

**Divergent Biophysical Responses of Western United States Forests to Wildfire Driven by
Eco-climatic Gradients ~~Forest Types Show Divergent Biophysical Responses After Fire:~~
~~Challenges to Ecological Modeling~~**

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1 **Abstract**

2 Understanding vegetation recovery after fire is critical for predicting vegetation-mediated
3 ecological dynamics in future climates. However, information characterizing vegetation recovery
4 patterns after fire and their determinants are limited over large geographical extents. This
5 study uses Moderate Resolution Imaging Spectroradiometer (MODIS) leaf area index (LAI) and
6 albedo to characterize patterns of post-fire biophysical dynamics across the western United States
7 (US) and further examines the influence of topo-climatic variables on the recovery of LAI and
8 albedo at two different time intervals, 10 and 20 years post-fire, using a random forest
9 model. Recovery patterns were derived for all wildfires that occurred between 1986 and 2017
10 across seven forest types and 21 level III ecoregions of the western US. We found differences in
11 characteristic trajectories of post-fire vegetation recovery across forest types and ecoclimatic
12 settings. LAI in some forest types recovered only 60% - 70% by 25 years after fire while it
13 recovered 120% to 150% of the pre-fire levels in other forest types, with higher absolute post-fire
14 changes in forest types and ecoregions that had a higher initial pre-fire LAI. Our random forest
15 results showed very little influence of fire severity on the recovery of both summer LAI and albedo
16 at both post-fire time intervals. Post-fire vegetation recovery was most strongly controlled
17 by elevation, with faster rates of recovery in lower elevations. Similarly, annual precipitation and
18 average summer temperature had significant impacts on the post-fire recovery of vegetation. Full
19 recovery was seldom observed when annual precipitation was less than 500 mm and average
20 summer temperature was above the optimal range i.e., 15-20°C. Climate influences, particularly
21 annual precipitation, was a major driver of post-fire summer albedo change through its impact on
22 ecological succession. This study provides quantitative measure of primary controls that could be
23 used to improve the modelling of ecosystem dynamics post-fire.

24

25 Keywords: wildfire; MODIS; post-fire recovery; biogeophysical; remote sensing; succession

26 **1. Introduction**

27 Wildfires have burned millions of hectares of forests in the western United States (Littell et al.,
28 2009; White et al., 2017) and have increased in both frequency and severity in recent decades. This
29 trend has been attributed to temperature increases, more frequent droughts, below average winter
30 precipitation and earlier spring snowmelt (Dale et al., 2001; Westerling et al., 2006; Rogers et al.,
31 2011; Ghimire et al., 2012; Dennison et al., 2014; Littell et al., 2015; Abatzoglou & Williams,
32 2016; Williams & Abatzoglou, 2016; Williams et al., 2021), making ecosystem resilience and
33 vegetation recovery post-fire a primary concern to researchers and land managers (Allen &
34 Breshears, 2015). Existing studies report that large wildfires in western U.S. forests have increased
35 four-fold since 1970-1986, with total burn area increasing by six and a half times (Westerling et
36 al., 2006). Expanded burning can profoundly alter a wide range of ecosystem characteristics such
37 as stand structure, species composition, leaf area, canopy ecophysiology, and microclimate (Liu et
38 al., 2005). The most immediate biophysical effect of wildfire on the land surface is the decrease in
39 live vegetation and the deposition of black carbon on the soil surface (De Sales et al., 2018). The
40 alteration in surface roughness directly influences the interaction between the land and the
41 atmosphere by, typically, reducing the turbulent mixing and net radiation (Chambers et al., 2005).
42 Moreover, the deposition of the black carbon on the surface changes net radiation through its
43 impact on surface albedo, which alters the partitioning of energy into latent heat and sensible heat
44 (Jin & Roy, 2005). Fires have the potential to modify local to regional climate through these long-
45 lived changes in land surface dynamics and other substantial forcing impacts such as greenhouse
46 gas fluxes and aerosols (Bonan et al., 1995). In this study, we use contemporary spaceborne
47 observing systems to quantify the magnitude and timing of ecosystem responses to severe wildfires
48 as a crucial step in assessing their associated ecological, hydrological, and biogeophysical impacts.

49 In addition to quantification, it is equally important to document the factors that determine
50 variability in post-fire recovery in order to develop a predictive understanding of ecosystem
51 dynamics in response to wildfire, especially considering present and expected future increases in
52 the frequency of large, severe wildfires (Scholze et al., 2006; IPCC, 2007; Seastedt et al., 2008;
53 Urza et al., 2017; Hankin et al., 2019). Vegetation recovery is likely to vary considerably across
54 the landscape, even when initial estimates of fire severity are similar (Keeley et al., 2008; Frazier
55 et al., 2018). Some forest ecosystems have shown to recover fully after large severe disturbances
56 (Rodrigo et al., 2004; Knox & Clarke, 2012), while others have recovered little towards pre-fire
57 levels (Barton, 2002; Rodrigo et al., 2004; Lippok et al., 2013). Variability in recovery rates has
58 been shown to depend on the interactive effects of numerous biotic and abiotic factors related to
59 nature of fire, life history traits of species, and environmental conditions following fire (Chambers
60 et al., 2016; Johnstone et al., 2016; Stevens-Rumann et al., 2018). For example, post-fire recovery
61 of dry mixed conifer forests in the western U.S. is strongly affected by fire severity (Chappell
62 1996; Meng et al., 2015; Kemp et al., 2016; Harvey et al., 2016; Meng et al., 2018; Vanderhoof et
63 al., 2020) and pre-fire condition (Martin-Alcon & Coll, 2016; Zhao et al., 2016). Other factors that
64 can be important to vegetation recovery after fire include vegetation type (Epting, 2005; Yang et
65 al., 2017); site topography including slope, aspect, and elevation (Wittenberg et al., 2007; Meng
66 et al., 2015; Liu et al., 2016; Chambers et al., 2018; Haffey et al., 2018), and post-fire climate
67 including temperature and moisture conditions (Chappell, 1996; Meng et al., 2015; Stevens-
68 Rumann et al., 2018; Kemp et al., 2019; Guz et al., 2021). Long-term assessment of post-fire
69 vegetation recovery across forest types can offer valuable insights to researchers and land
70 managers who seek to identify areas that could benefit from post-fire management and develop
71 potential management actions such as fuels treatment, prescribed fire, carbon management, etc.

72 Several studies have documented vegetation recovery and associated biogeophysical and
73 biogeochemical dynamics in response to wildfires by employing field-based observations
74 including flux tower measurements (Chambers & Chapin III, 2002; Jin & Roy, 20005; Amiro et
75 al., 2006; Randerson et al., 2006; Campbell et al., 2007; Dore et al., 2010; Kemp et al., 2016;
76 Hankin et al., 2019; Ma et al., 2020), remote sensing observations (Veraverbeke et all., 2012;
77 O’Halloran et al., 2014; Micheletty et al., 2014; Rogers et al., 2015; Bright et al., 2019; Vanderhoof
78 et al., 2020), and modeling approaches driven by remote sensing observations (Hicke et al., 2003;
79 Bond-Lamberty et al., 2009; Williams et al., 2012; Rogers et al., 2013; Maina et al., 2019). While
80 instructive and critical for mechanistic understanding, local field-based studies on post-fire
81 ecological dynamics tend to focus on small, localized areas, encompassing only a single or a few
82 wildfire events (Meigs et al., 2009; Montes-Helu et al., 2009; Downing et al., 2019). In contrast,
83 large-scale regional analyses using remotely sensed observations and modeling approaches tend
84 to focus on Mediterranean (Veraverbeke et all., 2012a, 2012b; Meng et al., 2014; Yang et al.,
85 2017) and boreal ecosystems (Amiro et al., 2000; Chambers & Chapin, 2003; Randerson et al.,
86 2006; Lyons et al., 2008; Amiro et al., 2010; Jin et al., 2012; Rogers et al., 2013; [Hislop et al.,](#)
87 [2020](#)), or on only a few forest types (mostly ponderosa pine and mixed conifer of western U.S.)
88 (Chen et al., 2011; Dore et al., 2012; Meng et al., 2015; Roche et al., 2018; Bright et al., 2019;
89 [Littlefield et al., 2020](#)). Moreover, such studies ~~have less explored~~ ~~did not examine~~ ~~failed to~~
90 ~~document~~ how ~~these~~ ~~their~~ results scale up to multiple fire events across broad regions.

91 The purpose of this study is to provide more precise estimate of wildfire impacts on LAI and
92 surface albedo in seven different forest types of the western US using observations derived from
93 the MODIS. Moreover, this study also examines the factors that influence the nature and rate of
94 vegetation recovery in the post-fire environment. The hypotheses for the work are that 1) the rate

95 of recovery of LAI following wildfire varies across forest types and ecoclimatic settings, 2) the
96 change in vegetation cover post-fire induces a change in the albedo which varies by forest types
97 and ecoclimatic settings, and 3) the variability in the post-fire response of albedo is attributable to
98 the same factors that explain variability in LAI post-fire.

99 2. Methods

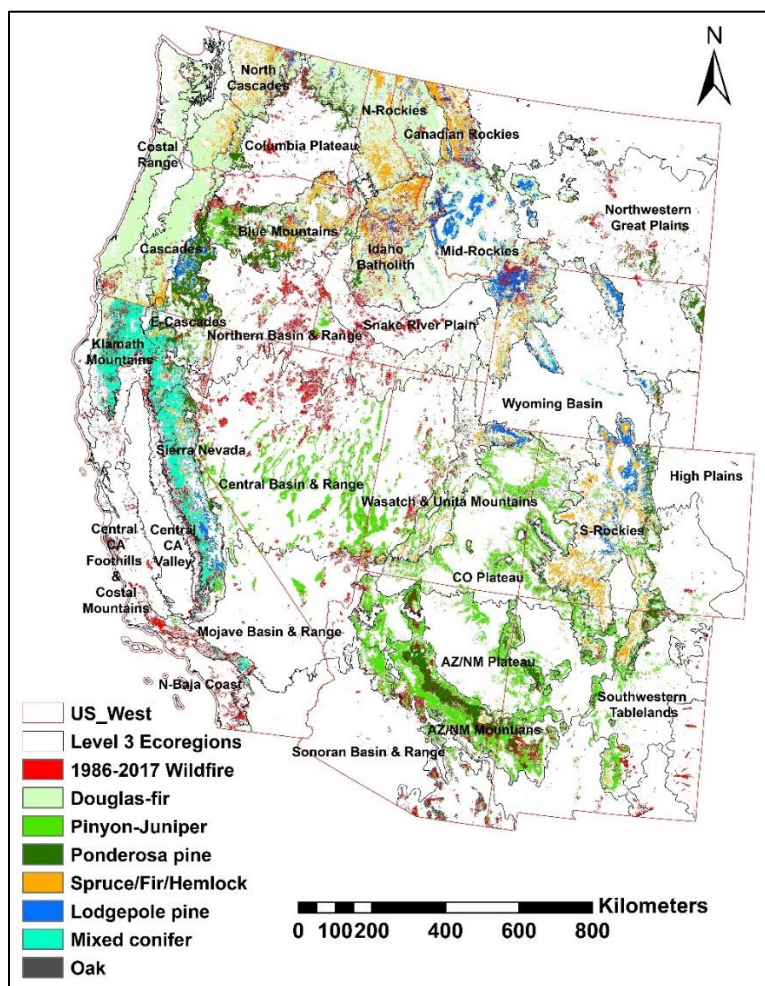
100 2.1. Study Area

101 This study was carried out in the western US, a region that has been severely disturbed by wildfires
102 in the last several decades. Its extent for the purpose of this study (Fig. 1) encompasses the
103 conterminous US west of the 100th meridian (Thompson et al., 2003). This region is geographically
104 diverse with high physiographic relief and strong local and regional climatic gradients (Bartlein &
105 Hostetler, 2003), including regions such as temperate rain forests, high mountain ranges, great
106 plains, and deserts (Thompson et al., 2003). Our study considered seven forest types that are
107 dominant across the western US, as defined by the US Forest Service's National Forest Type data
108 set (Ruefenacht et al., 2008), including Douglas-fir, Pinyon-Juniper, Ponderosa pine,
109 Spruce/Fir/Hemlock, Mixed conifer, Lodgepole pine, and Oak. Within these forest types, we only
110 considered areas that were burned with high severity as defined by Monitoring Trends in Burn

111 Severity (MTBS) to examine the post-fire biophysical dynamics. In case of attribution of postfire
112 recovery, we considered all fire severity classes from MTBS in our random forest model to
113 determine the influence of these classes on post-fire recovery of vegetation and surface albedo.

114 Within each ecoregion, we selected only those forest types that cover >10% of ecoregion's forest
115 area and had >1% pixels burned under high severity. As a result, only 21 out of 35 level III
116 ecoregions of the western US (Table S1) (Omernik, 1987) had a sufficient number of 500 m x 500
117 m pixels that saw high severity burning within these forest types to support the generation of forest-

118 type-specific chronosequences of post-fire ecological responses. Across these ecoregions, average
 119 annual precipitation (1981-2010) was 900 ± 490 mm yr⁻¹ (mean \pm SD), while mean summer
 120 minimum and maximum temperature were $23^\circ \pm 2.8^\circ\text{C}$ and $7^\circ \pm 2.5^\circ\text{C}$, respectively (PRISM; Daly
 121 et al., 2008).



122
 123 Figure 1: Distribution of 1986-2017 **burned area wildfires** (Eidenshink et al., 2007) and forest types
 124 (Ruefenacht et al., 2008) within study area extent.

125 2.2. Remote Sensing Data and Data Products

126 The burned area and fire severity data used in this study were obtained from Monitoring Trends in
 127 Burn Severity (MTBS) for the period of 1986-2017 (Eidenshink et al., 2007). We divided our study
 128 into different forest types to analyze the recovery of LAI and albedo post-fire, utilizing a USFS

129 forest type group map (Ruefenacht et al., 2008). We ~~resampled~~~~reprojected~~ the MTBS dataset from
130 its native 30 m resolution to a coarser 500 m resolution. During this process, we retained only
131 those 500 m pixels that contained at least 75% of the corresponding 30 m pixels burned, thus
132 reducing noise from pixels with an unclear mix of burn and unburn conditions. Similarly, we
133 resampled forest type grid from 250 m to 500 m resolution and selected pixels where at least 75%
134 of the forest within each pixel belonged to a single forest type based on the 250 m forest type group
135 map. We excluded pixels that were burned more than once between 1986 and 2017 as such pixels
136 can add noise to the post-fire trajectory of biophysical properties.

137 This study analyzed spatially and temporally consistent MODIS products: LAI and shortwave
138 white sky albedo to assess fire-induced change in vegetation and surface albedo in the western US.
139 The MODIS satellite data tile subsets (tiles h8v4, h8v5, h9v4, h9v5, h10v4, and h10v5) from 2001
140 to 2019 were downloaded from the MODIS data archive (<https://www.earthdata.nasa.gov/>).
141 Within each data tile, we employed the quality assurance (QA) bits embedded in the MODIS
142 products to ensure that only the highest-quality values (flagged as '0') were included. This process
143 involved removing all retrievals affected by cloud cover and those flagged for low quality. The
144 MODIS LAI product (MCD15A2H; Myneni et al., 2002) reports the green leaf area index which
145 represents the amount of one-sided green leaf area per unit ground area in broadleaf canopies or
146 half the total surface area of needles per unit ground area in coniferous canopies. The MODIS LAI
147 algorithm utilize a main look-up-table (LUT) based procedure that makes use of spectral
148 information contained in red and NIR bands along with a back-up algorithm that relies on an
149 empirical relationship between the Normalized Difference Vegetation Index (NDVI) and canopy
150 LAI, and fraction of photosynthetically active radiation (fPAR) (Myneni et al., 2002).

151 For albedo, we used the daily MODIS collection 6 bidirectional reflectance distribution function
152 (BRDF)/Albedo product at 500 m resolution (MCD43A3; Schaaf et al., 2002). The use of both
153 Terra and Aqua data in this product provides more diverse angular samplings and increased
154 probability of high input data that allow more accurate BRDF and albedo retrievals. The MODIS
155 albedo algorithm uses a bidirectional reflectance distribution and shortwave reflectances (0.3-5.0
156 μm) and provides both black-sky and white-sky albedos. We used shortwave broadband white sky
157 albedo for this study because it is less biased in complex terrain and less sensitive to view and
158 solar angles (Gao et al., 2005). We stratified the sampling of white-sky albedo by snow-free and
159 snow-covered conditions based on the presence or absence of snow, determined at a pixel level by
160 the MODIS daily snow cover 500 m product (MOD10A1; Salomonson and Appel, 2004). We
161 assigned snow-free and snow-covered conditions using a threshold of less than 30% and greater
162 than 75% snow cover. We chose these thresholds as a balance between inclusion for robust
163 sampling and exclusion to reduce noise from pixels with an unclear mix of snow and snow-free
164 conditions. We are aware that much of our study domain does not have considerable snow cover
165 during winter, and these snow-free winter albedos had similar patterns and magnitudes as summer
166 albedos (Fig. S1). Therefore, the average summer (June-August) albedo values presented here
167 represent the snow-free condition only, while the average winter (December – February) values
168 presented include only snow-covered conditions. We did not report winter albedos for all forest
169 types because of limits on the availability of high-quality snow-covered pixels.

170 As part of our attribution analysis that seeks to identify factors that influence the pattern of post-
171 fire biophysical dynamics, we acquired a suite of climate variables– monthly mean summer
172 precipitation, monthly mean summer temperature, monthly minimum summer temperature,
173 monthly maximum summer temperature, total annual precipitation– covering the 2001-2019

174 period from Parameter-Elevation Regressions on Independent Slopes Model (PRISM; Daly et al.,
175 2008). PRISM utilizes point measurements of precipitation and temperature to generate continuous
176 digital grid estimations for climate data with a 4 km spatial resolution (Daly et al., 1994). The
177 elevation of all burned pixels was taken from the US Geological Survey (USGS) National
178 Elevation Dataset (NED) at 30 m (U.S. Geological Survey, 2019). All topo-climatic variables were
179 re-gridded to the 500 m MODIS ~~resolution~~projection for uniformity.

180 **2.3. Generating Chronosequences of Post-fire LAI and Albedo**

181 To address unrealistic variation in MODIS land surface products (Cohen et al., 2006), we
182 computed mean monthly values by adding all samples and dividing it by the number of samples
183 in each month within our stratified design. For the summer season, we computed mean yearly
184 summer-season values of LAI and albedo by averaging the data from June, July, and August.
185 Similarly, for the winter season, yearly values of LAI and albedo were computed the same way
186 using data from December, January, and February. Next, we analyzed changes in post-fire LAI
187 and albedo relative to pre-fire by sampling each of them as an annual time series from three years
188 before wildfire events to all years of record after wildfire events. We grouped samples from each
189 fire event based on forest type, eco-climatic setting, and snow cover conditions. Within these
190 groups, we composited burn events from different years and aligned them temporally to represent
191 three years prior to the fire and all years after the fire. Consequently, chronosequences of
192 biophysical properties as a function of time since fire were created for a combination of seven
193 forest types, two snow cover conditions (in case of albedo), and 21 sub-ecoregions.

194 **2.4. Attribution of Recovery**

215 We explored the relationships between albedo and LAI recovery and topo-climatic factors, and
216 subsequently attributed the recovery at 10 years post-fire and 20 years post-fire using random
217 forest (RF) algorithms, implemented in R (Breiman 2001; Liaw & Wiener, 2002). We used a non-
218 parametric modeling method because most variable distributions were non-normal and RF does
219 not require the variables to be normally distributed. Additionally, RF can handle tens of thousands
220 of data points and provides variable importance scores. We initially selected seven explanatory
221 variables - fire severity class (low, medium, and high), three temperature variables, two
222 precipitation variables, and elevation. Although RFs do not require collinear variables to be
223 removed (Breiman, 2001), we employed a Variance Inflation Factor (VIF) analysis for
224 multicollinearity as a variable selection method to improve computation efficiency and enhance
225 interpretation, particularly with respect to variable importance. VIF analysis involves: a)
226 calculating VIF factors, b) removing the predictors from this set with $VIF > 10$, and c) repeating
227 until no variable has $VIF > 10$. This provided us with four uncorrelated predictors to be used in the
228 RF model - fire severity class, total annual precipitation, mean summer temperature (June –
229 August), and elevation. We pooled post-fire LAI and albedo responses across 21 ecoregions within
230 a given forest type for both time ~~intervals~~ horizons (10-year post-fire and 20-year post-fire). The
231 dataset was divided into training (80%) dataset to train the RF model and test (20%) dataset to
232 validate the model. We created four RF models with 500 binary decision trees for each forest type
233 (one for each time ~~horizon~~interval for both LAI and albedo) ~~using fire and topo-climatic variables~~
234 ~~to determine how fire severity, climate and topography variables contributed to the recovery of~~
235 ~~summer LAI and albedo at two different times after burning 10 years post fire and 20 years post~~
236 ~~fire~~. We tuned the model to generate a model with the highest accuracy i.e., the lowest out-of-bag
237 error among all tested combination of parameter values. The model's performance was assessed

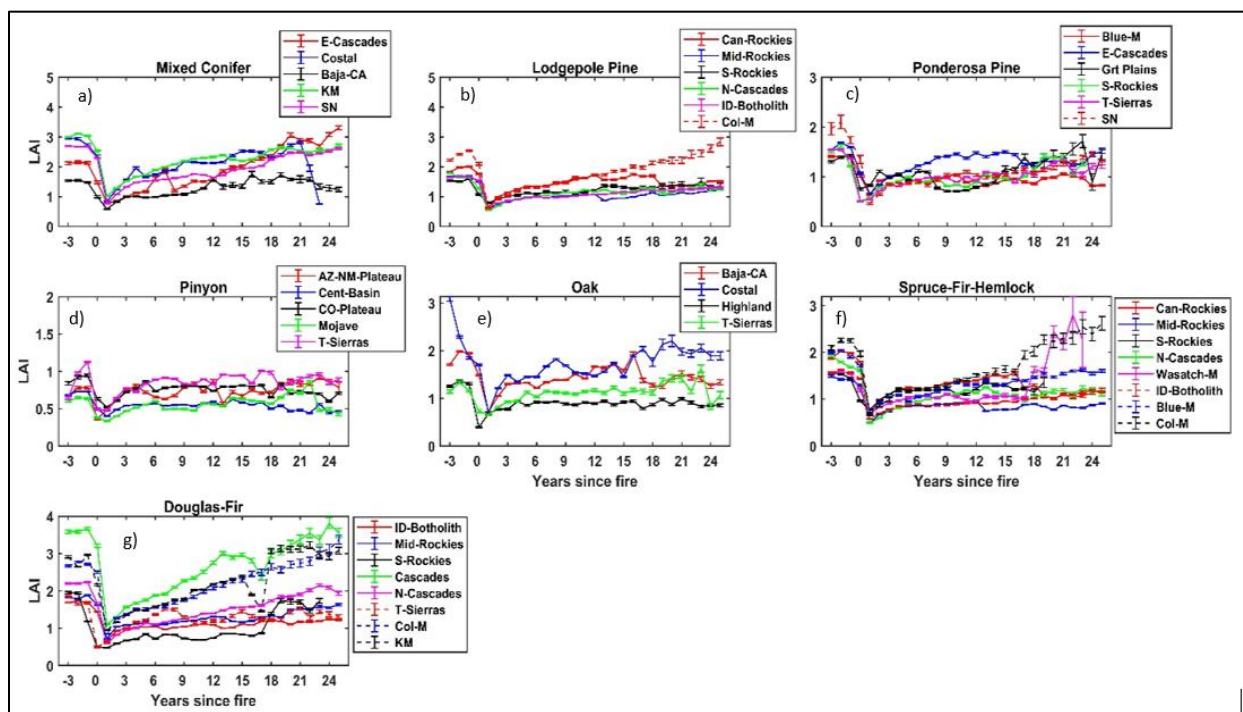
218 using the R^2 metric. We used unscaled permutation accuracy instead of the traditional Gini-based
219 importance metric to rank the relative importance among explanatory variables, as Gini-based
220 importance was shown to be more strongly biased towards continuous variables or variables with
221 more categories compared to other importance metrics (Strobl et al., 2007). The unscaled
222 permutation importance metric calculates variable importance scores as the amount of decrease in
223 the accuracy when a target variable is excluded. We used partial dependence plots (PDP) to
224 visualize the influence of each explanatory variable on the degree of 10 years and 20 years post-
225 fire recovery of LAI and albedo. PDP quantifies the marginal effects of a given variable on an
226 outcome and provides a mechanism to explore insight in big datasets, especially when the random
227 forest is dominated by lower-order interactions (Martin, 2014).

228 **3. Results**

229 **3.1. Post-fire Recovery of Land Surface Properties**

230 Burning caused a large decline in LAI for all forest types. Generally, high productivity forests
231 (e.g., Douglas-fir and Mixed conifers), compared to other forest types, experienced a larger decline
232 in LAI in year one after fire (Fig. 2a-g). Compared to pre-fire levels, the decline in LAI ranged
233 from 47% in Pinyon-Juniper to 76% in Ponderosa pine forests (Table S2). After this initial
234 decrease, the effects of vegetation regeneration became apparent. For all forest types, the
235 magnitude of LAI change decreases with increase in time since fire. However, LAI did not recover
236 to the pre-fire condition in most cases by the 25-year period of observation available for this study.
237 We found large differences in the timing of LAI recovery across forest types, with forest types
238 recovering at different rates, crossing the pre-fire levels at different times, and reaching different
239 peaks in LAI (Fig. 2a-g). For example, Douglas-fir in Columbia Mountains, Klamath Mountains,
240 and Southern Rockies (Fig. 2g) and Mixed conifers in Baja California and Eastern Cascades (Fig.

241 2a) showed complete recovery of LAI to pre-fire levels within the 25-year study period, while
 242 Lodgepole pine, Oak, and Ponderosa pine were characterized by a slower recovery rate and most
 243 did not recover to pre-fire levels by the 25-year period (Fig. 2 and Table S2). We also found varied
 244 recovery rates across geographic regions even within a single forest type, presumably related to
 245 climate and soils. For example, the characteristic post-fire LAI trajectories for the high
 246 productivity Douglas-fir forest type (Fig. 2g) showed a substantially faster recovery in Cascades,
 247 Klamath Mountains, and Columbia Mountains regions compared to the Idaho Batholith region of
 248 the western US. Based on observations from all forest types, in general, the faster recovery of LAI
 249 was observed in high elevation, wet areas with substantial maritime influences.

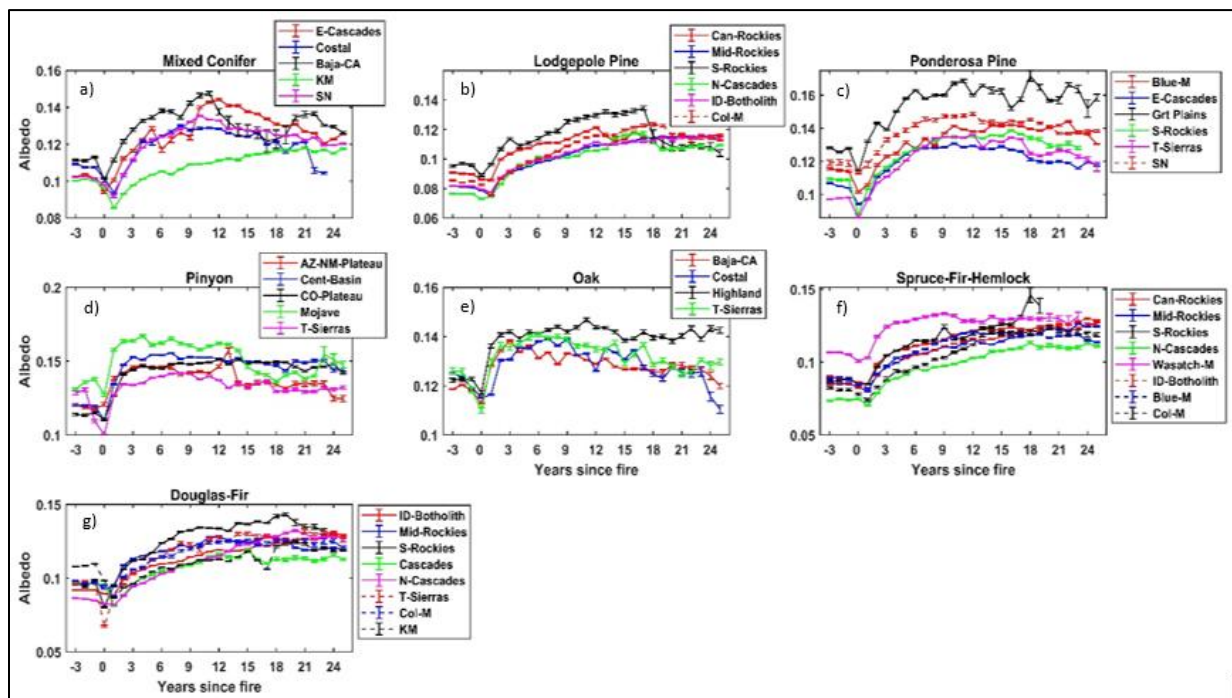


250
 251 Figure 2: Mean summer post-fire LAI (\pm SE) as a function of time since fire in seven different
 252 forest types of the western US. (Sub-ecoregions: E-Cascades = Eastern Cascades; Costal = Coastal
 253 sage; Baja-CA = Baja California; KM = Klamath Mountains; SN = Sierra Nevada; Can-Rockies
 254 = Canadian Rockies; Mid-Rockies = Middle Rockies; S-Rockies = Southern Rockies; N-Cascades
 255 = Northern Cascades; ID-Batholith: = Idaho Batholith; Col-M = Columbia Mountains; Blue-M =
 256 Blue Mountains; Grt Plains = Great Plains; T-Sierras = Temperate Sierras; AZ-NM-Plateau =
 257 Arizona-New Mexico Plateau; Cent-Basin = Central Basin; CO-Plateau = Colorado Plateau;

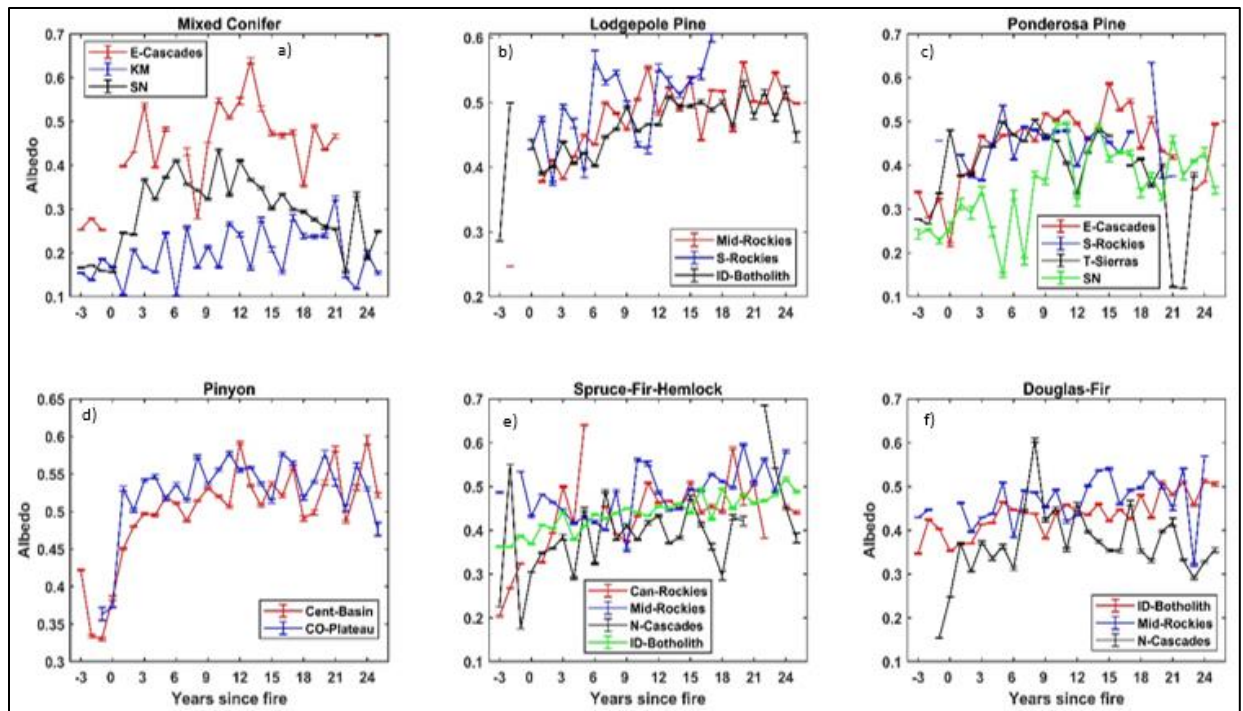
258 Mojave = Mojave Basin; Highland = North American Highland; Wasatch-M = Wasatch
259 Mountains).

260 Turning to albedo, we found significant changes in summer albedo post-fire of all forest types.
261 Three important trends, similar among forest types, emerged from these post-fire summer albedo
262 trajectories. First, for all forest types, summer albedo decreased immediately after fire (Fig. 3)
263 likely due to low reflectivity by black carbon deposition on the soil surface and dead tree boles
264 both common immediately after high severity burning. The decline in summer albedo ranged from
265 0.01-0.02 across forest types with the greatest decline (20% from pre-fire levels; Table S3)
266 observed in Douglas-fir forest of the Klamath Mountains region. Second, post-fire albedo
267 increased gradually from year two since fire, crossing the pre-fire levels at around 3 years post-
268 fire, and peaking at different time horizons~~intervals~~ for different forest types and regions (Fig. 3a-
269 g). Elevated post-burn albedo is presumably due to increasing canopy cover, the relative high
270 albedo of grasses and shrubs that establish in early succession, and the loss of black carbon
271 coatings on soil and woody debris (Chambers and Chapin, 2002). The timing and magnitude of
272 peak post-fire albedo varied across forest types. For example, Ponderosa pine showed its peak in
273 post-fire albedo at 18 years post-fire (Fig. 3c) and 11 years post-fire for one of the Mixed Conifer
274 regions (Fig. 3a), while slow growing species such as Spruce/Fir/Hemlock may not have reached
275 its peak by the end of the 25-year post-fire study period (Fig. 3f). Similarly, there were we see
276 significant regional differences in timing and magnitude of peak albedo for a given forest type
277 group. For example, Mixed Conifer post-fire albedo peaked at 11 years post-fire in Baja California,
278 while it continued to increase through to 25 years in Klamath Mountains (Fig. 3a). Third, as the
279 post-fire LAI approached the pre-fire LAI levels, post-fire albedo started to decline from the peak
280 towards its pre-fire albedo, but it did not reach the pre-fire albedo levels by the end of the 25-year
281 study period (Fig. 3a-g).

282 Post-fire winter albedo for each forest type had a similar pattern as summer albedo except with
 283 greater magnitude and that it increased immediately after fire (Fig. 4a-f and Table S4). We
 284 observed greater inter-annual variability in the timeseries of post-fire winter albedo likely related
 285 to ~~greater noise associated with~~ variability in snow cover and also [a smaller signal-to-noise ratio](#)
 286 [associated with](#) smaller sample sizes. The albedo response was more than three-fold larger in
 287 winter than in summer, peaking in the range of 0.4 to 0.6 across forest types and with an increase
 288 over pre-fire levels of about 0.25 to 0.50. Similar to summer albedos, winter albedos did not return
 289 to the pre-fire levels by the end of 25-year study period (Fig. 4a-f).



290
 291 Figure 3: Mean summer post-fire albedo (\pm SE) as a function of time since fire in seven different
 292 forest types of the western US.



293
 294 Figure: 4: Mean winter post-fire albedo (\pm SE) as a function of time since fire in seven different
 295 forest types of the western US.

296 3.2. Drivers of post-fire recovery of LAI and albedo

297 Our random forest model had high accuracy for recovery of both LAI and albedo 10 years and 20
 298 years post-fire. The out-of-bag (OOB) error rate of the random forest model for the relative
 299 recovery of 10-year post-fire LAI was around 3% - 8% ($r^2 = 0.66 - 0.78$), while it was around
 300 2.5% - 9% ($r^2 = 0.65 - 0.78$), 0.4% - 1.4% ($r^2 = 0.55 - 0.83$), and 0.3% - 1.6% ($r^2 = 0.52 - 0.83$)
 301 for 20-year post-fire LAI, 10-year post-fire albedo, and 20-year post-fire albedo, respectively
 302 (Table S5). The variable with greatest importance agreed well between 10-year LAI and 20-year
 303 post-fire LAI for all forest types indicating that the recovery of LAI at 10-year and 20-year post-
 304 fire were both largely determined by the same governing factors (Fig. S2). Among all the
 305 explanatory variables, the degree of post-fire LAI recovery at both 10-year and 20-year post-fire
 306 were largely dominated by elevation and total annual precipitation (Fig. S2). In contrast, the factor
 307 with greatest influence on post-fire summer albedo varied by forest type and time since fire. For

308 example, in the Mixed conifer forest type, annual precipitation was the major determinant of 10-
309 year post-fire albedo recovery, while it was average summer temperature in case of 20-year
310 postfire. Similarly, the degree of 10-year post-fire albedo recovery in the Spruce/Fir/Hemlock
311 forest type was largely determined by average summer temperature, while the recovery after 20-
312 year post-fire was mainly determined by elevation. Fire severity, on the other hand, showed almost
313 no explanatory power in predicting recovery of LAI and albedo at both times for all forest types
314 (Fig. S2,S3).

315 The degree of LAI recovery 10-year post-fire increased with an increase in total annual
316 precipitation for all forest types, but it varied little when the total annual precipitation exceeded
317 1000 mm. Annual precipitation was the major determinant of 10-year postfire LAI recovery for
318 dry forests like Ponderosa pine, Pinyon-Junipers, and Oak, and these forest types tended to recover
319 above pre-fire levels as the annual precipitation is increased. However, when the annual
320 precipitation is less than 500 mm, the relative change in LAI is below 0 for all forest types,
321 indicating that the complete recovery of LAI 10-year postfire was unlikely with annual
322 precipitation less than 500 mm (Fig. 5c). In contrast, five out of seven forest types recovered over
323 pre-fire levels 20-years post-fire with increased annual precipitation, indicating that Mixed
324 conifers and Douglas-fir need more time and higher annual precipitation to recover to the pre-fire
325 level. Only Oak and Ponderosa pine showed increased LAI 20-year post-fire as the annual
326 precipitation exceeded 2000 mm (Fig. 6c). As with LAI, annual precipitation was one of the major
327 determinants of both 10-year and 20-year post-fire albedo recovery. The post-fire ~~elevation~~
328 ~~of increase in~~ albedo ~~by 10 years~~ was ~~greater~~ larger for sites with less annual precipitation (Fig. 7c
329 and 8c), particularly noticeable in dry forest types such as Douglas-fir, Ponderosa pine, and Oak
330 where increased precipitation triggered a rapid increase in post-fire vegetation recovery. The Oak

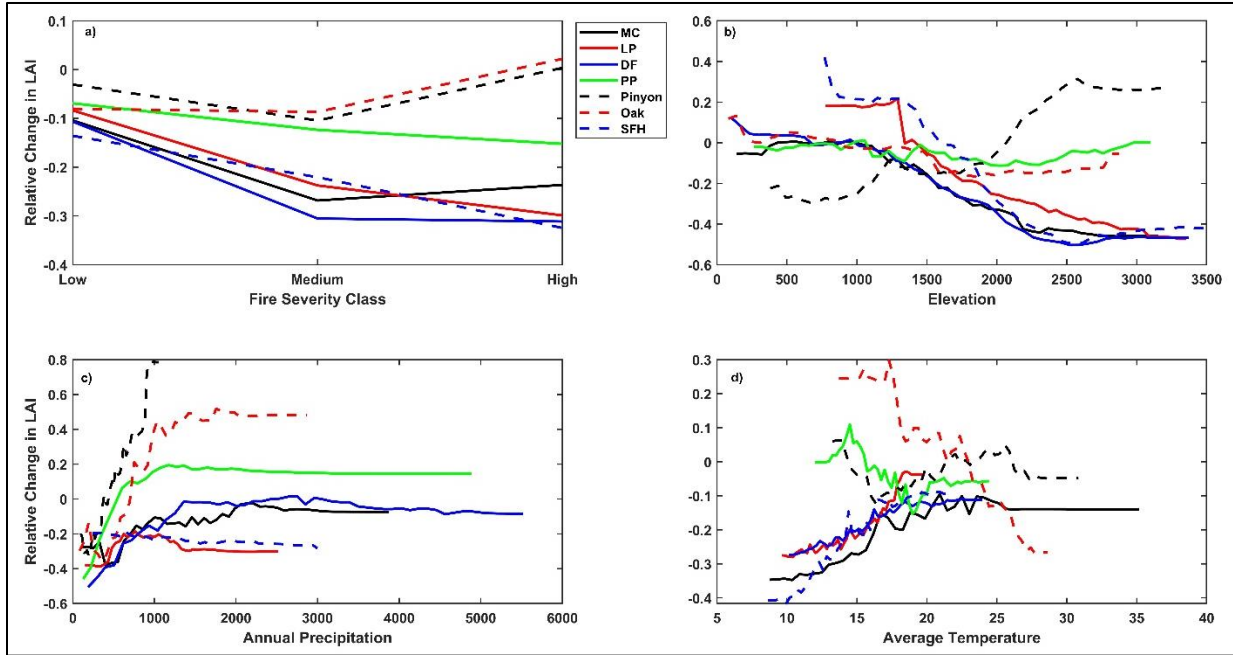
331 forest type showed a particular anomaly of albedo 20-years post-fire, exhibiting a decline of around
332 20% below pre-fire levels for sites with annual precipitation of 2000 mm or above (Fig. 8c),
333 consistent with a rapid increase in vegetation recovery.

334 Regarding average summer temperature, we found interesting divergence in the pattern of LAI
335 response between cool and hot climates. For forests growing in hotter conditions, the magnitude
336 of LAI recovery at both time ~~horizons~~~~intervals~~ decreased in areas with higher temperatures,
337 particularly in Oak, Pinyon-Junipers, and Ponderosa pine forest types, as these forest types grow
338 at warmer end of the species distribution. In contrast, increases in average summer temperature
339 assisted the recovery of forest types growing at the colder end of the species distribution such as
340 Lodgepole pine and Spruce/Fir/Hemlock (Fig. 5d and 6d), noting that LAI was consistently lower
341 than pre-fire levels for these forest types at both time ~~horizons~~~~intervals~~. Albedo does not show the
342 same divergence in pattern with warmer conditions, and instead we find a somewhat surprising
343 pattern. Hotter sites tend to ~~experiencesee~~ a larger ~~enhancement~~~~elevation~~ of summertime albedo
344 over the pre-fire condition at both time ~~horizons~~~~intervals~~ in spite of faster recovery of LAI with
345 hotter temperature (Fig. 7d and 8d).

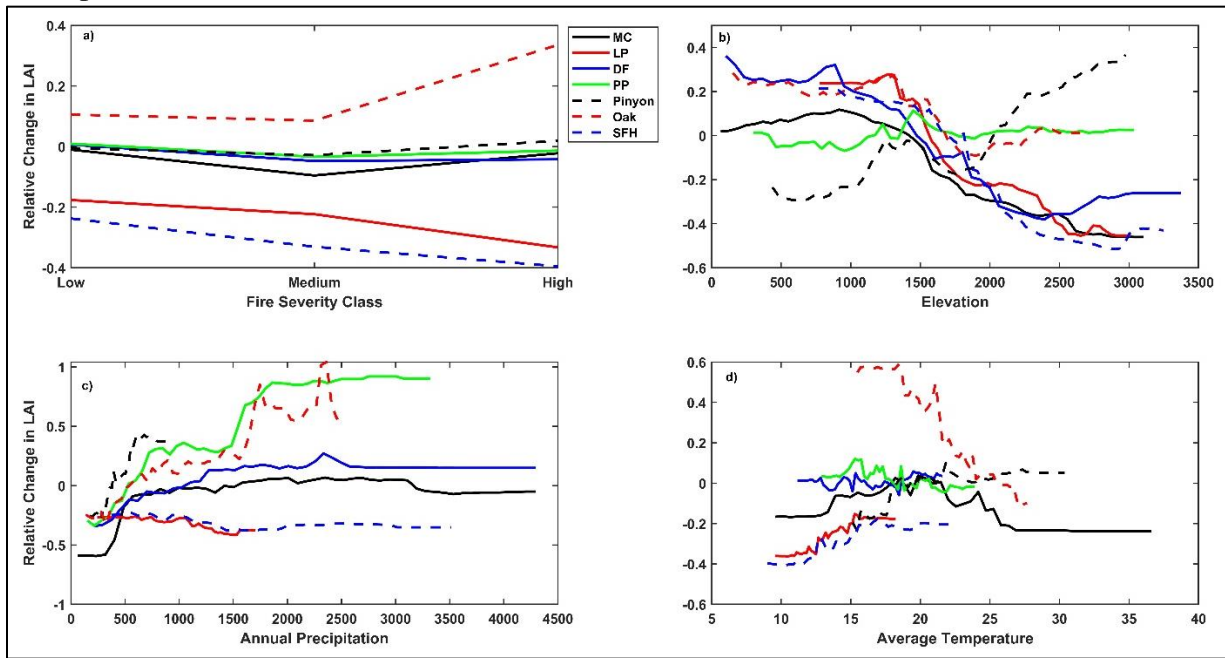
346 Elevation was consistently found to be an important variable in determining the trajectory of post-
347 fire vegetation recovery. The post-fire recovery of LAI was slower at higher elevation both 10-
348 years and 20-years post-fire. Most forest types showed complete recovery towards pre-fire levels
349 at an elevation below 1500 m. Only Pinyon-Junipers and Ponderosa pine forest types saw faster,
350 more complete recovery of LAI with higher elevation (Fig. 5b and 6b). Turning to albedo response,
351 we found that higher elevation led to a smaller increase in albedo over its pre-fire value for both
352 time periods for the two forest types for which elevation was the most important predictor of post-
353 fire albedo change, namely for Pinyon-Juniper and Ponderosa pine forests. This is consistent with

354 faster post-fire recovery of LAI at higher elevation portions of range for these two forest types. In
355 contrast, post-fire albedo of Douglas-fir, Mixed conifer and Oak forest types showed little
356 dependence on elevation (Fig. 7b and 8b).

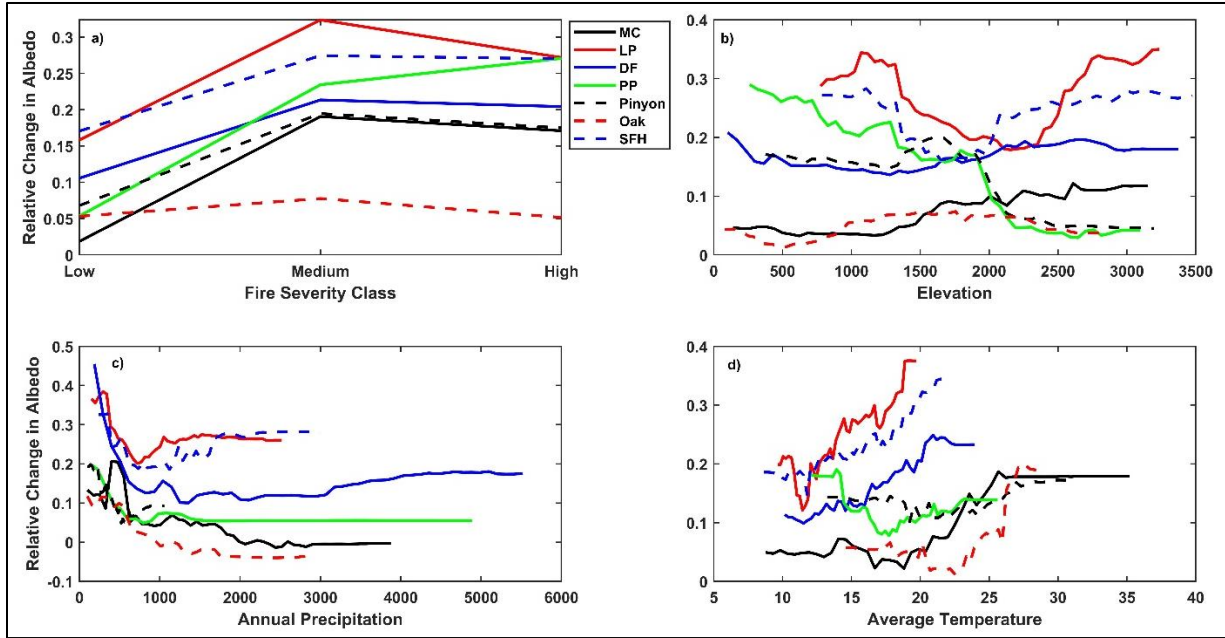
357 Although fire severity was the least important predictor of both post-fire LAI and albedo recovery
358 at both time horizonsevents, our results showed significant variation in post-fire recovery among
359 severity classes for all forest types. As expected, the overall recovery of LAI 10-year post-fire was
360 greater for low fire severity where the recovery ranged between 85% and 95% of pre-fire LAI
361 levels (Fig. 5a). Only in the case of Oak and Pinyon-Juniper forest types that burned with high
362 severity did we see full recovery of LAI at or above pre-fire levels by 10-years post-fire. By 20
363 years post-fire, Lodgepole pine and Spruce/Fir/Hemlock still show a suppression of LAI relative
364 to pre-burn and less recovery for more severe burn conditions (Fig. 6a) while Oak sees LAI
365 elevated over the pre-burn condition and saw the largest LAI at sites that had the highest severity
366 fires (Fig. 6a). The four other forest types had LAI equal to the pre-burn condition and showed no
367 variation across fire severity. For albedo, all forest types showed a larger elevation of albedo over
368 their pre-fire values under medium fire severity (Fig. 7a). Oak had the lowest change in albedo at
369 both time horizonsevents, owing to rapid post-fire recovery. Overall, post-fire albedo was
370 consistently higher than pre-fire levels at both time horizonsevents in all forest types indicating
371 that albedo requires more than two decades to return to pre-fire levels in these forest types (Fig.
372 7a and 8a).



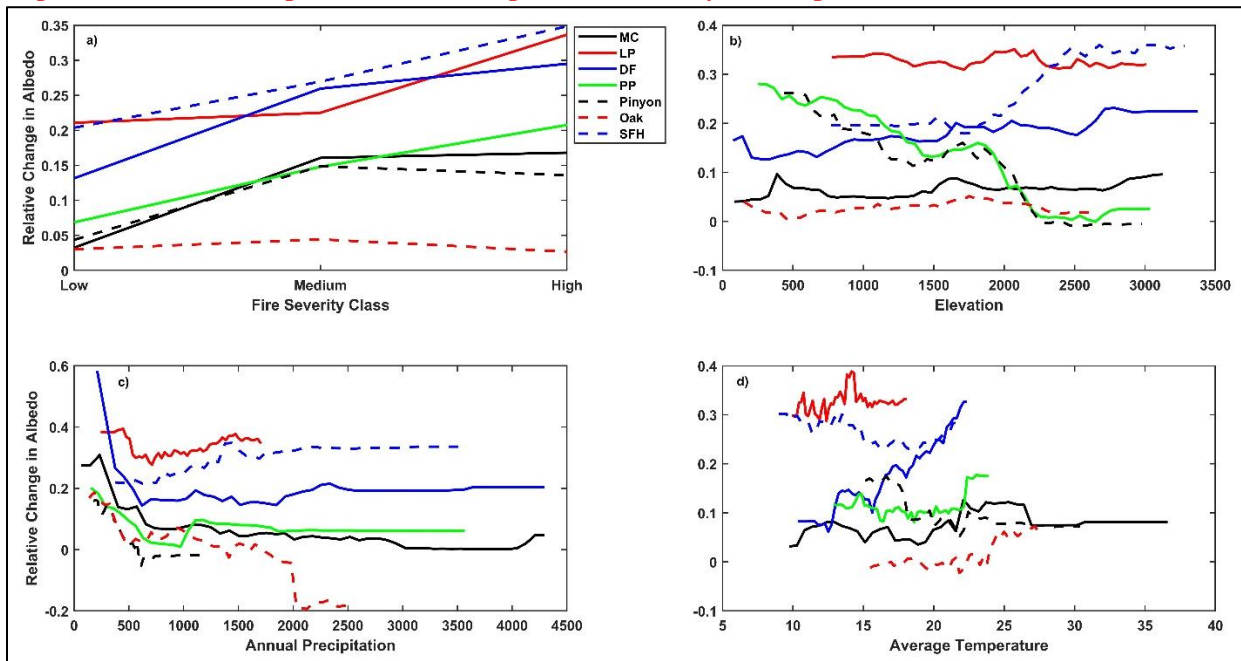
373
 374 Figure 5: Partial dependence of change in summer LAI 10-year post-fire relative to pre-fire on a)
 375 fire severity, b) elevation, c) annual precipitation, and d) mean monthly summer temperature.
 376 (Forest types: MC = Mixed Conifers; LP = Lodgepole pine; DF = Douglas-fir; PP = Ponderosa
 377 pine; Pinyon = Pinyon-Juniper; SFH = Spruce/Fir/Hemlock). The y-axis represents change in LAI
 378 post-fire relative to pre-fire (degree of recovery), where negative values represent recovery below
 379 pre-fire levels, 0 represents recovery to pre-fire levels, and positive values represent recovery
 380 above pre-fire levels.



381
 382 Figure 6: Partial dependence of change in summer LAI 20-year post-fire relative to pre-fire on a)
 383 fire severity, b) elevation, c) annual precipitation, and d) mean monthly summer temperature.



384
 385 Figure 7: Partial dependence of change in summer snow-free albedo 10-year post-fire relative to
 386 pre-fire on a) fire severity, b) elevation, c) annual precipitation, and d) mean monthly summer
 387 temperature. ~~The y axis represents change in albedo post fire relative to pre fire (degree of~~
 388 ~~recovery), where negative values represent recovery below pre fire levels, 0 represents recovery~~
 389 ~~to pre fire levels, and positive values represent recovery above pre fire levels.~~



390
 391 Figure 8: Partial dependence of change in summer snow-free albedo 20-year post-fire relative to
 392 pre-fire on a) fire severity, b) elevation, c) annual precipitation, and d) mean monthly summer
 393 temperature.

394 **4. Discussion and Conclusion**

395 Here, we extended the regional research by Shrestha et al., (2022) with a much broader sampling
396 to study post-fire responses for seven forest types in 21 sub-ecoregions of the western U.S. In
397 addition, this study also uses a machine learning approach (random forest) to examine the influence
398 of several topo-climatic variables on the nature and rate of vegetation recovery and associated
399 albedo in the post-fire environment.

400 **4.1. Post-fire Vegetation Recovery**

401 In this study, we used MODIS-derived LAI to increase our understanding of variability in the
402 recovery of vegetation in the post-fire environment across seven forest types and 21 sub-
403 ecoregions of the western United States. ~~Our study focused on the change of LAI over 25 years~~
404 ~~post-fire. During this timeframe, the recovery of LAI to the pre-fire condition can be expected to~~
405 ~~reflect establishment of new vegetation as well as the (re)growth and expansion of vegetation that~~
406 ~~managed to survive the wildfire.~~ Similar to other studies (Morresi et al., 2019; Vanderhoof et al.,
407 2020), we found rapid vegetation recovery in the first 10 years after fire. While LAI rebounded
408 rapidly in the initial 10 years post-fire, this cannot be taken as a definitive indicator of successional
409 trajectory, especially for slow growing forests like subalpine fir (Ferguson and Carlson, 2010) or
410 for forests with episodic post-fire germination such as Ponderosa pine (Savage et al., 1996; Brown
411 and Wu, 2005; Rodman et al., 2019). Leaf area recovery then slowed in most cases, and for many
412 it did not return to the pre-fire level by the end of study period. We anticipate that the recovery of
413 LAI to its pre-fire condition continues to unfold over time, extending beyond the 25-year duration
414 covered by our study. In some cases, we see LAI at 20 or 25 years post-fire exceeding that prior
415 to burning, suggesting that wildfire may have stimulated canopy renewal or release of the
416 understory. Evaluating post-fire LAI trajectories on these, and longer, timescales can be of value

417 from a management perspective, for example, to identify regions where there is a risk of
418 regeneration failure for dominant, native species (Welch et al., 2016).

419 Our findings ~~generally agree with basic biogeographic expectations. For example, demonstrated~~
420 differences in characteristic trajectories ~~exist~~ across forest types and ecoregions ~~related to climate~~
421 ~~as well as soils and the basic fire adaptation traits of the species.~~ Wildfire caused a similar
422 proportional reduction of LAI across forest types and ecoregions, generally with 30% to 70%
423 reduction in year 1 post-fire but with smaller reductions in some Pinyon-Juniper setting-
424 ~~Correspondingly, the absolute magnitude of LAI decline caused by fire was larger in forest types~~
425 ~~and regions that had a higher initial pre-fire LAI~~ (Table S2). We also found varied rates of LAI
426 recovery post-fire across forest types and ecoregions. Some forest types saw recovery to only 60
427 % to 70% by 25 years while others saw LAI recovery to 120% to 150% of the pre-fire condition
428 (Table S2). ~~Similar to the decline in LAI year 1 post fire, the absolute value of LAI increases 25~~
429 ~~years post fire was larger in settings that had a larger pre-fire LAI, meaning in eco-climatic settings~~
430 ~~that are relatively favorable for forest growth.~~ Many factors are likely to contribute to these patterns
431 across forest types and ecoclimatic settings. First and foremost, it is no surprise that areas more
432 suitable for growth have faster and more complete recovery with higher absolute LAI within a
433 given forest type. For example, Douglas-fir stands in Cascades, Columbia Mountains, and Klamath
434 Mountains had faster recovery rates and greater changes in absolute LAI after year 1 post-fire than
435 did stands in the Rockies and Temperate Sierras (Table S2). Similarly, we observed a consistent
436 slow trend in the rate of conifer regeneration in the interior of the western US with continental
437 climate where high severity fire is common. This is likely due to reduced seed availability in
438 response to larger high severity fires in these areas. ~~because much of dry montane conifers and~~
439 ~~subalpine forests in the east of North Cascades, compared to western side, are characterized by~~

440 ~~higher proportion of high severity burn patches during dry years, and as the fires get larger, the~~
441 ~~interior area of the burn patches increases significantly resulting in reduced establishment rates~~
442 ~~due to reduced seed availability~~ (Cansler and McKenzie, 2014). ~~While we did not examine the~~
443 ~~evidence of seed availability being a limitation for LAI recovery post fire, it may become a~~
444 ~~growing limitation in these forests with wildfire becoming more severe in recent decades~~
445 ~~(Westerling et al., 2006; Parks and Abatzoglou, 2020) and the likely increase in persistent burned~~
446 ~~patch density under more extreme fire weather condition~~ (Krawchuk et al., 2016). Other factors
447 include ~~T~~the regeneration capacity of the dominant tree species post-fire ~~is also likely to play a~~
448 ~~role~~, with some readily and actively resprouting or having serotiny, while other lack these fire-
449 adaptation traits (Howard, 2003; Meng et al., 2018), and competition with species such as early
450 colonizers common after burning (Hansen et al., 2016; Stoddard et al., 2018). ~~that can be important~~
451 ~~for ecological resilience. Post-fire regeneration may also be impacted by secondary factors like~~
452 ~~competition with other species such as early colonizers common after burning. This is particularly~~
453 ~~true in Ponderosa pine and Lodgepole pine stands as these species can be outcompeted by aspen~~
454 ~~over the first 10-15 years postfire~~ (Hansen et al., 2016; Stoddard et al., 2018; Vanderhoof et al.,
455 2020). ~~The post-fire dynamics presented here are not stratified by post-fire species composition,~~
456 only characterizing the biophysical characteristics that unfold after burning of a particular forest
457 type. Naturally, post-fire species composition can differ from pre-fire depending on seed and
458 nutrient availability, fire severity, and climate and these effects are embedded in the post-fire
459 biophysical trajectories that we present. Further exploration of how post-fire species composition
460 and other regeneration characteristics influence biophysical trajectories is warranted.

461 Our findings of post-fire LAI trajectories across ecoclimatic settings suggest that the range of
462 Douglas-fir stands may be less ~~vulnerable~~ limited due to climate warming compared to Ponderosa

463 pine, as their current range tends to extend into cooler and moist~~er~~ areas where they recover
464 above pre-fire levels ~~within 25 years post fire~~. This indicates that the worsening of climate changes
465 in the future (more periods of prolonged drought) can have implications for migration of ponderosa
466 pine due to worsening regeneration under climate stress. ~~Such fire catalyzed vegetation shift in~~
467 ~~coming years to decades can significantly affect the ecosystem services and economic activities~~
468 ~~provided by these widespread forest types (Rogers et al., 2011; Coop et al., 2020); thus, it is~~
469 ~~critically important to gain a comprehensive understanding of how the ranges of species may~~
470 ~~expand as tree growth becomes more feasible in higher elevations and higher latitudes (Lenoir et~~
471 ~~al., 2008) for forest management of burned areas in coming decades.~~ Although Pinyon-Juniper
472 forests recovered rapidly in the first few post-fire years, our observed decline in the rate of pinyon-
473 juniper recovery is consistent with the findings of Vanderhoof et al., (2020). This forest type is
474 recognized for its slow regeneration and susceptibility to drought (Hartsell et al., 2020). Existing
475 studies in post-fire recovery of Pinyon-Juniper suggest that this forest type recovers to pre-fire
476 condition in <5 years after fire in the case of low to moderate fire (Jameson, 1962; Dwyer and
477 Preper, 1967), while it takes >100 years for recovery to pre-fire condition under high severity with
478 heavy Pinyon-Juniper mortality (Erdman, 1970; Koniak, 1985). Other forest types showed faster
479 or similar rates of recovery, for instance, Mixed conifer recovered completely in most of the
480 ecoregions of the western US possibly due to richer species diversity and relatively higher
481 precipitation (Bright et al., 2019).

482 **4.2. Post-fire albedo Changes**

483 Our results provide evidence for significant effects of wildfires on the albedo across forest types
484 and eco-climatic settings in the western US, with post-fire albedo being much higher ~~albedo~~ in
485 winter than in summer. ~~The post fire albedo trajectories obtained from this study are broadly~~

486 ~~consistent with those obtained from the literature (Beringer et al., 2003; Randerson et al., 2006;~~
487 ~~Lyons et al., 2008; Montes Helu et al., 2009; Gleason et al., 2019).~~ All forest types showed
488 noticeable age-dependent albedo patterns, with a transient peak in summer albedo around 10-18
489 years post-fire. We observed a decline in summer albedo during the first year after fire except for
490 Pinyon-Juniper (Table S3) presumably from charred surface and the deposition of black carbon.
491 The increase in albedo in first year after fire in Pinyon-Juniper may be associated with low pre-
492 fire LAI leading to lower levels of charcoal and black carbon deposition that absorb incoming
493 radiation. Our finding is comparable to previously published findings that report albedo drops in
494 the range of 0.01-0.05 using MODIS albedo (Jin and Roy, 2005; Randerson et al., 2006; Lyons et
495 al., 2008; Veraverbeke et al., 2012). The slight differences are likely related to the variability in
496 the domain of each study (e.g., western US vs. boreal, western US vs. Mediterranean), spatial
497 resolution of MODIS pixels (500 m) that includes unburned patches and non-forest fractions,
498 illumination conditions of the MODIS albedo products (black sky, white sky, blue sky) and method
499 used to calculate albedo differences. Regarding the latter, we compared a pixel to itself between
500 pre-and-post-fire years. The approach of comparing burned pixels to unburned neighboring pixels
501 as control is also common (e.g., Myhre et al., 2005; Randerson et al., 2006; Lyons et al., 2008;
502 Gatebe et al., 2014). One issue with this approach is that it does not consider heterogeneity of the
503 land surface. Burned and control pixels may not be equivalent in the pre-burn period (Dintwe et
504 al., 2017), as they do not necessarily represent a comparable vegetation state and therefore may
505 not be a good proxy to pre-fire state. ~~This characteristic decline in summer albedo immediately~~
506 ~~after fire contributed to differences in albedo patterns with other disturbance types (harvest, beetle~~
507 ~~outbreak). For example, in the first year following a disturbance event, Mohammad et al., (2019)~~

508 ~~reported higher summer albedo in a post-harvest stand than in a post-fire stand because of high~~
509 ~~charcoal occurrence on the soil surface in the latter case.~~

510 Soon after fire, we observed an increased in post-fire albedo during the summer period presumably
511 due to combination of char removal and presence of early-successional plants (Johnstone et al.,
512 2010) that have higher albedo than mature species (Betts and Ball, 1997; Pinty et al., 2000; Amiro
513 et al., 2006; Dintwe et al., 2017). Summer post-fire albedo recovered faster than LAI regardless of
514 vegetation type. This pattern suggests that, in contrast to findings of Pinty et al., (2000) and
515 Tsuyuzaki et al., (2009), post-fire recovery of albedo is driven by multiple factors in addition to
516 the early regeneration of vegetation such as vegetation destruction and charcoal left behind (Jin et
517 al., 2012), differences in fuel combustion and consumption (Jin and Roy, 2005), species
518 composition during early succession (Beck et al., 2011), and seasonal variation in soil moisture
519 and removal of black carbon (Montes-Helu et al., 2009; Veraverbeke et al., 2012). As the
520 regenerating vegetation matures, the increase in post-fire albedo progressively weakens as
521 suggested by Amiro et al., (2006), reaching peak at ~ 10-18 years post-fire which then gradually
522 decline towards pre-fire levels. We did not observe the complete recovery of post-fire albedo
523 within the study period of 25 years post-fire. Many studies using remote sensing technique suggest
524 that albedo in post-fire stands commonly equilibrates at ~40-80 years post-fire (Randerson et al.,
525 2006; Lyons et al., 2008; Kuusinen et al., 2014; Bright et al., 2015; Abdul Halim et al., 2019, Potter
526 et al., 2020).

527 We found the greatest increase in post-fire albedo during winter, a finding consistent with others
528 (Liu et al., 2005; Randerson et al., 2006; Montes-Helu et al., 2009; Gleason et al., 2019) due to
529 increased exposure of snow resulting from the loss of canopy and tree mortality. In our analysis,
530 post-fire winter snow-covered albedo increased with time since fire until a peak was reached, the

531 timing of which varied across forest types. We hypothesize that this increase with time may result
532 from the fall of standing dead snags (O'Halloran et al., ~~2012~~2014) and lower rate of
533 reestablishment during succession (Fig. S4). ~~On average, it takes 5–15 years after fire for half of~~
534 ~~the dead snags to fall in post-fire environment in coniferous forests in western North America~~
535 ~~(Russell et al., 2006), which coincides with the timing of peak in winter albedo in our study.~~ Our
536 finding showed similar post-fire winter albedo patterns across forest types in a region. For
537 example, winter albedo in Lodgepole pine, Spruce/Fir/Hemlock, and Douglas-fir forest types in
538 the Idaho Batholith region increased at a similar rate with time since fire which corresponds to
539 consistent lower LAI recovery rate across these forest types in this region (Fig. S4b,f,g) ~~related to~~
540 ~~climate and soil~~. However, variation in winter albedo was greater across ecoregions within a forest
541 type (e.g., Mixed conifer) owing to variable rates of post-fire LAI recovery (Fig. S4a). Overall,
542 our findings indicate a strong dependency of post-fire seasonal albedo on the proportion of
543 vegetative cover, irrespective of forest types, on the post-fire environment. This observed effect
544 provides a strong connection between albedo and successional patterns observed in these specific
545 forest types.

546 **4.3. Controls on post-fire recovery of biophysical parameters**

547 One of the major contributions of our approach is that it not only generates the post-fire trajectories
548 of land surface biophysical properties across a range of forest types and geographic regions, but
549 also distinguishes the contribution of nature of fire, climate, and topography on post-fire LAI and
550 albedo recovery for each forest type. Previous work has shown fire severity to be an important
551 driver of regeneration, ~~with high fire severity associated with lower post-fire regeneration~~
552 (Crotteau et al., 2013; Meng et al., 2015; Chambers et al., 2016; Vanderhoof et al., 2020). In
553 contrast, our analysis suggested fire severity was of relatively low importance relative to other

554 variables considered (Fig. S2). ~~Despite being of lesser importance, We-we~~ found that higher rates
555 of post-fire recovery were associated with low severity fire and lowest recovery rates were
556 associated with high fire severity. The lower recovery rates associated with high fire severity are
557 possibly due to lower seed availability and greater distance to live seed sources (Haire &
558 McGarigal, 2010; Kemp et al., 2016; Kemp et al., 2019), but high fire severity can also create
559 mineral seed beds and free up essential resources such as moisture, light, and nutrients which
560 promote the growth of vegetation (Gray et al., 2005; Moghaddas et al., 2008). Only Oak and
561 Pinyon-Juniper showed higher recovery rates under high fire severity among forest types which is
562 primarily due to rapid regeneration by resprouting in Oak (Meng et al., 2018) and colonization by
563 resprouting shrubs in Pinyon-Juniper (Wangler & Minnich, 1996). The low importance of fire
564 severity in determining post-fire vegetation growth indicates that the variability across a single fire
565 may be outweighed at a regional level by climate and its proxies. It also suggests that at some sites,
566 the impact of wildfire may be restricted to causing tree mortality under changing climate, rather
567 than also significantly influencing the post-fire regeneration with its impact on seed availability
568 (Kemp et al., 2019).

569 Our analysis indicated that among all the factors considered, elevation had the highest variable
570 importance score in predicting the LAI 10-year and 20-year post-fire. We found greater rates of
571 vegetation recovery in lower elevation. Less successful recovery at higher elevations is likely
572 associated with cooler temperatures at higher elevations for many of the forest types, and those
573 cool temperatures appear to still limit forest establishment and growth, even under general
574 warming in the region (Stevens-Rumann et al., 2018). ~~A possible secondary reason could be soil
575 conditions in the mountainous terrain and slope, with a higher occurrence of steep slopes at higher
576 elevations than lower elevations. Slope has been shown to result in lower regeneration density~~

577 ~~compared to shallower slopes (Lyderson & North, 2012; Kemp et al., 2016).~~ Only Pinyon-Juniper
578 showed increased recovery with elevation (Fig. 5b and 6b) likely due to relief from the hot, dry
579 conditions at lower elevations but also possibly due to resistance to invasion that increases with
580 elevation in this forest type (Urza et al., 2017), suggesting that warming temperatures are having
581 a detrimental effect on post-fire regeneration at warmer sites, but not yet promoting post-fire
582 regeneration at cooler sites at all spatial scales (Harvey et al., 2016). Elevation was found to be
583 important in various studies of post-fire regeneration of conifer forests in the western U.S., but
584 with opposite directionality (Casady et al., 2010; Rother & Veblen, 2016; Vanderhoof et al., 2020).
585 However, Mantgem et al., (2006) reported a strongly negative correlation with seedling density of
586 Mixed conifer forests in the Sierra Nevada. In higher elevation forests such as Lodgepole pine,
587 most studies demonstrated increased recovery post-fire (e.g., Harvey et al., 2016) which contrasted
588 with our findings. ~~However, modeling evidence suggests that Lodgepole pine regeneration post-~~
589 ~~fire could experience significant declines in coming decades as a result of both increased fire~~
590 ~~frequency (Westerling et al., 2011) and changing climatic conditions (Coops & Waring, 2011).~~
591 These findings collectively highlight that there exists a large degree of uncertainty around
592 individual forest type responses to post-fire climatic variability.

593 Our study adds to a growing body of literature emphasizing the importance of climate for post-fire
594 vegetation growth among different forest types (Meng et al., 2015; Buechling et al., 2016; Rother
595 and Veblen, 2017; Hankin et al., 2019; Vanderhoof et al., 2020). Our data suggests that high
596 average summer temperatures and low water availability limit the recovery of LAI 10-year and
597 20-year postfire on these forest types. Drier forests such as Oak, Ponderosa pine, Douglas-fir, and
598 Pinyon-Juniper were strongly associated with annual precipitation and mean summer temperature,
599 which is consistent with the findings of Meng et al., (2015) and Kemp et al., (2019)~~who reported~~

600 ~~a positive relationship between five year post-fire NDVI values and wet season precipitation~~
601 ~~anomaly in Mixed conifers of Sierra Nevada. Similarly, Kemp et al., (2019) found mean summer~~
602 ~~temperature to be very important indicator of post-fire regeneration for Douglas-fir and Ponderosa~~
603 ~~pine with decreased potential for successful regeneration under warmer summer temperatures.~~ Our
604 analysis also suggests that the critical thresholds for annual precipitation and mean summer
605 temperature are 500 mm and 15-20°C, respectively, in these forest types. Our finding of higher
606 sensitivity of Oak, Ponderosa pine, Douglas-fir, and Pinyon-Juniper to annual precipitation and
607 average summer temperature suggests that future increases in temperature and water deficit may
608 affect these forest types more so than other forest types. ~~For example, Rehfeldt et al., (2014)~~
609 ~~predicted a 50% decline in Ponderosa pine habitat range by 2060 in response to climate change.~~
610 With a trend toward warmer springs and summers in recent decades throughout the western US
611 (Westerling, 2006; Ghimire et al., 2012; IPCC, 2013; Williams et al., 2021), conditions for post-
612 fire vegetation growth and survival are changing, as even a slight increase in water deficit on the
613 drier sites can have adverse effects on tree regeneration (Stevens-Rumann et al., 2018). While
614 warming temperature has been shown to affect the post-fire regeneration of conifer forests growing
615 at the warmer end of the species distribution such as Douglas-fir and Ponderosa pine (Haffey et
616 al., 2018; Kemp et al., 2019), it could promote the rate of post-fire recovery for conifer forests
617 growing at the colder end of the species distribution previously limited by frozen soils, cold
618 temperatures, and snow (Stevens-Rumann et al., 2018; Vanderhoof et al., 2020).

619 Similar to LAI, our results of variable importance in random forests showed low importance of
620 fire severity compared to other variables in post-fire recovery of summer albedo at both time
621 ~~horizons~~intervals (Fig. S3). However, we noticed a difference in albedo change across fire severity
622 classes. For example, we found lower albedo values in low fire severity areas compared to medium

623 and high severity areas at both time ~~horizons~~intervals, which is associated with a greater degree of
624 LAI recovery in low severity areas as vegetation has lower albedo than bare areas. Moreover,
625 lower albedo 10-years post-fire in high severity compared to medium severity could be due to
626 standing snags absorbing sunlight, with it taking 5-15 years for just half of dead snags to fall
627 (Russell et al., 2006). We did not find significant impact of elevation on post-fire albedo change
628 in these forest types except for Pinyon-Juniper and Ponderosa pine, which showed decreased
629 albedo post-fire in response to increased LAI with elevation. As expected, climate, particularly
630 annual precipitation, was the major determinant of post-fire albedo change. Annual precipitation
631 was found to be highly associated with changes in post-fire albedo in all forest types, where
632 increased precipitation decreased the albedo post-fire with impact more prominent in 20-year post-
633 fire. Annual precipitation impacts post-fire albedo through two different mechanisms. First,
634 increased annual precipitation is associated with greater recovery of LAI in these forest types (Fig.
635 6c) where the mid-age stands replace the initial post-fire establishments, reducing albedo
636 (Chambers and Chapin, 2002). Second, soil moisture depends on precipitation. With greater
637 precipitation leading to increased soil water content, ~~we could expect~~there is a corresponding
638 decrease in albedo due to darkening of soil particularly in open canopy conditions where the soil
639 received direct radiation (Montes-Helu et al., 2009; ~~Domingo et al., 2009~~), ~~and~~ Furthermore, an
640 increase in leaf area within the understory during the wet season could have a similar effect, as
641 reported in Thompson et al. (Thompson et al., 2004). Regarding temperature, the pattern of albedo
642 recovery did not correspond well with the pattern of LAI recovery at both time ~~horizons~~intervals
643 in these forest types. Albedo is elevated over the pre-fire condition more in the warmer part of a
644 forest type's range even in forest types that have a faster recovery of LAI in that warmer domain.
645 We might expect that a higher LAI would be associated with a lower albedo, but evidently the

646 association is not as simple, and it might have something to do with species composition rather
647 than simply leaf area. Our results point to the importance of climate patterns as a driver of post-
648 fire summer albedo recovery through their influence on ecological succession on the post-fire
649 environment.

650 **4.4. Significance and limitations of our Analysis**

651 Our results should be interpreted in light of four constraints. First, the accuracy of MODIS product
652 algorithm is dependent on biome-specific values, which following extensive fire-caused mortality,
653 can introduce additional uncertainty due to assumption of fixed land cover type. ~~For instance, the~~
654 ~~use of look up table (LUT) for different biomes in the MODIS fPAR/LAI algorithm can~~
655 ~~potentially lead to errors in LAI derivation in post-fire environment if an incorrect biome~~
656 ~~classification is applied.~~ In addition, we utilized the recovery of MODIS LAI as an indicator of
657 vegetation recovery. ~~However, it is important to acknowledge that LAI is a valuable yet imperfect~~
658 ~~indicator of vegetation change resulting from wildfires.~~ One significant limitation of LAI-based
659 analysis is that it captures some of the aggregate effects of mortality and regrowth but does not
660 fully characterize shifted species composition and community structure on the ground. ~~We~~
661 ~~recognize that short-term LAI following wildfire represents relative vegetation cover rather than a~~
662 ~~direct measure of forest regeneration.~~ Therefore, detailed, intensive field monitoring of vegetation
663 structure both before and after fires can serve as a valuable complement to LAI-based analysis
664 (Williams et al., 2014). Additionally, incorporating additional remote observations at the species
665 level from the fusion of very high spatial resolution, lidar, or hyperspectral data (Huesca et al.,
666 2013; Polychronaki et al., 2013; Kane et al., 2014) can further enhance the assessment. ~~Moreover,~~
667 ~~establishing connection between field level data and satellite observations can enhance the~~
668 ~~interpretability of satellite observations (Hudak et al., 2007) and offer a means to scale up ground~~

669 ~~observations to effectively characterize full landscapes.~~ Second, in terms of albedo, we used a 500
670 m MODIS albedo product which reflects a somewhat larger area (Campagnolo et al., 2016). Each
671 500 m grid may in fact include a mix of burned and unburned patches which could result in
672 underestimation of post-fire albedo. ~~Moreover, the algorithm used to calculate albedo may result~~
673 ~~in an underestimation, as it might disproportionately consider structural elements (e.g., snags and~~
674 ~~surviving trees) in the post-fire landscape. A modeling study by Hovi et al (2019) corroborated~~
675 ~~this who reported strong link between the effective spatial resolution of the MODIS albedo product~~
676 ~~and forest structure.~~ Although the use of MODIS data with its relatively low spatial resolution will
677 miss some of the details of fine-scale spatial variability in burn severity, land cover type and so
678 forth (Key, 2006), MODIS data has advantages in terms of higher temporal frequency of sampling
679 that can be important in post-fire biophysical dynamics (Lhermitte et al, 2010; Veraverbeke et al.,
680 2010, 2012) and these data also have good temporal coverage going back decades. Furthermore,
681 higher resolution datasets on biophysical properties are still not operationally available. Third, the
682 quality of our results may be constrained by the accuracy of fire severity from the MTBS product
683 as dNBR is not a perfect metric of severity and may struggle to capture some variations in severity
684 (Roy et al., 2006; De Santis and Chuvieco, 2009). However, several new generation fire remote
685 sensing products (Csiszar et al., 2014; Parks et al., 2014; Boschetti et al., 2015) are emerging in
686 recent years, which hold the potential for further improvements in post-fire recovery studies.
687 Finally, ~~the processes driving~~ post-fire vegetation recovery in burned areas may vary from one
688 location to another, ~~influenced by several other factors that this study did not cover.~~ ~~The~~
689 ~~interaction among all the determinant of post fire forest recovery is complex and measurements of~~
690 ~~fine resolution topo-climatic variables may not adequately explain the processes involved in forest~~
691 ~~regeneration and survival in the post fire environment. There are several other factors that~~

692 ~~influence post-fire regeneration that this study did not consider but could be important like species~~
693 ~~competition (Hansen et al., 2016; Stoddard et al., 2018), distance to seed tree (Kemp et al., 2016;~~
694 ~~Stevens-Rumann and Morgan, 2019), and other pre-fire disturbances (Buma and Wessman, 2011).~~
695 ~~The majority of the studies on post-fire recovery presented here have attributed the slower rates of~~
696 ~~recovery to post-fire climate conditions.~~ To gain a comprehensive understanding of the trajectory
697 of post-fire vegetation recovery, future studies, in addition to topo-climatic variables, should
698 consider species competition, scorching of the seed bank, distance to seed tree, other post-fire
699 disturbances, physiology of cones, seeds, and seedlings, as well as the interactions among all
700 influencing drivers in these settings.

701 Despite these limitations, by aggregating across multiple fire events in 21 different sub-ecoregions
702 and arraying observations along a 25-years chronosequence, our results demonstrate the spatial
703 and temporal variability of fire effects on post-fire environment. ~~While forest regeneration may be~~
704 ~~low in burned areas, it is highly variable spatially which is evident from the difference in recovery~~
705 ~~rates between moist, cooler northern sub-ecoregions and dry, hot southern sub-ecoregions.~~
706 Understanding such variability of fire effects and vegetation in space and time is important for
707 comprehensive understanding of the drivers of natural regeneration and vegetation recovery in
708 post-fire environments (Stevens-Rumann and Morgan, 2019). Our analysis could also help
709 improve the modeling of post-fire recovery pathways by identifying the most important predictors
710 of post-fire recovery and by approximating related thresholds of response. For example, our results
711 suggest a full recovery of LAI in dry, low elevation forest types like Pinyon-Juniper, Ponderosa
712 pine, and Oak within 10 years post-fire when the annual precipitation exceeds the threshold of 500
713 mm and average summer temperature is ~15-20°C. A quantitative measure of primary controls is

714 needed if efforts to develop realistic post-fire LAI trajectories for ecohydrological modeling
715 studies are to be successful, as suggested by McMichael et al., (2004).

716 One major significance of our approach and findings is its potential to advance the land surface
717 models (LSMs) embedded in Earth system models (ESMs). Currently, these models lack robust
718 representations of the ecological and biophysical consequences resulting from wildfire events
719 (Lawrence and Chase, 2007; Williams et al., 2009). Modelers could use the pattern of post-fire
720 biophysical dynamics as a function of time since fire, emerged from our data analysis, to inform
721 the LSMs to more accurately represent biophysical and ecological functions of severely disturbed
722 landscapes.

~~723 For instance, the patterns emerged from our data analysis could be utilized to inform model~~
~~724 parameters that describe wildfire impacts on biophysical properties of a landscape. A common~~
~~725 practice in land surface modeling is to define a set of parameter values that are relatively constant~~
~~726 for specific biomes all over the world (for example, Betts et al., 2007) and therefore, misses the~~
~~727 local ecological dynamics of each biome, weakening the model based assessments (Myhre et al.,~~
~~728 2005; Barnes & Roy, 2010). This holds true in post-fire environment and is evident from this study~~
~~729 that suggests that the parameter values associated with biophysical, hydrological, and~~
~~730 biogeochemical processes such as LAI and albedo vary over space and environmental condition,~~
~~731 even within a specific vegetation type. Therefore, subtle changes to response functions and~~
~~732 parameterization that govern rates of carbon, energy, and water fluxes in relation to disturbance~~
~~733 events can yield divergent modeled responses of ecosystems to disturbance events. Currently,~~
~~734 these models lack robust representations of the ecological and biophysical consequences resulting~~
~~735 from wildfire events (Lawrence and Chase, 2007; Williams et al., 2009). In this research, we have~~
~~736 quantified the post-fire changes in biophysical properties of land surface as a function of time since~~

737 ~~fire. Modelers could use these annual values to inform the LSMs to more accurately represent~~
738 ~~biophysical and ecological functions of severely disturbed landscapes.~~

739 **4.5. Implications of Our Research**

740 There is mounting evidence of increased extreme fire incidents in the western US due to ongoing
741 climate change (Westerling et al., 2006; Williams et al., 2014), leading to rapid alteration and
742 considerable uncertainty regarding species composition (McDowell et al., 2015) and ecological
743 dynamics (Johnstone et al., 2016). This study provides an estimate of the effect of the post-fire
744 environment on vegetation and surface albedo balance of the western US. The chronosequence
745 data show clear patterns with time since fire for both biophysical parameters. Our results
746 ~~quantitatively suggest~~show that conifer forest ecosystems, particularly Douglas-fir and Ponderosa
747 pine, are slower to recover post-fire, which may indicate they face greater risks ~~more vulnerable~~
748 ~~in the~~from the projected increase in fire severity and frequency as forecasted for drier interiors of
749 the western US ~~exposed to high severity fires and this vulnerability is projected to increase in~~
750 ~~coming decades as wildfires continue to increase in severity and size under warmer and drier~~
751 ~~climate conditions~~ (Abatzoglou and Williams, 2016; Littell et al., 2018). The post-fire biophysical
752 changes documented here could be of significance for local to regional climates, potentially
753 eliciting feedbacks that influence regional climate change and needs for adaptation.

754 **Code and Data Availability**

755 All of the research input data and codes supporting the results reported in this paper are available
756 in a repository~~can be accessed through~~ (<https://doi.org/10.5281/zenodo.7927852>, Shrestha et al.,
757 2023).

758 **Author Contribution**

759 The first author conceptualized and designed the research, curated data, ran the analysis and wrote
760 a draft. The second author (Dr. Christopher A. Williams) provided substantial input in research
761 conceptualization, research framework, and polishing of the manuscript. Drs. Brendan M. Rogers,
762 John Rogan, and Dominik Kulakowski offered insight into the manuscript's data analysis
763 presentation and contributed to the draft manuscript's finalization.

764 **Conflict of Interest**

765 The authors declare that they have no known competing financial interests or personal
766 relationships that could have appeared to influence the work reported in this paper.

767

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