Online Resource

Post-fire delayed tree mortality in mesic coniferous forests reduces fire refugia and seed sources

Landscape Ecology

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Resource A Post-Classification Change Detection

SuperDove (PSB.SD), the newest sensor that has been active since mid-March 2020, was acquired when available. During periods in 2020 when the PSB.SD sensor imagery was not available for the study area, the Dove-R (PS2.SD) sensor was acquired, which has similar radiometric sensitivity to the PSB.SD sensor. Imagery from both sensors was harmonized to match Sentinel-2 satellite imagery's spectral response, which minimizes variance in time series and from ambient conditions (Planet Team 2023). The imagery was selected with < 5% cloud cover to minimize atmospheric distortions, and the imagery was collected closest to the summer solstice to minimize geometric distortions, except for the imagery collected in October 2020 to capture the first-order fire effects (Table A1).

Table A1 PlanetScope imagery dates collected for each fire annually. For post-fire years other than 2020, imagery was collected as close to the summer solstice with less than 5% cloud cover. For instances with multiple image dates, a mosaic was created using the average value of overlapping pixels.

Year	Riverside	Beachie Creek	Lionshead	Holiday Farm	Archie Creek
2020	October 25	October 25	November 2	October 25	October 25
2021	June 17	June 17	June 18	June 17	June 19
2022	June 21, 26, & 27	June 21	July 14	June 25	June 25
2023	July 1	June 30	June 30	June 30	July 1

From the initial set of predictors that were sampled (Table A.2), multicollinearity was reduced based on the variance inflation factor (VIF) with a cutoff of 10, and a final set of predictors was selected for training which included near-infrared, NDVI, GNDVI, brightness, standard deviation in brightness, and RdNBR. The fire name was also included as a categorical predictor. Several models were compared for performance, including a decision tree from the *parsnip* package (Kuhn et al. 2024), a random forest from the *randomForest* package (Liaw and Wiener 2002), and a boosted regression tree (BRT) from the *gbm* package (Ridgeway et al. 2024). Each model was trained using 1,000 epochs (i.e., training iterations). Over-sampling of the minority class was performed using the ROSE package in R (Lunardon et al. 2014) to create a balanced training set, which was performed rather than under-sampling due to the already low number of training observations.

Table A.2 List of all remote-sensing indices tested in the forest classification methodology.

Index	Definition	Reason for inclusion
*Brightness	Mean of red, green, and blue bands.	To create a composite of the visual wavelengths (red, green, and blue) that measures surface brightness.
False-color brightness (FCB)	Mean of red, blue, and near-infrared bands.	To create a composite of wavelengths that emphasizes seasonal differences in vegetation (Key & Benson 2005).

*Normalized difference vegetation index (NDVI)	Normalized difference in red and near-infrared bands.	Vegetation presence and health.
*Green normalized difference vegetation index (GNDVI)	Normalized difference in near-infrared and green bands.	An alternative to the NDVI for improving sensitivity to vegetation health in dense vegetation with a high leaf-area index (Jones & Vaugha 2010).
Red-green vegetation index (RGVI)	Normalized difference in red and green bands.	An alternative for vegetation health that is insensitive to differences in illumination (Rodman et al. 2019).
Local minima (LM)	Metric to identify pixels that are darker than their surroundings at multiple spatial scales (Rodman et al. 2019).	Local minima is said to help classify individual trees on ridge tops, south-facing slopes, and in grasslands (Rodman et al. 2019).
*Sum of standard deviation in brightness (SSDB)	Summing the standard deviation in brightness for multiple window sizes (Rodman et al. 2019).	Distinguish between dark forests from homogenous areas including water bodies and shadows (Rodman et al. 2019)
Segment mean shift (SMS)	Unsupervised machine learning algorithm that clusters continuous raster data into groups based on similar spectral and spatial characteristics (ESRI 2023). A minimum segment size was set to the size of 1 pixel to allow for individual trees to be categorized separately from a patch of trees.	Separating various features in an image including forest, individual tree, ground, water, and roads (Blaschke 2010; Rodman et al. 2019).

*Index used as a final predictor in the forest classification model

Forest classification model performance was evaluated using the Area Under the Receiver Operating Characteristic Curve (hereby referenced as AUC). A 10-fold cross-validation procedure was executed for each model to assess the performance of the binary classifier based on the producer's accuracy, the user's accuracy, and the overall accuracy. Of the three models tested, the BRT model had the highest mean AUC score overall and was used to predict forest cover across the wildfire perimeters and 1-km buffer (Table A.3).

Table A.3 Summary statistics for forest classification AUC scores using 10-fold cross-validation.

	Producer's Accuracy		User's Accuracy		Overall Accuracy
	Forest	Non-Forest	Forest	Non-Forest	
Mean	0.98	0.85	0.97	0.90	0.96
Min	0.96	0.82	0.96	0.82	0.94
Max	0.99	0.88	0.96	0.93	0.97

Several filtering methods were applied following forest classification. First, shadows were considered to result in classification errors and were most prevalent in the October 2020 imagery due to a low solar altitude angle. Shadows were identified annually based on a brightness threshold of 100. If a shadowed pixel was classified as non-forest but then classified as forest the subsequent year, the pixel was classified as forest in the original year. Otherwise, shadowed pixels were classified as non-forest. Second, a data mask (Table A.4) was created to remove problematic pixels that included (a) PS UDM2 masks that identify clouds and other atmospheric interference (Planet Team 2023), (b) water features (i.e., lakes, reservoirs, and rivers) from the USGS National Hydrography Dataset (U.S. Geological Survey 2018), (c) post-fire harvests digitized by (Zuspan et al. 2024) along with additional manually digitized salvage areas for logging and/or hazardous tree removal, (d) locations that were previously burned since 1984 according to the MTBS dataset (Eidenshink et al. 2007), and (e) any areas outside of the western Cascades ecoregion. Third, a minimum mapping unit was defined as 9 m^2 to represent the capability of the 3-meter PS imagery to detect an individual tree. To conform to this minimum mapping unit and reduce the presence of misclassified pixels, a focal majority filter with a 3x3 moving window was applied to the forest cover rasters. The majority filter also acts as a smoothing method. Lastly, if a pixel was classified as non-forest it could not be classified as forest the subsequent year(s).

Table A.4 Summary statistics of area removed (ha) from analysis by fire along with percentage of total fire area with 1-kilometer boundary in parentheses. Since the areas removed by each mask can overlap, the total area removed may not be a sum of its parts.

Fire	**Water**	**Salvage Logging**	**Reburn**	**Shadow***	**Western Cascades****	**Total**
Riverside	393 (0.5%)	4,284 (5.9%)	2,361 (3.2%)	17,438 (23.9%)	8 (<0.001%)	22,694 (31.1%)
Beachie Creek	1,454 (1.4%)	5,634 (5.4%)	0 (0%)	16,198 (15.6%)	4,775 (4.6%)	26,723 (25.8%)
Lionshead	902 (1.1%)	776 (0.7%)	17,966 (21.2%)	14,778 (17.4%)	0 (0%)***	32,300 (38.1%)
Holiday Farm	801 (0.9%)	8,957 (9.7%)	352 (0.4%)	14,628 (15.9%)	326 (0.4%)	23,759 (25.8%)
Archie Creek	291 (0.4%)	6,854 (10.1%)	6,909 (10.1%)	13,194 (19.4%)	3,951 (5.8%)	27,912 (41.0%)

*Locations with shadows were not always removed based on the methodology outlined in the text.
**Western Cascades encompasses western cascades valley and lowlands, western cascades montane highlands, and the cascade crest montane forests.
***The Lionshead fire extends into the east Cascades ecoregion, however, this area is not included in the analysis.

Resource B Forest Classification and Mapping of Delayed Mortality

Table B.5 The proportion of forested area lost due to delayed mortality from October 2020 through June 2023 by fire and immediate burn severity as of October 2020. In parenthesis, the extent (hectares) by conditions is shown.

Fire	Low	Moderate	High
Riverside	0.64 (2,681 ha)	0.29 (1,199 ha)	0.07 (278 ha)
Beachie Creek	0.51 (2,914 ha)	0.39 (2,232 ha)	0.10 (602 ha)
Lionshead	0.66 (4,850 ha)	0.27 (2,002 ha)	0.06 (451 ha)
Holiday Farm	0.53 (1,994 ha)	0.38 (1,437 ha)	0.10 (361 ha)
Archie Creek	0.58 (1,992 ha)	0.34 (1,162 ha)	0.08 (264 ha)

Table B.6 Summary statistics for the absolute percent change in area from October 2020 through June 2023 for patch area and core area by immediate burn severity as of October 2020.

Immediate burn severity (October 2020)	% change in patch area (June 2023)	% change in core area (if applicable) (June 2023)
Low	13.2%	24.9%
Moderate	54.5%	NA
High	77.2%	NA

Table B.7 Percent change in Euclidean distance to fire refugia from post-fire in October 2020 to 3 years post-fire. The range of percent change is across all individual fires. Positive changes represent increased isolation.

Distance (m)	Year	Area (ha)	% Change (range by fire)
0 – 200	2020	136,251	-27.1% (-57.6% – 28.1%)
	2023	99,306	
200 – 400	2020	39,558	16.2% (-22.9% – 41.8%)
	2023	45,982	
>400	2020	37,958	80.4% (24.7% – 313.4%)
	2023	68,480	

Table B.8 Percent change in D^2WD to fire refugia from post-fire in October 2020 to 3 years post-fire. The range of percent change is across all individual fires. Negative changes represent increased isolation and a reduction in seed source availability.

D^2WD class	Year	Area (ha)	% Change (range by fire)
0 – 0.082	2020	158,212	14.4% (10.1% – 90.8%)

	2023	181,070	
0.082 – 0.271	2020	47,327	-36.5% (-53.9% – -25.3%)
	2023	30,030	
0.271 – 1	2020	8,229	-67.6% (-94.5% – -61.1%)
	2023	2,667	

Resource C Characterizing the Influence of Tree Species and Structure on Fire Resistance

Post-fire tree mortality is influenced by both species-level functional traits and structural attributes that vary with tree size. To explore whether remotely sensed immediate and/or delayed post-fire tree mortality outcomes were associated with these factors, we developed quantitative and regionally specific fire resistance classifications, for each major species in our study area (Table 1), using regional Forest Inventory and Analysis (FIA) data and the First Order Fire Effects Model (FOFEM; Lutes 2020). The FIA program is a statistically representative and spatially balanced sample of all forest land in the continental United States, that includes tree- and stand- (plot) level observations. The FOFEM software includes species-level, regionally specific logistic regression models that can be used to predict the probability of post-fire tree mortality based on a user-supplied surface flame length and tree-level structural attributes (i.e., diameter, height, and live crown ratio; crown scorch model [CRNSCH]).

First, in R, we subset FIA data from the Oregon FIA Database (Burrill et al. 2021) at the plot level to retain only forested, single-condition plots with an estimated stand age greater than 10, within the western Cascades ecoregion, that were measured during the most recent completed inventory panel 2010-2019 (EVALID 411901). Next, each sampled tree record was classified into one of three diameter age class groups, based on recorded diameter at breast height (DBH), that represent structurally distinct stages of forest development: young (2.5 – 25.4cm; ~10-60 years), mature (25.5 – 50.8cm; ~60-120 years), or supermature (> 50.8cm; ~>120 years). Next, we summarized mean tree diameter, height, and live crown ratio attributes across plots at the species and diameter age class levels, weighting means by each tree's representative abundance in the sampling design (trees per acre; TREE.TPA_UNADJ). Mean tree attributes by species and stand age class summarized in the previous step were then used as inputs to the FOFEM software to derive predicted post-fire tree mortality probabilities using species- and region- (Pacific West) specific crown scorch models and an assumed 1.8-meter surface flame length (Jain et al. 2020). For each intersection of species and diameter age class, we classified each group as having sensitive (low), tolerant (moderate), or resistant (high) fire resistance depending on whether the FOFEM predicted tree mortality probability was > 0.75, 0.25-0.75, or < 0.25, respectively (Table C.9).

Finally, to relate our FIA- and FOFEM-derived species and diameter age class fire resistance identity to each 3-meter PlanetScope pixel on the landscape, each 3-meter pixel was assigned a stand age class and forest type (i.e., dominant species) based on its spatial intersection with Lemma GNN layers a) Quadratic mean diameter of all dominant and codominant trees (QMD_DOM; converted from centimeters to inches) and forest type (FORTYPBA).

Table C.9 Attributes used in the FOFEM classification of fire resistance based species and diameter at breast height (DBH).

Species	Diameter class	DBH	Height	Crown ratio	Probability of mortality	Sensitivity class
Douglas-fir	1TO10	4.31	31.54	49.58	0.98	Sensitive
Douglas-fir	10TO20	14.06	88.45	41.00	0.12	Resistant
Douglas-fir	>20	30.01	144.76	39.96	0.12	Resistant
Engelmann spruce	1TO10	3.91	19.51	48.67	0.99	Sensitive
Engelmann spruce	10TO20	14.78	74.30	53.50	0.85	Sensitive
Engelmann spruce	>20	27.18	129.11	63.65	0.52	Tolerant
lodgepole pine	1TO10	3.33	21.50	45.56	1	Sensitive
lodgepole pine	10TO20	12.08	70.53	38.33	0.24	Resistant
mountain hemlock	1TO10	3.99	19.51	55.76	1	Sensitive
mountain hemlock	10TO20	13.74	66.74	51.82	0.68	Tolerant
mountain hemlock	>20	24.53	100.49	48.49	0.12	Resistant
noble fir	1TO10	4.33	23.54	57.24	1	Sensitive
noble fir	10TO20	13.99	76.38	45.05	0.27	Tolerant
noble fir	>20	28.24	128.30	35.47	0.08	Resistant
Pacific silver fir	1TO10	3.50	18.61	43.71	1	Sensitive
Pacific silver fir	10TO20	13.49	74.52	44.87	0.99	Sensitive
Pacific silver fir	>20	24.81	115.27	48.14	0.16	Resistant
subalpine fir	1TO10	2.96	14.07	49.00	1	Sensitive
subalpine fir	10TO20	12.68	52.03	53.95	0.99	Sensitive
subalpine fir	>20	23.72	89.40	52.40	0.16	Resistant
western hemlock	1TO10	3.61	23.49	45.12	1	Sensitive
western hemlock	10TO20	13.77	82.98	49.38	0.33	Tolerant
western hemlock	>20	26.54	128.25	52.22	0.1	Resistant

western red cedar	1TO10	3.48	21.60	44.25	1	Sensitive
western red cedar	10TO20	13.93	72.01	47.85	0.49	Tolerant
western red cedar	>20	28.39	118.12	48.37	0.12	Resistant
white/grand fir	1TO10	3.43	21.42	48.07	1	Sensitive
white/grand fir	10TO20	13.94	81.15	46.00	0.16	Resistant
white/grand fir	>20	25.90	125.04	48.00	0.16	Resistant

References

Blaschke T (2010) Object based image analysis for remote sensing. ISPRS J Photogramm Remote Sens 65:2–16. https://doi.org/10.1016/j.isprsjprs.2009.06.004

Burrill EA, DiTommaso AM, Turner JA, Pugh SA, Menlove J, Christiansen G, Perry CJ, Conkling BL (2021) The Forest Inventory and Analysis Database: database description and user guide version 9.0.1 for Phase 2. U.S. Department of Agriculture, Forest Service. 1026 p. [Online]. Available at web address: https://www.fia. fs.usda.gov/library/database-documentation/

Eidenshink J, Schwind B, Brewer K, Zhu ZL, Quayle B, Howard S (2007) A project for monitoring trends in burn severity. Fire Ecol 3:3–21. https://doi.org/10.4996/fireecology.0301003

ESRI (2023) ArcGIS Pro Desktop: Version 3.1.4. Redlands, CA: Earth Systems Research Institute

Jain TB, Fried JS, Loreno SM (2020). Simulating the effectiveness of improvement cuts and commercial thinning to enhance fire resistance in west coast dry mixed conifer forests. For Sci 66(2):157–177. https://doi.org/10.1093/forsci/fxz071

Jones H, Vaugha R (2010) Use of spectral information for sensing vegetation properties and for image classification. Remote Sensing of Vegetation: Principles, Techniques, and Applications

Key CH, Benson NC (2005) Landscape assessment: remote sensing of severity, the normalized burn ratio and ground measure of severity, the composite burn index. In: Lutes DC, Keane RE, Caratti JF, Key CH, Benson NC, Sutherland S, Gangi LJ (eds) FIREMON: Fire effects monitoring and inventory system, General Technical Report RMRS-GTR-164-CD, Ogden, Utah, USDA Forest Service, Rocky Mountain Research Station, pp LA-1-55

Kuhn M, Vaughan D, Hvitfeldt E, et al (2024) parsnip: a common API to modeling and analysis functions (Version 1.2.1). https://cran.r-project.org/web/packages/parsnip/index.html

Liaw A, Wiener M (2002). Classification and regression by randomForest. R News 2(3):18-22. https://CRAN.R-project.org/doc/Rnews/

Lutes DC (2020) FOFEM: First Order Fire Effects Model. Version 6.7. https://research.fs.usda.gov/firelab/products/dataandtools/software/fofem/spatialfofem-fire-effects-model

Planet Team (2023) Planet Application Program Interface: In Space for Life on Earth. https://api.planet.com

Ridgeway G, Edwards D, Kriegler B, Schroedl S, Southworth H, Greenwell B, et al (2024). gbm: generalized boosted regression models (Version 2.1.9). https://cran.r-project.org/web/packages/gbm/index.html

Rodman KC, Veblen TT, Saraceni S, Chapman TB (2019) Wildfire activity and land use drove 20th‐century changes in forest cover in the Colorado front range. Ecosphere 10:e02594. https://doi.org/10.1002/ecs2.2594

U.S. Geological Survey (2018) USGS National Hydrography Dataset Plus High Resolution (NHDPlus HR) for 4-digit Hydrologic Unit

Zuspan A, Reilly MJ, Henry Lee E (2024) Long-term patterns of post-fire harvest diverge among ownerships in the Pacific West, U.S.A. Environ Res Lett 19:124075. https://doi.org/10.1088/1748-9326/ad8e75