fire regimes.

Prediction for the 2025 fires

Comparisons between predicted SBS (*p*-SBS) from the 'all-in-one' LightGBM model and the corresponding actual SBS maps for the 2025 fires are shown in Fig. 5. The model generally captured the overall spatial gradients of SBS, with high-SBS patches aligning well with actual SBS patterns for the 53,000 ha Gifford Fire and smaller 1300 ha Sunset Fire. However, discrepancies were evident in complex topographic settings, such as the steep canyons of the 13,000 ha Emigrant Fire and 8,000 ha Bear Gulch Fire, where the model tended to overpredict high and moderate-SBS (Fig. 5h).

The quantitative evaluation (Table 3) yielded moderate overall accuracies (0.43–0.65), with $F1$ scores for the high-SBS class ranging from 0.11 to 0.42. The low $F1$ scores for the high-SBS class ($F1 \leq 0.20$) in the Emigrant and Bear Gulch fires suggest that the model struggled to capture extreme burn conditions, whereas the higher $F1$ scores observed in the Gifford and Sunset fires indicate better identification of high-SBS areas.

Notably, the Emigrant Fire largely overlaps with the burn area of the 2009 Tumblebug Fire, and the model accurately delineated many of these re-burn regions (pink box in Fig. 5e), even where substantial vegetation successional growth had occurred across large portions of the

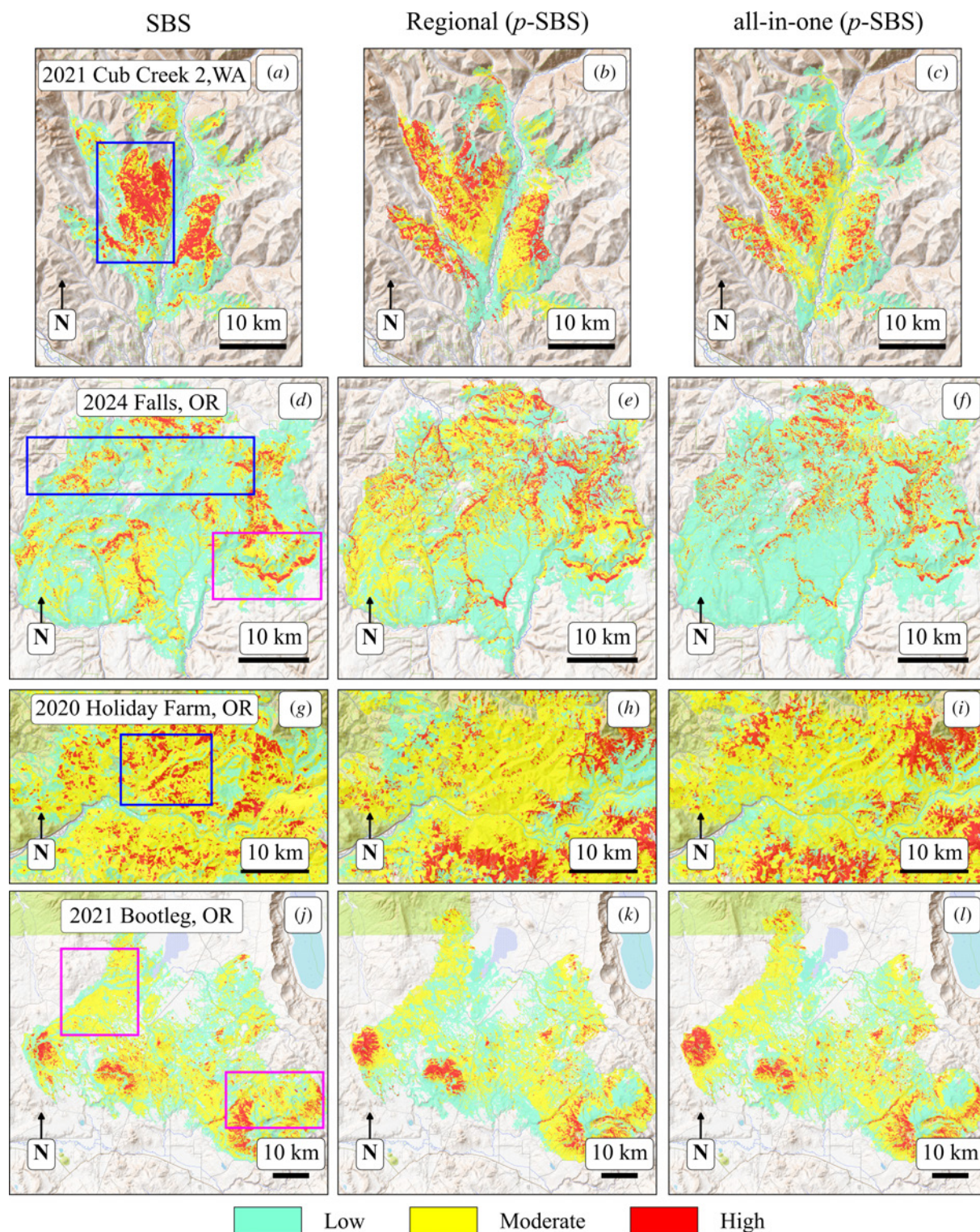


Fig. 4. Comparison of actual soil burn severity (SBS; Burned Area Emergency Response (BAER)-derived) and predicted SBS (p -SBS) from the regional Light Gradient Boosting Machine (LightGBM) and 'all-in-one' LightGBM models for four representative wildfires in the Pacific Northwest. Panels (a–c) show the 2021 Cub Creek 2 Fire (WA; North Cascades), (d–f) the 2024 Falls Fire (OR; Blue Mountains), (g–i) the 2020 Holiday Farm Fire (OR; Cascades), and (j–l) the 2021 Bootleg Fire (OR; Eastern Cascades). Blue boxes highlight regions where model predictions differ and are less accurate, whereas pink boxes indicate consistent and accurate predictions across models.

Table 3. Performance of regional and ‘all-in-one’ Light Gradient Boosting Machine (LightGBM) models for soil burn severity (SBS) classification at 30 m resolution. Regional models were trained within individual ecoregions, whereas the all-in-one model was trained using pooled data under the leave-one-fire-out (LOFO) framework. Results are presented for one representative fire from each ecoregion for regional comparison, and for four independent 2025 fires to assess the performance of the all-in-one LightGBM model beyond the training domain (2018–2024).

Fire name (ecoregion)	Model	Overall accuracy (OA)	F1 score		
			Low	Moderate	High
Regional evaluation					
2021 Cub Creek 2, WA (North Cascades)	Regional	0.51	0.59	0.44	0.45
	all-in-one	0.49	0.60	0.35	0.43
2024 Falls Fire, OR (Blue Mountains)	Regional	0.58	0.68	0.48	0.36
	all-in-one	0.59	0.73	0.27	0.38
2020 Holiday Farm, OR (Cascades)	Regional	0.59	0.43	0.72	0.30
	all-in-one	0.55	0.30	0.70	0.28
2021 Bootleg, OR (Eastern Cascades)	Regional	0.60	0.59	0.62	0.52
	all-in-one	0.59	0.60	0.66	0.51
Evaluation for 2025 fires					
2025 Gifford, CA	all-in-one	0.65	0.63	0.67	0.42
2025 Sunset Fire, ID		0.43	0.41	0.47	0.41
2025 Emigrant Fire, OR		0.45	0.47	0.48	0.11
2025 Bear Gulch, WA		0.55	0.69	0.30	0.20

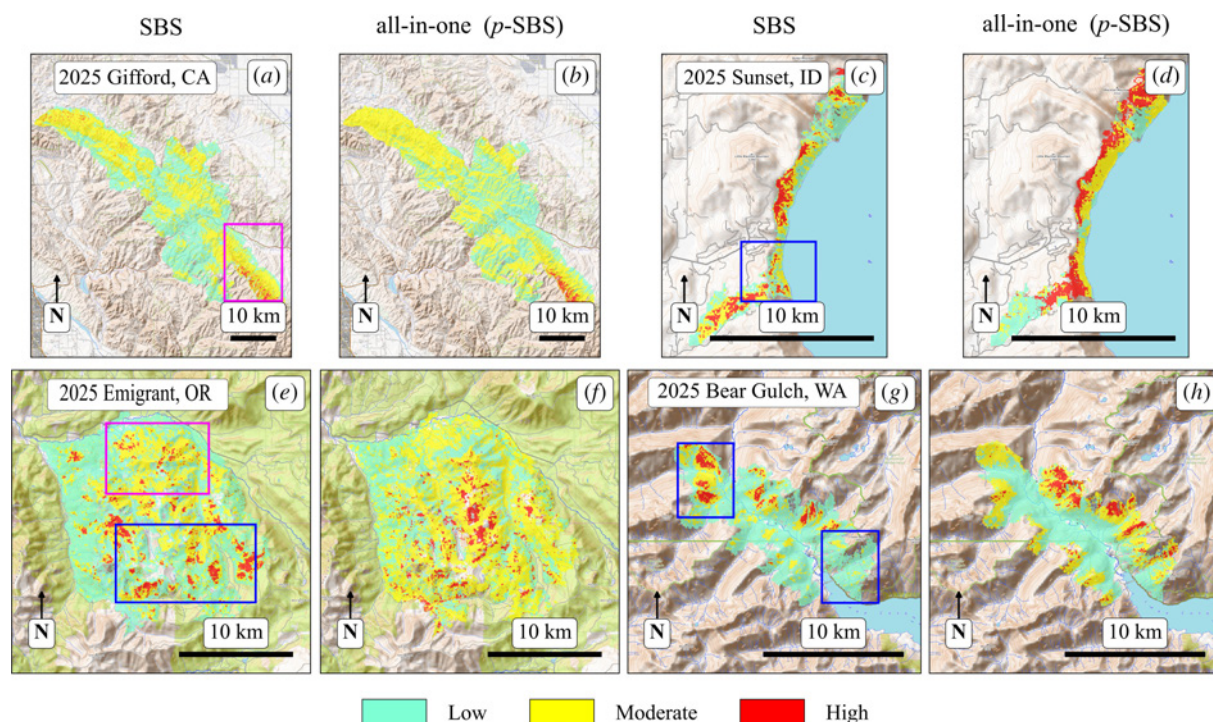


Fig. 5. Comparison of ‘all-in-one’ model predicted-SBS (*p*-SBS) with actual soil burn severity (SBS; Burned Area Emergency Response (BAER)-derived) for four recent (2025) wildfire events across the western US. Panels (a–b), (c–d), (e–f), and (g–h) show spatial comparisons for the 2025 Gifford Fire (CA), Sunset Fire (ID), Emigrant Fire (OR) and Bear Gulch Fire (WA), respectively. Blue boxes highlight regions where predictions differ from BAER-derived actual SBS, whereas pink boxes indicate areas where model predictions agree and are more accurate.

fire area (see Supplementary Fig. S4 for pre-fire vegetation growth). However, several areas in the southern portion of the fire were predicted to burn more severely than observed due to their high fuel availability. Examination of ancillary environmental data indicated that these areas were generally located at higher elevations and received greater precipitation than the surrounding landscape, which may have promoted cooler and moister conditions that reduced actual fire severity despite high fuel availability. In addition, vegetation regeneration following the previous fire likely altered spectral characteristics and reduced the separability of vegetation classes in satellite-derived indices (Supplementary Fig. S5). Together, these findings highlight limitations of the trained LightGBM model in complex re-burn environments, where prior fire history alters fuel structure and vegetation recovery, while local environmental controls such as elevation and associated moisture gradients can further influence SBS patterns (Holden *et al.* 2010; Weber *et al.* 2022).

The training dataset is dominated by single-burn events, with only ~13% representing re-burn conditions. As a result, the model may not adequately capture the complex and case-specific processes governing SBS in re-burned landscapes. The model performed well for the 2024 Pioneer Fire but less so for the 2025 Emigrant Fire, despite both being re-burns. This indicates that model performance in re-burn environments is inconsistent and influenced by site-specific factors such as fuel recovery and prior burn severity (Tortorelli *et al.* 2024), emphasizing the need to develop specialized models.

Ecological controls and biophysical factors driving soil burn severity

The Normalized Difference Moisture Index (NDMI) ranked highest in overall importance and exhibited negative SHAP values at higher NDMI magnitudes for the low-SBS class (Fig. 6a; Table 4), indicating that the likelihood of low-SBS decreases with increasing NDMI. In contrast, low NDMI values—typical of sparse, patchy and generally lower biomass—produced positive SHAP contributions and favored low-SBS. Povak *et al.* (2025) similarly identified NDMI-based fuel biomass as top predictors of burn severity, consistent with our SBS results. Likewise, sparsely vegetated sites at low elevation (ranks 2) promoted low-SBS, whereas high-elevation, forested zones promotes high-SBS, which is also consistent with literature noting terrain (elevation/slope) modulates fire intensity (Trang *et al.* 2023). Fuel moisture conditions played a key role in modulating SBS, with higher soil moisture (SM), precipitation and 100 h dead fuel moisture consistently reducing SBS (particularly in the Blue Mountains and Eastern Cascades; Supplementary Figs S6 and S7), whereas drier conditions promoted higher SBS, with some exceptions. Wasserman and Mueller (2023) noted that while wetter conditions

can contribute to fuel buildup, hotter and drier climates are more likely to promote fire severity. Finally, greater distance from lightning/ignition sources and closer proximity to water bodies increased the likelihood of low-SBS, consistent with findings reported by Hantson *et al.* (2022). These relationships characterize low-SBS environments as fuel-limited, moisture-rich and topographically sheltered, reflecting conditions that constrain combustion intensity.

Moderate-SBS conditions displayed (Fig. 6b) transitional SHAP patterns that reflected the balance between fuel availability, moisture and energy. NDMI, Normalized Difference Snow Index (NDSI), SM and precipitation remained prominent but exhibited near-zero mean SHAP values, suggesting context-dependent effects (Povak *et al.* 2025). SM and precipitation were not as high (wet) as in low-SBS areas but not as low (dry) as in high-SBS areas. In other words, moderate SBS occurred under neither excessively dry nor wet antecedent conditions, consistent with the notion that both fuel amount and moisture jointly shape severity. Moderate-SBS was most likely at mid-elevation, moderately drained sites where fuels and energy demand co-occurred. This pattern aligns with Van and Lee (2025), demonstrating that beyond a certain elevation threshold, the likelihood of moderate to high burn severity increases due to greater fuel exposure and upslope fire spread. Proximity to ignition points and roads modestly increased moderate SBS, with stronger effects observed in the North Cascades and Cascades (Supplementary Figs S8 and S9). Collectively, these trends indicate that moderate SBS occurs within ecotonal zones of balanced moisture and topographic exposure, where neither fuel limitation nor high evaporative demand (as indicated by Evaporative Stress Index (ESI) and Evapotranspiration (ETa)) dominates.

High-SBS was most strongly influenced by vegetation biomass, evaporative demand and topographic exposure, a triad broadly consistent with fire ecology literature across the Western US (Fig. 6c) (Birch *et al.* 2015; Parks *et al.* 2018; Povak *et al.* 2020). NDMI exhibited increasingly positive SHAP values at high magnitudes, indicating that dense, biomass-rich canopies (typical of high NDMI) elevated high-SBS risk under pre-fire desiccation. Conversely, SM (ranks 6) showed positive SHAP contributions only at low values, confirming that dry soils facilitate high-SBS. Evaporative-demand variables provided reinforcing influence. Actual ETa and ESI (ranks 7 and 9) showed positive contributions to SBS, indicating that higher evaporative stress conditions enhance SBS. These patterns align with other ML-based burn and SBS studies (Pascolini-Campbell *et al.* 2025; Sanna *et al.* 2025). Topographic factors, especially elevation (ranks 3) and Saturated Hydraulic conductivity (Ksat), were also positively associated with SBS. Steep, exposed, and well-drained slopes accelerated fuel drying and wind-driven spread—particularly

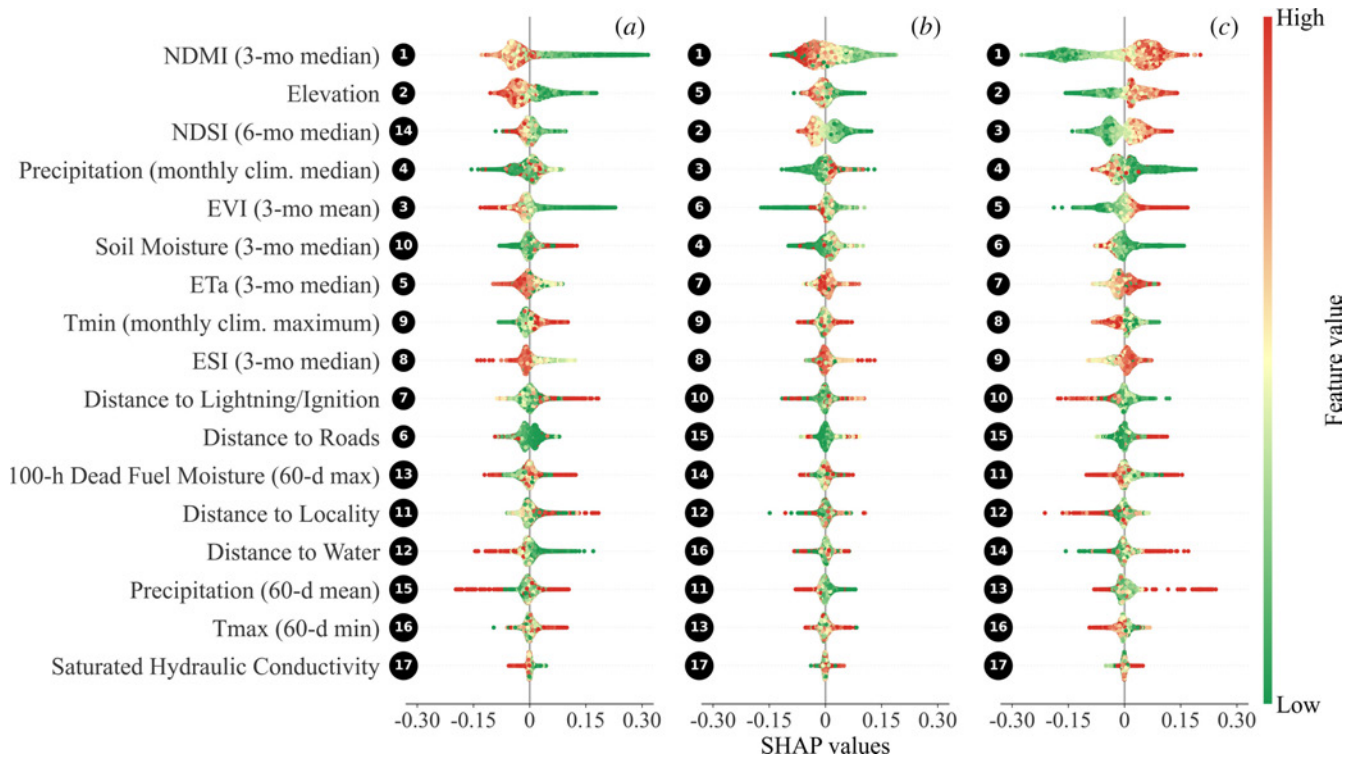


Fig. 6. SHapley Additive exPlanations (SHAP) beeswarm plots illustrate the relative importance and directional influence of predictors on soil burn severity (SBS) for (a) low, (b) moderate, and (c) high severity classes. Predictors are ordered from top to bottom based on their overall importance across all classes. The numbered labels (1–17) indicate feature importance ranks computed separately for each class, with lower numbers indicating greater importance. Each point represents an individual sample, with SHAP values indicating the contribution of each feature to increasing (positive values) or decreasing (negative values) the likelihood of the corresponding SBS class. Point colors denote normalized feature values, ranging from low (green) to high (red). NDMI: Normalized Difference Moisture Index; NDSI: Normalized Difference Snow Index; EVI: Enhanced Vegetation Index; ETa: Evapotranspiration; ESI: Evaporative Stress Index.

in the Cascades, where Ksat effects were slightly stronger (Supplementary Fig. S9). Precipitation generally suppressed burn severity; however, localized anomalies were evident in the Cascades, where moist but fuel-continuous areas and certain high-elevation, cold environments still exhibited high-SBS (Cansler and McKenzie 2014). These anomalies may reflect episodic drought or short-term moisture deficits that temporarily reduced fuel moisture and increased fuel flammability despite generally moist environmental conditions (Littell et al. 2016). These relationships define high-SBS as the combined result of heavy fuel load, vegetation and soil desiccation, high evaporative energy demand and terrain exposure.

Across all SBS classes, vegetation biomass indices, including the NDMI and Enhanced Vegetation Index (EVI), and topographic metrics emerged as the primary ecological controls, while atmospheric aridity variables (temperature and evapotranspiration) played secondary, reinforcing roles. SHAP patterns further revealed region-dependent responses, with the influence of moisture-related variables

varying across ecoregions and reflecting regional differences in fuel structure, biomass and climate.

Challenges, limitations and future scopes

Scientific practice is moving beyond the reliance on post-fire SBS mapping for hydrological and environmental applications toward advanced, data-driven forecasting frameworks that can anticipate SBS prior to fire events. Pre-fire burn severity prediction methods, including spectral time-series based prediction approaches, ML-based susceptibility models and regression-classification frameworks (Gholinejad and Khesali 2021; Miller et al. 2024; Lee et al. 2024; Pascolini-Campbell et al. 2025; Klimas et al. 2025; Supplementary Table S5), perform well for burn severity prediction; however, their applicability to SBS is limited. Burn severity can be derived from satellite time series, whereas SBS relies on post-fire field assessments (e.g. BAER) to capture subsurface effects and is therefore typically available as a single post-fire map per event, restricting the range of applicable modeling approaches (Wilson and Prentice 2024).

Table 4. SHapley Additive exPlanations (SHAP)-derived influence of key predictors on soil burn severity (SBS). (↑ = higher feature values increase likelihood of the given SBS class; ↓ = higher feature values decrease likelihood of the given SBS class; ± = mixed or context-dependent effect). Regional SHAP summary plots are provided in the Supplementary Material.

Predictor	Effects on SBS classes			Interpretation summary (overall)	Regional summary	Similar findings
	Low	Moderate	High			
Normalized Difference Moisture Index (NDMI)	↓	±	↑	High NDMI (dense, moist and continuous biomass) lowers low-SBS probability but can promote high-SBS under drought stress.	Similar trends across all eco-regions.	Povak et al. (2025)
Elevation	↓	±	↑	High, exposed terrain enhances SBS through wind and slope effects, while low, sheltered areas favor low-SBS.	Stronger influence in the North Cascades.	Trang et al. (2023) ; Van and Lee (2025)
Normalized Difference Snow Index (NDSI)	↓	↓	↑	High NDSI (snow/bright-moist conditions) typically suppresses SBS, but with a six-month pre-fire window it also reflects spring snow at high elevations that later dry and burn severely.	Stronger influence in the Blue Mountains and Cascades.	Goldman et al. (2025)
Precipitation (monthly median/60-d mean)	↑	↑	↓	Greater antecedent precipitation dampens high-SBS.	Exceptions occur in the Cascades, where some high-SBS patches are observed in wetter areas.	Wasserman and Mueller (2023)
Enhanced Vegetation Index (EVI)	↓	±	↑	High biomass increases potential fire intensity when fuels are dry.	Stronger influence in the Blue Mountains and Cascades.	Parks et al. (2018)
Soil Moisture (SM)	↑	±	↓	Higher SM favors low-SBS and suppresses high-SBS.	Moderate influence in the Cascades; however, some high-SBS areas occurred under wet soil conditions.	Krueger et al. (2023)
Evapotranspiration (ETa)	↓	↑	↑	High atmospheric energy demand increases moderate- and high-SBS.	Stronger in the Eastern and North Cascades.	Pascolini-Campbell et al. (2025)
Temperature (Tmax 60-d min/Tmin monthly max)	↑	±	↓	Climatic gradient proxy; cooler, high elevation, fuel-rich environments linked to higher SBS potential.	Strong influence in Cascades.	Shrestha et al. (2024)
Evaporative Stress Index (ESI)	↓	↑	↑	High evaporative stress (drier pre-fire conditions) reduces low-SBS likelihood and promotes moderate and high SBS.	Stronger influence in the Eastern and North Cascades.	Sanna et al. (2025)
Distance to lightning/ignition	↑	±	↓	Greater distance from lightning/ignition lowers SBS; proximity increases moderate–high-SBS likelihood.	Stronger in North Cascades and Cascades.	Hantson et al. (2022)
Distance to roads	↓	±	↑	Remote areas (farther from roads) exhibit higher SBS due to reduced suppression and greater fuel continuity, while proximity to roads favors low SBS.	Stronger influence in Cascades and North Cascades.	Chamberlain et al. (2024)
100 h dead fuel moisture	↑	±	↓	Lower dead fuel moisture enhances ignition probability, fire spread and fire intensity, ultimately leading to higher SBS.	Mixed effects in the North Cascades and Cascades.	Ferguson et al. (2002)
Distance to locality	±	±	↓	Human influence proxy; proximity to settlements could increase SBS due to ignition pressure.	Mixed effects in the North and Eastern Cascades.	Hantson et al. (2022)
Distance to water	↓	±	↑	Proximity to water Low SBS; distance from water sources elevates high-SBS likelihood.	Strong effects in the Cascade regions.	Kobziar and McBride (2006)

(Continued on next page)

Table 4. (Continued)

Predictor	Effects on SBS classes			Interpretation summary (overall)	Regional summary	Similar findings
	Low	Moderate	High			
Saturated hydraulic conductivity (Ksat)	↓	±	↑	High Ksat (well-drained soil) promotes high-SBS through rapid drying; low Ksat retains moisture, reducing SBS.	Limited regional variation.	Ramirez et al. (2024)

In addition, SBS maps have limited spatial and temporal coverage—largely restricted to the early 2000s onward—and often lack consistent metadata (e.g. mapping protocols, data acquisition details), which limits comparability across fires and constrains robust modeling (Parsons et al. 2010). Although spatially continuous SBS maps are increasingly available, corresponding point-scale field observations remain scarce. As a result, SBS prediction models are primarily trained on pixel-based maps, which may not fully represent underlying actual surface conditions and can limit predictive performance.

SBS prediction is inherently challenging because it reflects subsurface, fine-scale and highly nonlinear fire–soil interaction processes that are weakly observable from remotely sensed data (Key and Benson 2004; Miller et al. 2024). Furthermore, pronounced microscale variability in fire–environment processes across regions limits the generalizability of large-scale models. For instance, in moist temperate forests (e.g. the Cascades), vegetation indices such as EVI and NDMI show limited variability and reduced predictive power due to uniformly dense and moist vegetation, whereas in drier mountainous regions (e.g. the North Cascades), elevation and associated climatic gradients exert stronger control on SBS patterns (Klimas et al. 2025). Consequently, even with diverse predictors, the models are constrained in capturing fine-scale (~30 m) variability due to scale mismatches and pronounced regional heterogeneity, leading to underfitting in large-scale modeling.

A critical constraint is the coarse and static resolution of many input datasets. Climate reanalysis products (GridMET, Daymet) (Abatzoglou 2013; Thornton et al. 2022), soil property maps, and fuel datasets often operate at spatial and temporal scales too coarse to capture microscale variability in fuel continuity, soil texture, or canopy structure—key factors in fire–soil interactions—and are not always updated in a timely manner. While downscaling helps, this limitation can be further reduced by integrating high-resolution datasets (e.g. Light Detection and Ranging (LiDAR), field observations), dynamic predictors (e.g. live fuel moisture), and process-based modeling frameworks such as the Weather Research and Forecasting (WRF) model to better resolve microscale variability (Sikink and Keane 2012; Lee et al. 2022; Vahdat-Aboueshagh and McKenna 2025).

The ML models (such as LightGBM, Random Forest) do not explicitly account for dynamic subsurface processes, such as organic matter loss, soil heating and fire-induced

hydrophobicity, which are particularly important in re-burn areas where legacy effects alter long-term fuel profiles (Moody et al. 2013). Improved representation of fire–soil processes through ML models, particularly heat transfer and subsurface dynamics, remains an important area for future research (Robichaud et al. 2025).

Furthermore, wildfire retardants, suppression activities and prior wildfire effects can influence SBS and modify natural fire–soil processes, effects that are typically not accounted for in ML modeling (Wiard-Greene et al. 2025). Incorporating fire history variables (e.g. time since last burn, prior severity) and external factors such as retardant effects as surrogate inputs could help reduce uncertainty; however, progress is constrained by the limited availability of high-quality historical SBS data and associated metadata for legacy fires.

These challenges are reflected in the persistent difficulty of accurately predicting high-SBS (Miller and Thode 2007; Lydersen et al. 2016). Nevertheless, the ML models used in this study effectively capture broad-scale spatial patterns of SBS for most fires, particularly large fires. Although pixel-level accuracy is lower for high-SBS classes in smaller fires, the models still successfully identify high-risk areas, even in complex environments, supporting targeted fuel management and mitigation efforts.

Importantly, this model is not intended to replace post-fire BARC/SBS products. Its primary contribution lies in predicting SBS (named *p*-SBS) before fires occur, supporting proactive planning for water utilities, land managers and emergency-response agencies, and post-fire hazard mitigation efforts, including landslide and debris-flow risk assessment, particularly in regions lacking timely post-fire SBS mapping. Future work should prioritize improving the representation of fine-scale and subsurface processes by integrating higher-resolution soil, vegetation and climate datasets, incorporating fire history and multi-sensor satellite observations, and developing physics-informed ML approaches to better capture fire–environment interactions, particularly fire–vegetation–soil linkages, and enhance model robustness.

Conclusions

This study developed a data-driven ML framework to predict SBS classes (low, moderate, high) using pre-fire environmental conditions across the Pacific Northwest, US.

Using 62 fires, three models (RF, XGBoost and LightGBM) were evaluated with CV and LOFO approaches. The models showed similar performance under CV (OA $\approx$ 0.58), whereas LOFO performance varied across fire-size classes and environmental conditions. LightGBM achieved slightly higher and more consistent LOFO OA, and prediction of high-SBS improved with increasing fire size, with significantly higher accuracy for large fires ($\geq 20,000$ ha; Spearman's $\rho = 0.43$, $P < 0.001$ between fire size and high-SBS F1-score).

Using the LOFO evaluation framework, region-specific models (trained independently for each ecoregion) were compared with a pooled (all-in-one) LightGBM model trained across all regions. The all-in-one model showed comparable OA, while region-specific models performed slightly better within their respective ecoregions. Application of the all-in-one model to four independent 2025 fires demonstrated that the models reproduced broad SBS patterns beyond the training domain (2018–2024) indicating moderate cross-regional transferability, with performance declined in wetter environments and re-burn areas likely due to variability in fuel moisture and legacy soil–fuel effects.

SHAP analysis identified vegetation (NDMI, EVI), evaporative demand (ESI, ETa), terrain (elevation) and moisture-related variables (SM, Precipitation) as key drivers of SBS. High-SBS was associated with high biomass, low moisture availability and strong evaporative stress, whereas moist, low-fuel areas generally exhibited low SBS, with regional exceptions in wetter Cascade regions.

This study demonstrates the feasibility of predicting SBS using exclusively pre-fire environmental data and complements existing fire behavior models (e.g. FlamMap, FAR-SITE) by explicitly predicting SBS. This framework supports proactive fire and water-resource management but requires further refinement to improve robustness across diverse environmental conditions, particularly in moisture-rich and reburned landscapes.

Supplementary material

Supplementary material can be accessed from the article page online.

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Data availability. All data sets used in this study are publicly available; no proprietary data were used.

Declaration of use of AI. The authors used ChatGPT and Gemini during the preparation of this work solely for grammar checking and for improving clarity and readability. All core content, ideas and interpretations remain entirely from the authors. The final version has been fully reviewed and approved by the authors.

Conflicts of interest. The authors declare that they have no conflicts of interest.

Declaration of funding. This work was supported by the National Aeronautics and Space Administration (NASA) under award number 80NSSC22K0920P00006.

Author contributions. Subhankar Das led the data processing, analysis, software uses and initial drafting of the manuscript. The study was conceptualized and supervised by Mariana Dobre, with additional methodological support from Erin S. Brooks and Roger Lew. Data curation, visualization and manuscript review were provided by Sarah A. Lewis, Peter R. Robichaud, Anurag Srivastava, Mary Ellen Miller, Alex M. Watanabe and Marta Basso. Erin S. Brooks also contributed to conceptual development, and Peter R. Robichaud offered additional supervisory guidance.

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