Divergent Biophysical Responses of Western United States Forests to Wildfire Driven by Eco-climatic Gradients

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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 study

5 uses Moderate Resolution Imaging Spectroradiometer (MODIS) leaf area index (LAI) and albedo

6 to characterize patterns of post-fire biophysical dynamics across the western United States (US)

7 and further examines the influence of topo-climatic variables on the recovery of LAI and albedo

8 at two different time horizons, 10 and 20 years post-fire, using a random forest model. Recovery

9 patterns were derived for all wildfires that occurred between 1986 and 2017 across seven forest

10 types and 21 level III ecoregions of the western US. We found differences in characteristic

11 trajectories of post-fire vegetation recovery across forest types and ecoclimatic settings. LAI in

12 some forest types recovered only 60% - 70% by 25 years after fire while it recovered 120% to

13 150% of the pre-fire levels in other forest types, with higher absolute post-fire changes in forest

14 types and ecoregions that had a higher initial pre-fire LAI. Our random forest results showed very

15 little influence of fire severity on the recovery of both summer LAI and albedo at both post-fire

16 time horizons. Post-fire vegetation recovery was most strongly controlled by elevation, with faster

17 rates of recovery in lower elevations. Similarly, annual precipitation and average summer

18 temperature had significant impacts on the post-fire recovery of vegetation. Full recovery was

19 seldom observed when annual precipitation was less than 500 mm and average summer

20 temperature was above the optimal range i.e., 15-20°C. Climate influences, particularly annual

21 precipitation, was a major driver of post-fire summer albedo change through its impact on

22 ecological succession. This study provides quantitative measures of primary controls that could be

23 used to improve the modelling of ecosystem dynamics post-fire.

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

1. Introduction

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

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

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

The purpose of this study is to provide a more precise estimate of wildfire impacts on LAI and surface albedo in seven different forest types of the western US using observations derived from the MODIS. Moreover, this study also examines the factors that influence the nature and rate of 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

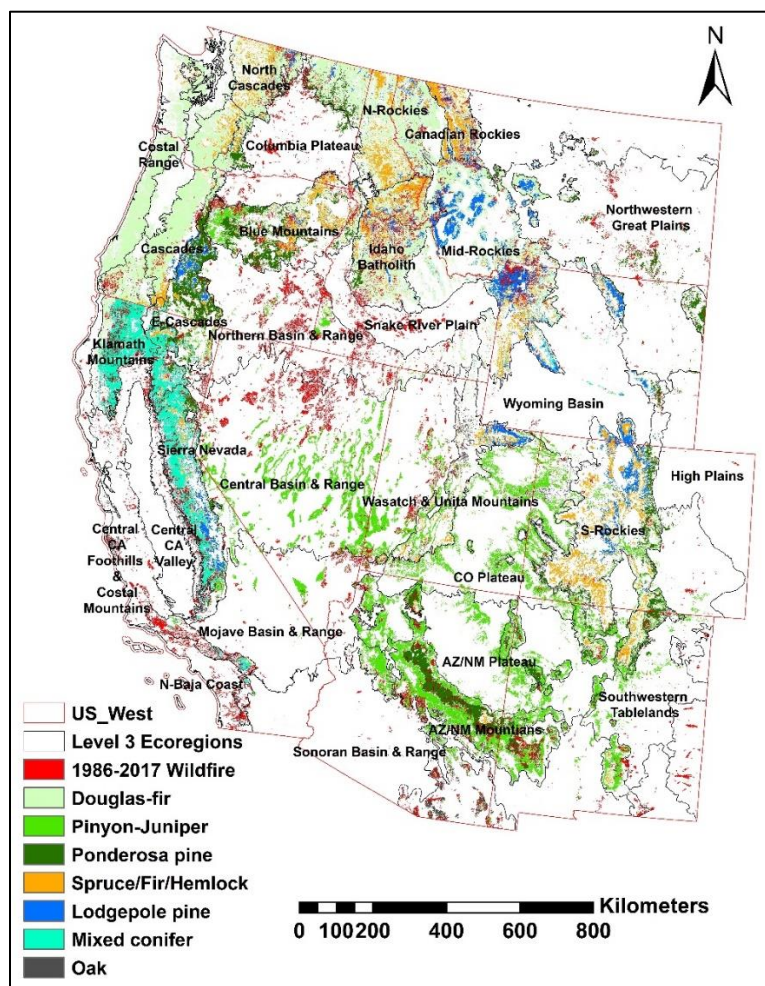
116   ecoregions of the western US (Table S1) (Omernik, 1987) had a sufficient number of 500 m x 500

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 $23° \pm 2.8°C$ and $7° \pm 2.5°C$, respectively (PRISM; Daly

121   et al., 2008).

122
123   Figure 1: Distribution of 1986-2017 burned area (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 the MTBS dataset from its native

130   30 m resolution to a coarser 500 m resolution. During this process, we retained only those 500 m

131   pixels that contained at least 75% of the corresponding 30 m pixels burned, thus reducing noise

132   from pixels with an unclear mix of burn and unburn conditions. Similarly, we resampled forest

133   type grid from 250 m to 500 m resolution and selected pixels where at least 75% of the forest

134   within each pixel belonged to a single forest type based on the 250 m forest type group map. We

135   excluded pixels that were burned more than once between 1986 and 2017 as such pixels can add

136   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 for uniformity.

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 summer-

184 season values of LAI and albedo by averaging the data from June, July, and August. Similarly, for

185 the winter season, yearly values of LAI and albedo were computed the same way using data from

186 December, January, and February. Next, we analyzed changes in post-fire LAI and albedo relative

187 to pre-fire by sampling each of them as an annual time series from three years before wildfire

188 events to all years of record after wildfire events. We grouped samples from each fire event based

189 on forest type, eco-climatic setting, and snow cover conditions. Within these groups, we

190 composited burn events from different years and aligned them temporally to represent three years

191 prior to the fire and all years after the fire. Consequently, chronosequences of biophysical

192 properties as a function of time since fire were created for a combination of seven forest types, two

193 snow cover conditions (in case of albedo), and 21 sub-ecoregions.

2.4. Attribution of Recovery

195   We explored the relationships between albedo and LAI recovery and topo-climatic factors, and

196   subsequently attributed the recovery at 10 years post-fire and 20 years post-fire using random

197   forest (RF) algorithms, implemented in R (Breiman 2001; Liaw & Wiener, 2002). We used a non-

198   parametric modeling method because most variable distributions were non-normal and RF does

199   not require the variables to be normally distributed. Additionally, RF can handle tens of thousands

200   of data points and provides variable importance scores. We initially selected seven explanatory

201   variables - fire severity class (low, medium, and high), three temperature variables, two

202   precipitation variables, and elevation. Although RFs do not require collinear variables to be

203   removed (Breiman, 2001), we employed a Variance Inflation Factor (VIF) analysis for

204   multicollinearity as a variable selection method to improve computation efficiency and enhance

205   interpretation, particularly with respect to variable importance. VIF analysis involves: a)

206   calculating VIF factors, b) removing the predictors from this set with VIF>10, and c) repeating

207   until no variable has VIF>10. This provided us with four uncorrelated predictors to be used in the

208   RF model - fire severity class, total annual precipitation, mean summer temperature (June –

209   August), and elevation. We pooled post-fire LAI and albedo responses across 21 ecoregions within

210   a given forest type for both time horizons (10-year post-fire and 20-year post-fire). The dataset

211   was divided into training (80%) dataset to train the RF model and test (20%) dataset to validate

212   the model. We created four RF models with 500 binary decision trees for each forest type (one for

213   each time horizon for both LAI and albedo). We tuned the model to generate a model with the

214   highest accuracy i.e., the lowest out-of-bag error among all tested combination of parameter

215   values. The model's performance was assessed using the R^2 metric. We used unscaled permutation

216   accuracy instead of the traditional Gini-based importance metric to rank the relative importance

217   among explanatory variables, as Gini-based importance was shown to be more strongly biased

218 towards continuous variables or variables with more categories compared to other importance

219 metrics (Strobl et al., 2007). The unscaled permutation importance metric calculates variable

220 importance scores as the amount of decrease in the accuracy when a target variable is excluded.

221 We used partial dependence plots (PDP) to visualize the influence of each explanatory variable on

222 the degree of 10 years and 20 years post-fire recovery of LAI and albedo. PDP quantifies the

223 marginal effects of a given variable on an outcome and provides a mechanism to explore insight

224 in big datasets, especially when the random forest is dominated by lower-order interactions

225 (Martin, 2014).

226 **3. Results**

227 **3.1. Post-fire Recovery of Land Surface Properties**

228 Burning caused a large decline in LAI for all forest types. Generally, high productivity forests

229 (e.g., Douglas-fir and Mixed conifers), compared to other forest types, experienced a larger decline

230 in LAI in year one after fire (Fig. 2a-g). Compared to pre-fire levels, the decline in LAI ranged

231 from 47% in Pinyon-Juniper to 76% in Ponderosa pine forests (Table S2). After this initial

232 decrease, the effects of vegetation regeneration became apparent. For all forest types, the

233 magnitude of LAI change decreases with increase in time since fire. However, LAI did not recover

234 to the pre-fire condition in most cases by the 25-year period of observation available for this study.

235 We found large differences in the timing of LAI recovery across forest types, with forest types

236 recovering at different rates, crossing the pre-fire levels at different times, and reaching different

237 peaks in LAI (Fig. 2a-g). For example, Douglas-fir in Columbia Mountains, Klamath Mountains,

238 and Southern Rockies (Fig. 2g) and Mixed conifers in Baja California and Eastern Cascades (Fig.

239 2a) showed complete recovery of LAI to pre-fire levels within the 25-year study period, while

240 Lodgepole pine, Oak, and Ponderosa pine were characterized by a slower recovery rate and most

241 did not recover to pre-fire levels by the 25-year period (Fig. 2 and Table S2). We also found varied

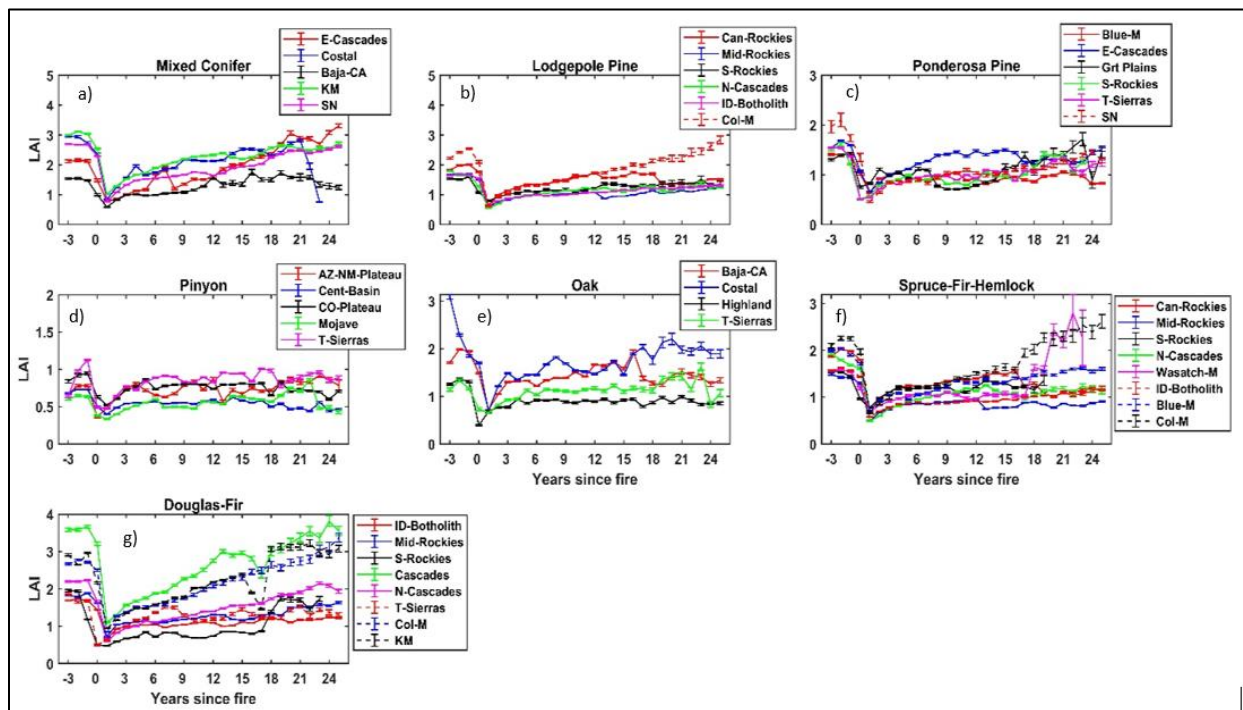
242 recovery rates across geographic regions even within a single forest type, presumably related to

243 climate and soils. For example, the characteristic post-fire LAI trajectories for the high

244 productivity Douglas-fir forest type (Fig. 2g) showed a substantially faster recovery in Cascades,

245 Klamath Mountains, and Columbia Mountains regions compared to the Idaho Batholith region of

246 the western US. Based on observations from all forest types, in general, the faster recovery of LAI

247 was observed in high elevation, wet areas with substantial maritime influences.

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

258 Turning to albedo, we found significant changes in summer albedo post-fire of all forest types.

259 Three important trends, similar among forest types, emerged from these post-fire summer albedo

260 trajectories. First, for all forest types, summer albedo decreased immediately after fire (Fig. 3)

261 likely due to low reflectivity by black carbon deposition on the soil surface and dead tree boles

262 both common immediately after high severity burning. The decline in summer albedo ranged from

263 0.01-0.02 across forest types with the greatest decline (20% from pre-fire levels; Table S3)

264 observed in Douglas-fir forest of the Klamath Mountains region. Second, post-fire albedo

265 increased gradually from year two since fire, crossing the pre-fire levels at around 3 years post-

266 fire, and peaking at different time horizons for different forest types and regions (Fig. 3a-g).

267 Elevated post-burn albedo is presumably due to increasing canopy cover, the relative high albedo

268 of grasses and shrubs that establish in early succession, and the loss of black carbon coatings on

269 soil and woody debris (Chambers and Chapin, 2002). The timing and magnitude of peak post-fire

270 albedo varied across forest types. For example, Ponderosa pine showed its peak in post-fire albedo

271 at 18 years post-fire (Fig. 3c) and 11 years post-fire for one of the Mixed Conifer regions (Fig. 3a),

272 while slow growing species such as Spruce/Fir/Hemlock may not have reached its peak by the end

273 of the 25-year post-fire study period (Fig. 3f). Similarly, there were significant regional differences

274 in timing and magnitude of peak albedo for a given forest type group. For example, Mixed Conifer

275 post-fire albedo peaked at 11 years post-fire in Baja California, while it continued to increase

276 through to 25 years in Klamath Mountains (Fig. 3a). Third, as the post-fire LAI approached the

277 pre-fire LAI levels, post-fire albedo started to decline from the peak towards its pre-fire albedo,

278 but it did not reach the pre-fire albedo levels by the end of the 25-year study period (Fig. 3a-g).

279 Post-fire winter albedo for each forest type had a similar pattern as summer albedo except with

280 greater magnitude and that it increased immediately after fire (Fig. 4a-f and Table S4). We

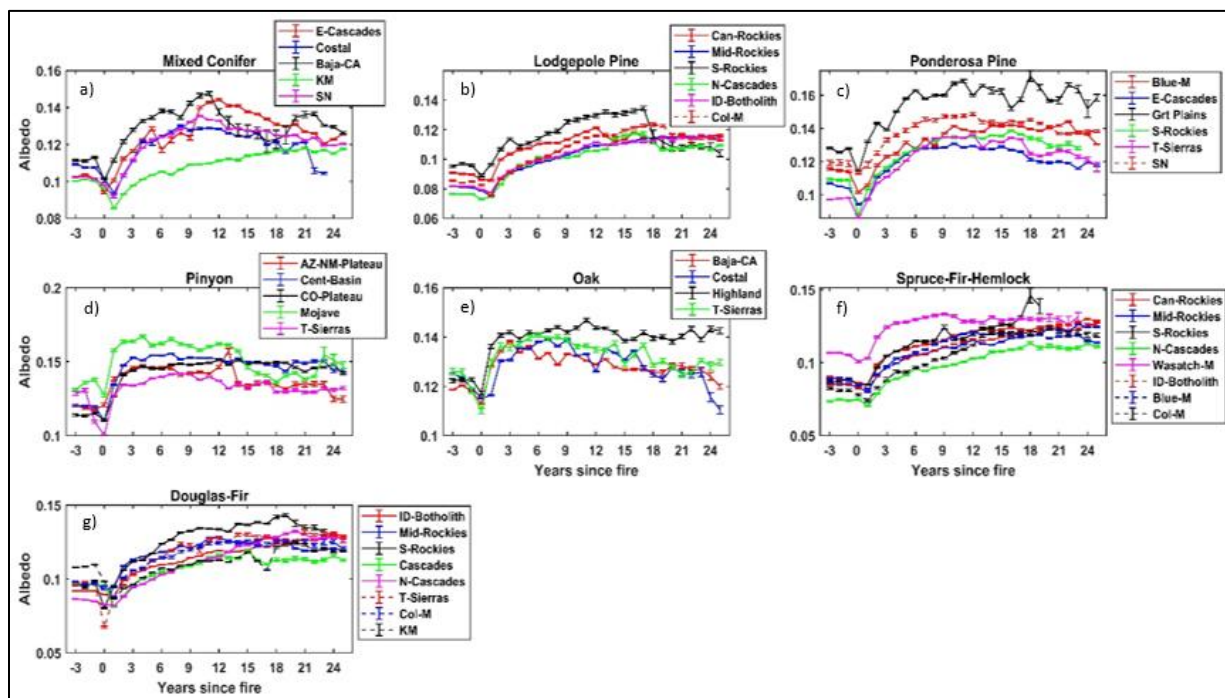
281 observed greater inter-annual variability in the timeseries of post-fire winter albedo likely related

282 to variability in snow cover and also a smaller signal-to-noise ratio associated with smaller sample

283 sizes. The albedo response was more than three-fold larger in winter than in summer, peaking in

284 the range of 0.4 to 0.6 across forest types and with an increase over pre-fire levels of about 0.25 to

285 0.50. Similar to summer albedos, winter albedos did not return to the pre-fire levels by the end of

286 25-year study period (Fig. 4a-f).

287

288 Figure 3: Mean summer post-fire albedo (± SE) as a function of time since fire in seven different
289 forest types of the western US.

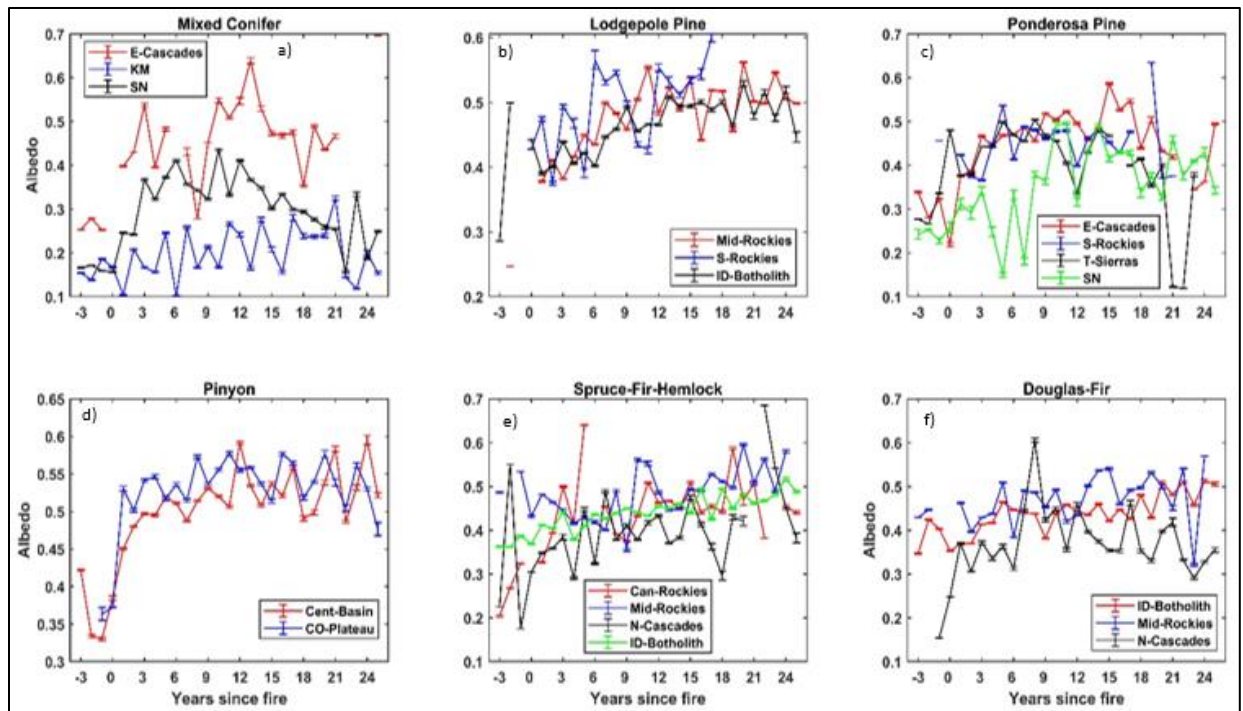



Figure: 4: Mean winter post-fire albedo (± SE) as a function of time since fire in seven different forest types of the western US.

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

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

305 example, in the Mixed conifer forest type, annual precipitation was the major determinant of 10-

306 year post-fire albedo recovery, while it was average summer temperature in case of 20-year

307 postfire. Similarly, the degree of 10-year post-fire albedo recovery in the Spruce/Fir/Hemlock

308 forest type was largely determined by average summer temperature, while the recovery after 20-

309 year post-fire was mainly determined by elevation. Fire severity, on the other hand, showed almost

310 no explanatory power in predicting recovery of LAI and albedo at both times for all forest types

311 (Fig. S2,S3).

312 The degree of LAI recovery 10-year post-fire increased with an increase in total annual

313 precipitation for all forest types, but it varied little when the total annual precipitation exceeded

314 1000 mm. Annual precipitation was the major determinant of 10-year postfire LAI recovery for

315 dry forests like Ponderosa pine, Pinyon-Junipers, and Oak, and these forest types tended to recover

316 above pre-fire levels as the annual precipitation is increased. However, when the annual

317 precipitation is less than 500 mm, the relative change in LAI is below 0 for all forest types,

318 indicating that the complete recovery of LAI 10-year postfire was unlikely with annual

319 precipitation less than 500 mm (Fig. 5c). In contrast, five out of seven forest types recovered over

320 pre-fire levels 20-years post-fire with increased annual precipitation, indicating that Mixed

321 conifers and Douglas-fir need more time and higher annual precipitation to recover to the pre-fire

322 level. Only Oak and Ponderosa pine showed increased LAI 20-year post-fire as the annual

323 precipitation exceeded 2000 mm (Fig. 6c). As with LAI, annual precipitation was one of the major

324 determinants of both 10-year and 20-year post-fire albedo recovery. The post-fire increase in

325 albedo was greater for sites with less annual precipitation (Fig. 7c and 8c), particularly noticeable

326 in dry forest types such as Douglas-fir, Ponderosa pine, and Oak where increased precipitation

327 triggered a rapid increase in post-fire vegetation recovery. The Oak forest type showed a particular

328   anomaly of albedo 20-years post-fire, exhibiting a decline of around 20% below pre-fire levels for

329   sites with annual precipitation of 2000 mm or above (Fig. 8c), consistent with a rapid increase in

330   vegetation recovery.

331   Regarding average summer temperature, we found interesting divergence in the pattern of LAI

332   response between cool and hot climates. For forests growing in hotter conditions, the magnitude

333   of LAI recovery at both time horizons decreased in areas with higher temperatures, particularly in

334   Oak, Pinyon-Junipers, and Ponderosa pine forest types, as these forest types grow at warmer end

335   of the species distribution. In contrast, increases in average summer temperature assisted the

336   recovery of forest types growing at the colder end of the species distribution such as Lodgepole

337   pine and Spruce/Fir/Hemlock (Fig. 5d and 6d), noting that LAI was consistently lower than pre-

338   fire levels for these forest types at both time horizons. Albedo does not show the same divergence

339   in pattern with warmer conditions, and instead we find a somewhat surprising pattern. Hotter sites

340   tend to experience a larger enhancement of summertime albedo over the pre-fire condition at both

341   time horizons in spite of faster recovery of LAI with hotter temperature (Fig. 7d and 8d).

342   Elevation was consistently found to be an important variable in determining the trajectory of post-

343   fire vegetation recovery. The post-fire recovery of LAI was slower at higher elevation both 10-

344   years and 20-years post-fire. Most forest types showed complete recovery towards pre-fire levels

345   at an elevation below 1500 m. Only Pinyon-Junipers and Ponderosa pine forest types saw faster,

346   more complete recovery of LAI with higher elevation (Fig. 5b and 6b). Turning to albedo response,

347   we found that higher elevation led to a smaller increase in albedo over its pre-fire value for both

348   time periods for the two forest types for which elevation was the most important predictor of post-

349   fire albedo change, namely for Pinyon-Juniper and Ponderosa pine forests. This is consistent with

350   faster post-fire recovery of LAI at higher elevation portions of range for these two forest types. In

351   contrast, post-fire albedo of Douglas-fir, Mixed conifer and Oak forest types showed little

352   dependence on elevation (Fig. 7b and 8b).

353   Although fire severity was the least important predictor of both post-fire LAI and albedo recovery

354   at both time horizons, our results showed significant variation in post-fire recovery among severity

355   classes for all forest types. As expected, the overall recovery of LAI 10-year post-fire was greater

356   for low fire severity where the recovery ranged between 85% and 95% of pre-fire LAI levels (Fig.

357   5a). Only in the case of Oak and Pinyon-Juniper forest types that burned with high severity did we

358   see full recovery of LAI at or above pre-fire levels by 10-years post-fire. By 20 years post-fire,

359   Lodgepole pine and Spruce/Fir/Hemlock still show a suppression of LAI relative to pre-burn and

360   less recovery for more severe burn conditions (Fig. 6a) while Oak sees LAI elevated over the pre-

361   burn condition and saw the largest LAI at sites that had the highest severity fires (Fig. 6a). The

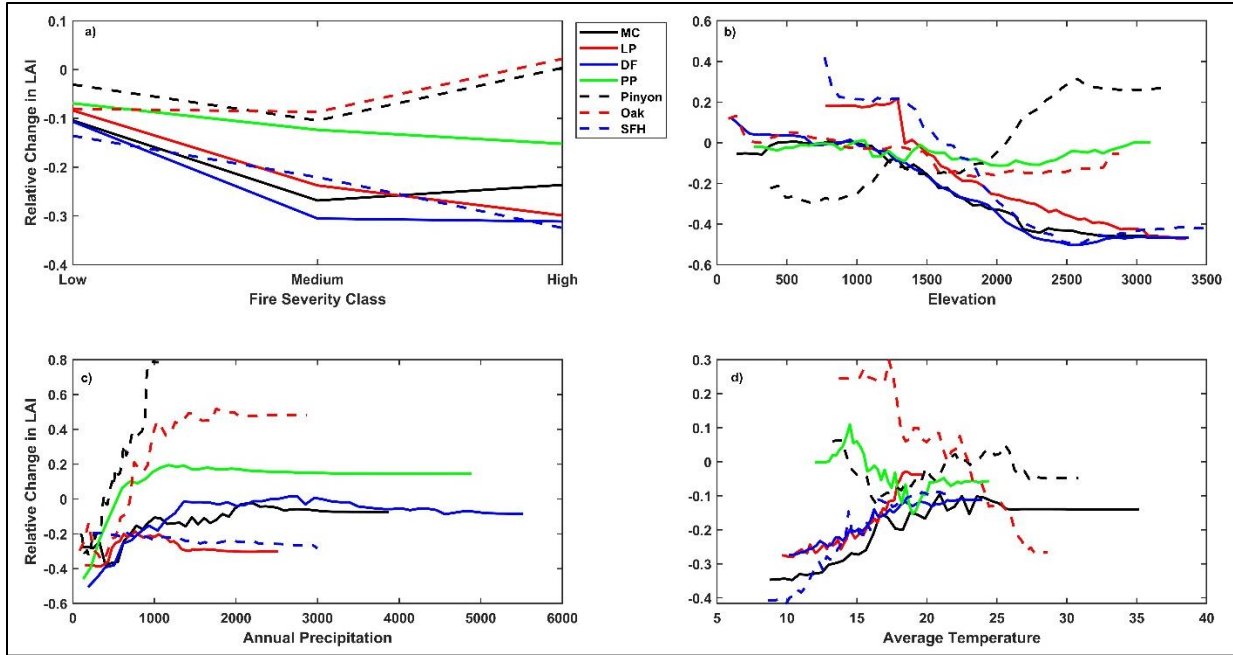
362   four other forest types had LAI equal to the pre-burn condition and showed no variation across fire

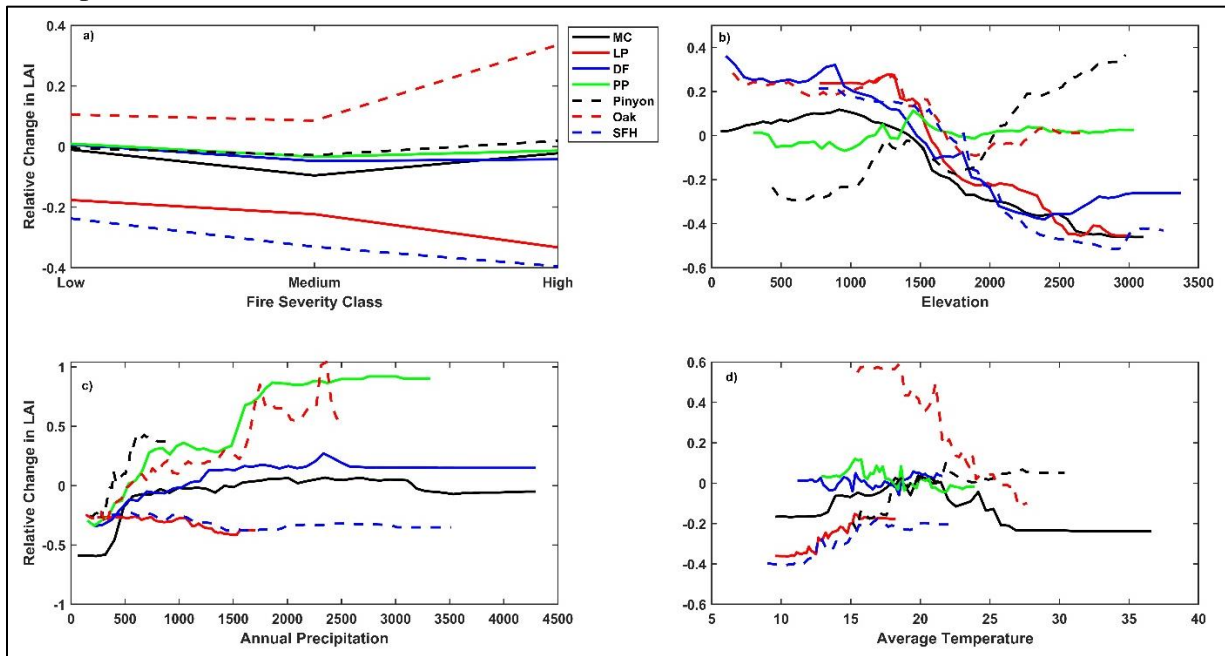
363   severity. For albedo, all forest types showed a larger elevation of albedo over their pre-fire values

364   under medium fire severity (Fig. 7a). Oak had the lowest change in albedo at both time horizons,

365   owing to rapid post-fire recovery. Overall, post-fire albedo was consistently higher than pre-fire

366   levels at both time horizons in all forest types indicating that albedo requires more than two

367   decades to return to pre-fire levels in these forest types (Fig. 7a and 8a).

368

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

376

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

379

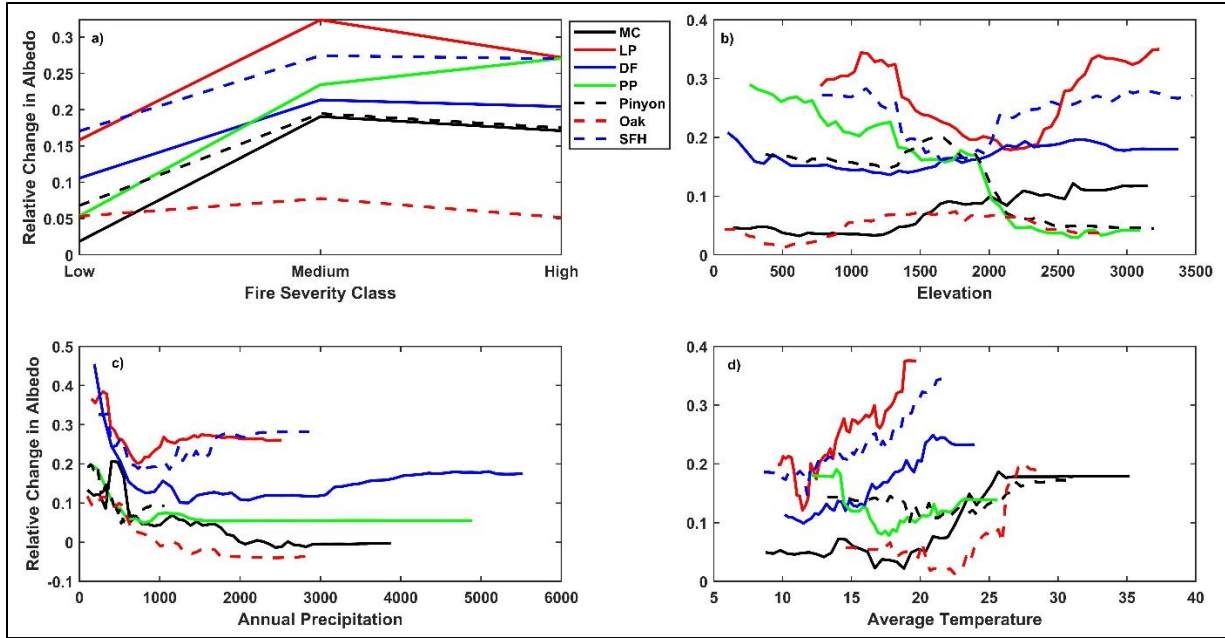



Figure 7: Partial dependence of change in summer snow-free albedo 10-year post-fire relative to pre-fire on a) fire severity, b) elevation, c) annual precipitation, and d) mean monthly summer temperature.

383

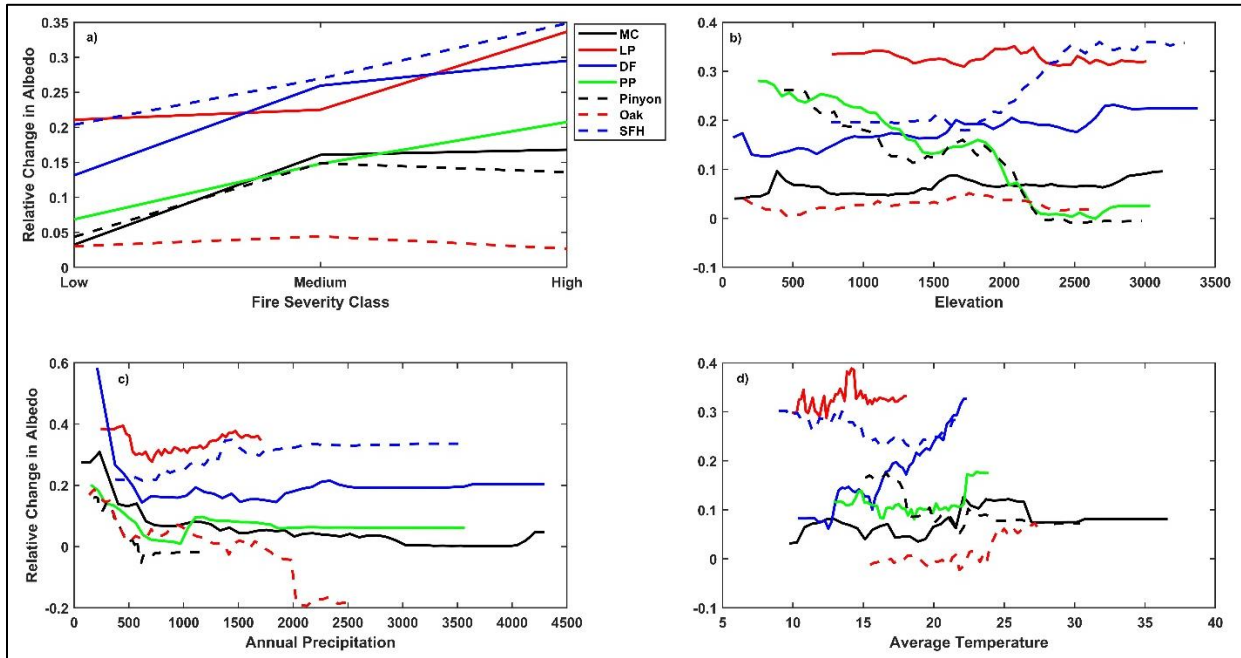



Figure 8: Partial dependence of change in summer snow-free albedo 20-year post-fire relative to pre-fire on a) fire severity, b) elevation, c) annual precipitation, and d) mean monthly summer temperature.

4. Discussion and Conclusion

388   Here, we extended the regional research by Shrestha et al., (2022) with a much broader sampling

389   to study post-fire responses for seven forest types in 21 sub-ecoregions of the western U.S. In

390   addition, this study also uses a machine learning approach (random forest) to examine the influence

391   of several topo-climatic variables on the nature and rate of vegetation recovery and associated

392   albedo in the post-fire environment.

393   **4.1. Post-fire Vegetation Recovery**

394   In this study, we used MODIS-derived LAI to increase our understanding of variability in the

395   recovery of vegetation in the post-fire environment across seven forest types and 21 sub-

396   ecoregions of the western United States. Similar to other studies (Morresi et al., 2019; Vanderhoof

397   et al., 2020), we found rapid vegetation recovery in the first 10 years after fire. While LAI

398   rebounded rapidly in the initial 10 years post-fire, this cannot be taken as a definitive indicator of

399   successional trajectory, especially for slow growing forests like subalpine fir (Ferguson and

400   Carlson, 2010) or for forests with episodic post-fire germination such as Ponderosa pine (Savage

401   et al., 1996; Brown and Wu, 2005; Rodman et al., 2019). Leaf area recovery then slowed in most

402   cases, and for many it did not return to the pre-fire level by the end of study period. We anticipate

403   that the recovery of LAI to its pre-fire condition continues to unfold over time, extending beyond

404   the 25-year duration covered by our study. In some cases, we see LAI at 20 or 25 years post-fire

405   exceeding that prior to burning, suggesting that wildfire may have stimulated canopy renewal or

406   release of the understory. Evaluating post-fire LAI trajectories on these, and longer, timescales can

407   be of value from a management perspective, for example, to identify regions where there is a risk

408   of regeneration failure for dominant, native species (Welch et al., 2016).

409   Our findings demonstrated differences in characteristic trajectories across forest types and

410   ecoregions. Wildfire caused a similar proportional reduction of LAI across forest types and

411   ecoregions, generally with 30% to 70% reduction in year 1 post-fire but with smaller reductions

412   in some Pinyon-Juniper setting (Table S2). We also found varied rates of LAI recovery post-fire

413   across forest types and ecoregions. Some forest types saw recovery to only 60 % to 70% by 25

414   years while others saw LAI recovery to 120% to 150% of the pre-fire condition (Table S2). Many

415   factors are likely to contribute to these patterns across forest types and ecoclimatic settings. First

416   and foremost, it is no surprise that areas more suitable for growth have faster and more complete

417   recovery with higher absolute LAI within a given forest type. For example, Douglas-fir stands in

418   Cascades, Columbia Mountains, and Klamath Mountains had faster recovery rates and greater

419   changes in absolute LAI after year 1 post-fire than did stands in the Rockies and Temperate Sierras

420   (Table S2). Similarly, we observed a consistent slow trend in the rate of conifer regeneration in

421   the interior of the western US with continental climate where high severity fire is common. This

422   is likely due to reduced seed availability in response to larger high severity fires in these areas.

423   (Cansler and McKenzie, 2014). Other factors include the regeneration capacity of the dominant

424   tree species post-fire, with some readily and actively resprouting or having serotiny, while other

425   lack these fire-adaptation traits (Howard, 2003; Meng et al., 2018), and competition with species

426   such as early colonizers common after burning (Hansen et al., 2016; Stoddard et al., 2018). The

427   post-fire dynamics presented here are not stratified by post-fire species composition, only

428   characterizing the biophysical characteristics that unfold after burning of a particular forest type.

429   Naturally, post-fire species composition can differ from pre-fire depending on seed and nutrient

430   availability, fire severity, and climate and these effects are embedded in the post-fire biophysical

431   trajectories that we present. Further exploration of how post-fire species composition and other

432   regeneration characteristics influence biophysical trajectories is warranted.

433   Our findings of post-fire LAI trajectories across ecoclimatic settings suggest that the range of

434   Douglas-fir stands may be less limited due to climate warming compared to Ponderosa pine, as

435   their current range tends to extend into cooler and moister areas where they recover above pre-fire

436   levels. This indicates that the worsening of climate changes in the future (more periods of

437   prolonged drought) can have implications for migration of ponderosa pine due to worsening

438   regeneration under climate stress. Although Pinyon-Juniper forests recovered rapidly in the first

439   few post-fire years, our observed decline in the rate of pinyon-juniper recovery is consistent with

440   the findings of Vanderhoof et al., (2020). This forest type is recognized for its slow regeneration

441   and susceptibility to drought (Hartsell et al., 2020). Existing studies in post-fire recovery of

442   Pinyon-Juniper suggest that this forest type recovers to pre-fire condition in <5 years after fire in

443   the case of low to moderate fire (Jameson, 1962; Dweyer and Preper, 1967), while it takes >100

444   years for recovery to pre-fire condition under high severity with heavy Pinyon-Juniper mortality

445   (Erdman, 1970; Koniak, 1985). Other forest types showed faster or similar rates of recovery, for

446   instance, Mixed conifer recovered completely in most of the ecoregions of the western US possibly

447   due to richer species diversity and relatively higher precipitation (Bright et al., 2019).

448   **4.2. Post-fire albedo Changes**

449   Our results provide evidence for significant effects of wildfires on the albedo across forest types

450   and eco-climatic settings in the western US, with post-fire albedo being much higher in winter

451   than in summer. All forest types showed noticeable age-dependent albedo patterns, with a transient

452   peak in summer albedo around 10-18 years post-fire. We observed a decline in summer albedo

453   during the first year after fire except for Pinyon-Juniper (Table S3) presumably from charred

454   surface and the deposition of black carbon. The increase in albedo in first year after fire in Pinyon-

455   Juniper may be associated with low pre-fire LAI leading to lower levels of charcoal and black

456   carbon deposition that absorb incoming radiation. Our finding is comparable to previously

457   published findings that report albedo drops in the range of 0.01-0.05 using MODIS albedo (Jin and

458   Roy, 2005; Randerson et al., 2006; Lyons et al., 2008; Veraverbeke et al., 2012). The slight

459   differences are likely related to the variability in the domain of each study (e.g., western US vs.

460   boreal, western US vs. Mediterranean), spatial resolution of MODIS pixels (500 m) that includes

461   unburned patches and non-forest fractions, illumination conditions of the MODIS albedo products

462   (black sky, white sky, blue sky) and method used to calculate albedo differences. Regarding the

463   latter, we compared a pixel to itself between pre-and-post-fire years. The approach of comparing

464   burned pixels to unburned neighboring pixels as control is also common (e.g., Myhre et al., 2005;

465   Randerson et al., 2006; Lyons et al., 2008; Gatebe et al., 2014). One issue with this approach is

466   that it does not consider heterogeneity of the land surface. Burned and control pixels may not be

467   equivalent in the pre-burn period (Dintwe et al., 2017), as they do not necessarily represent a

468   comparable vegetation state and therefore may not be a good proxy to pre-fire state.

469   Soon after fire, we observed an increased in post-fire albedo during the summer period presumably

470   due to combination of char removal and presence of early-successional plants (Johnstone et al.,

471   2010) that have higher albedo than mature species (Betts and Ball, 1997; Pinty et al., 2000; Amiro

472   et al., 2006; Dintwe et al., 2017). Summer post-fire albedo recovered faster than LAI regardless of

473   vegetation type. This pattern suggests that, in contrast to findings of Pinty et al., (2000) and

474   Tsuyuzaki et al., (2009), post-fire recovery of albedo is driven by multiple factors in addition to

475   the early regeneration of vegetation such as vegetation destruction and charcoal left behind (Jin et

476   al., 2012), differences in fuel combustion and consumption (Jin and Roy, 2005), species

477   composition during early succession (Beck et al., 2011), and seasonal variation in soil moisture

478   and removal of black carbon (Montes-Helu et al., 2009; Veraverbeke et al., 2012). As the

479   regenerating vegetation matures, the increase in post-fire albedo progressively weakens as

480   suggested by Amiro et al., (2006), reaching peak at ~ 10-18 years post-fire which then gradually

481   decline towards pre-fire levels. We did not observe the complete recovery of post-fire albedo

482   within the study period of 25 years post-fire. Many studies using remote sensing technique suggest

483   that albedo in post-fire stands commonly equilibrates at ~40-80 years post-fire (Randerson et al.,

484   2006; Lyons et al., 2008; Kuusinen et al., 2014; Bright et al., 2015; Abdul Halim et al., 2019, Potter

485   et al., 2020).

486   We found the greatest increase in post-fire albedo during winter, a finding consistent with others

487   (Liu et al., 2005; Randerson et al., 2006; Montes-Helu et al., 2009; Gleason et al., 2019) due to

488   increased exposure of snow resulting from the loss of canopy and tree mortality. In our analysis,

489   post-fire winter snow-covered albedo increased with time since fire until a peak was reached, the

490   timing of which varied across forest types. We hypothesize that this increase with time may result

491   from the fall of standing dead snags (O'Halloran et al., 2014) and lower rate of reestablishment

492   during succession (Fig. S4). Our finding showed similar post-fire winter albedo patterns across

493   forest types in a region. For example, winter albedo in Lodgepole pine, Spruce/Fir/Hemlock, and

494   Douglas-fir forest types in the Idaho Batholith region increased at a similar rate with time since

495   fire which corresponds to consistent lower LAI recovery rate across these forest types in this region

496   (Fig. S4b,f,g). However, variation in winter albedo was greater across ecoregions within a forest

497   type (e.g., Mixed conifer) owing to variable rates of post-fire LAI recovery (Fig. S4a). Overall,

498   our findings indicate a strong dependency of post-fire seasonal albedo on the proportion of

499   vegetative cover, irrespective of forest types, on the post-fire environment. This observed effect

500   provides a strong connection between albedo and successional patterns observed in these specific

501   forest types.

4.3. Controls on post-fire recovery of biophysical parameters

One of the major contributions of our approach is that it not only generates the post-fire trajectories of land surface biophysical properties across a range of forest types and geographic regions, but also distinguishes the contribution of nature of fire, climate, and topography on post-fire LAI and albedo recovery for each forest type. Previous work has shown fire severity to be an important driver of regeneration (Crotteau et al., 2013; Meng et al., 2015; Chambers et al., 2016; Vanderhoof et al., 2020). In contrast, our analysis suggested fire severity was of relatively low importance relative to other variables considered (Fig. S2). Despite being of lesser importance, we found that higher rates of post-fire recovery were associated with low severity fire and lowest recovery rates were associated with high fire severity. The lower recovery rates associated with high fire severity are possibly due to lower seed availability and greater distance to live seed sources (Haire & McGarigal, 2010; Kemp et al., 2016; Kemp et al., 2019), but high fire severity can also create mineral seed beds and free up essential resources such as moisture, light, and nutrients which promote the growth of vegetation (Gray et al., 2005; Moghaddas et al., 2008). Only Oak and Pinyon-Juniper showed higher recovery rates under high fire severity among forest types which is primarily due to rapid regeneration by resprouting in Oak (Meng et al., 2018) and colonization by resprouting shrubs in Pinyon-Juniper (Wangler & Minnich, 1996). The low importance of fire severity in determining post-fire vegetation growth indicates that the variability across a single fire may be outweighed at a regional level by climate and its proxies. It also suggests that at some sites, the impact of wildfire may be restricted to causing tree mortality under changing climate, rather than also significantly influencing the post-fire regeneration with its impact on seed availability (Kemp et al., 2019).

524 Our analysis indicated that among all the factors considered, elevation had the highest variable

525 importance score in predicting the LAI 10-year and 20-year post-fire. We found greater rates of

526 vegetation recovery in lower elevation. Less successful recovery at higher elevations is likely

527 associated with cooler temperatures at higher elevations for many of the forest types, and those

528 cool temperatures appear to still limit forest establishment and growth, even under general

529 warming in the region (Stevens-Rumann et al., 2018). Only Pinyon-Juniper showed increased

530 recovery with elevation (Fig. 5b and 6b) likely due to relief from the hot, dry conditions at lower

531 elevations but also possibly due to resistance to invasion that increases with elevation in this forest

532 type (Urza et al., 2017), suggesting that warming temperatures are having a detrimental effect on

533 post-fire regeneration at warmer sites, but not yet promoting post-fire regeneration at cooler sites

534 at all spatial scales (Harvey et al., 2016). Elevation was found to be important in various studies

535 of post-fire regeneration of conifer forests in the western U.S., but with opposite directionality

536 (Casady et al., 2010; Rother & Veblen, 2016; Vanderhoof et al., 2020). However, Mantgem et al.,

537 (2006) reported a strongly negative correlation with seedling density of Mixed conifer forests in

538 the Sierra Nevada. In higher elevation forests such as Lodgepole pine, most studies demonstrated

539 increased recovery post-fire (e.g., Harvey et al., 2016) which contrasted with our findings. These

540 findings collectively highlight that there exists a large degree of uncertainty around individual

541 forest type responses to post-fire climatic variability.

542 Our study adds to a growing body of literature emphasizing the importance of climate for post-fire

543 vegetation growth among different forest types (Meng et al., 2015; Buechling et al., 2016; Rother

544 and Veblen, 2017; Hankin et al., 2019; Vanderhoof et al., 2020). Our data suggests that high

545 average summer temperatures and low water availability limit the recovery of LAI 10-year and

546 20-year postfire on these forest types. Drier forests such as Oak, Ponderosa pine, Douglas-fir, and

547   Pinyon-Juniper were strongly associated with annual precipitation and mean summer temperature,

548   which is consistent with the findings of Meng et al., (2015) and Kemp et al., (2019). Our analysis

549   also suggests that the critical thresholds for annual precipitation and mean summer temperature

550   are 500 mm and 15-20°C, respectively, in these forest types. Our finding of higher sensitivity of

551   Oak, Ponderosa pine, Douglas-fir, and Pinyon-Juniper to annual precipitation and average summer

552   temperature suggests that future increases in temperature and water deficit may affect these forest

553   types more so than other forest types. With a trend toward warmer springs and summers in recent

554   decades throughout the western US (Westerling, 2006; Ghimire et al., 2012; IPCC, 2013; Williams

555   et al., 2021), conditions for post-fire vegetation growth and survival are changing, as even a slight

556   increase in water deficit on the drier sites can have adverse effects on tree regeneration (Stevens-

557   Rumann et al., 2018). While warming temperature has been shown to affect the post-fire

558   regeneration of confer forests growing at the warmer end of the species distribution such as

559   Douglas-fir and Ponderosa pine (Haffey et al., 2018; Kemp et al., 2019), it could promote the rate

560   of post-fire recovery for conifer forests growing at the colder end of the species distribution

561   previously limited by frozen soils, cold temperatures, and snow (Stevens-Rumann et al., 2018;

562   Vanderhoof et al., 2020).

563   Similar to LAI, our results of variable importance in random forests showed low importance of

564   fire severity compared to other variables in post-fire recovery of summer albedo at both time

565   horizons (Fig. S3). However, we noticed a difference in albedo change across fire severity classes.

566   For example, we found lower albedo values in low fire severity areas compared to medium and

567   high severity areas at both time horizons, which is associated with a greater degree of LAI recovery

568   in low severity areas as vegetation has lower albedo than bare areas. Moreover, lower albedo 10-

569   years post-fire in high severity compared to medium severity could be due to standing snags

570   absorbing sunlight, with it taking 5-15 years for just half of dead snags to fall (Russell et al., 2006).

571   We did not find significant impact of elevation on post-fire albedo change in these forest types

572   except for Pinyon-Juniper and Ponderosa pine, which showed decreased albedo post-fire in

573   response to increased LAI with elevation. As expected, climate, particularly annual precipitation,

574   was the major determinant of post-fire albedo change. Annual precipitation was found to be highly

575   associated with changes in post-fire albedo in all forest types, where increased precipitation

576   decreased the albedo post-fire with impact more prominent in 20-year post-fire. Annual

577   precipitation impacts post-fire albedo through two different mechanisms. First, increased annual

578   precipitation is associated with greater recovery of LAI in these forest types (Fig. 6c) where the

579   mid-age stands replace the initial post-fire establishments, reducing albedo (Chambers and Chapin,

580   2002). Second, soil moisture depends on precipitation. With greater precipitation leading to

581   increased soil water content, we could expect a corresponding decrease in albedo due to darkening

582   of soil particularly in open canopy conditions where the soil received direct radiation (Montes-

583   Helu et al., 2009). Furthermore, an increase in leaf area within the understory during the wet season

584   could have a similar effect, as reported in Thompson et al. (Thompson et al., 2004). Regarding

585   temperature, the pattern of albedo recovery did not correspond well with the pattern of LAI

586   recovery at both time horizons in these forest types. Albedo is elevated over the pre-fire condition

587   more in the warmer part of a forest type's range even in forest types that have a faster recovery of

588   LAI in that warmer domain. We might expect that a higher LAI would be associated with a lower

589   albedo, but evidently the association is not as simple, and it might have something to do with

590   species composition rather than simply leaf area. Our results point to the importance of climate

591   patterns as a driver of post-fire summer albedo recovery through their influence on ecological

592   succession on the post-fire environment.

4.4. Significance and limitations of our Analysis

Our results should be interpreted in light of four constraints. First, the accuracy of MODIS product algorithm is dependent on biome-specific values, which following extensive fire-caused mortality, can introduce additional uncertainty due to assumption of fixed land cover type. In addition, we utilized the recovery of MODIS LAI as an indicator of vegetation recovery. One significant limitation of LAI-based analysis is that it captures some of the aggregate effects of mortality and regrowth but does not fully characterize shifted species composition and community structure on the ground. Therefore, detailed, intensive field monitoring of vegetation structure both before and after fires can serve as a valuable complement to LAI-based analysis (Williams et al., 2014). Additionally, incorporating additional remote observations at the species level from the fusion of very high spatial resolution, lidar, or hyperspectral data (Huesca et al., 2013; Polychronaki et al., 2013; Kane et al., 2014) can further enhance the assessment. Second, in terms of albedo, we used a 500 m MODIS albedo product which reflects a somewhat larger area (Campagnolo et al., 2016). Each 500 m grid may in fact include a mix of burned and unburned patches which could result in underestimation of post-fire albedo. Although the use of MODIS data with its relatively low spatial resolution will miss some of the details of fine-scale spatial variability in burn severity, land cover type and so forth (Key, 2006), MODIS data has advantages in terms of higher temporal frequency of sampling that can be important in post-fire biophysical dynamics (Lhermitte et al, 2010; Veraverbeke et al., 2010, 2012) and these data also have good temporal coverage going back decades. Furthermore, higher resolution datasets on biophysical properties are still not operationally available. Third, the quality of our results may be constrained by the accuracy of fire severity from the MTBS product as dNBR is not a perfect metric of severity and may struggle to capture some variations in severity (Roy et al., 2006; De Santis and Chuvieco, 2009). However,

several new generation fire remote sensing products (Csiszar et al., 2014; Parks et al., 2014; Boschetti et al., 2015) are emerging in recent years, which hold the potential for further improvements in post-fire recovery studies. Finally, post-fire vegetation recovery in burned areas may vary from one location to another, influenced by several other factors that this study did not cover. To gain a comprehensive understanding of the trajectory of post-fire vegetation recovery, future studies, in addition to topo-climatic variables, should consider species competition, scorching of the seed bank, distance to seed tree, other post-fire disturbances, physiology of cones, seeds, and seedlings, as well as the interactions among all influencing drivers in these settings.

Despite these limitations, by aggregating across multiple fire events in 21 different sub-ecoregions and arraying observations along a 25-years chronosequence, our results demonstrate the spatial and temporal variability of fire effects on post-fire environment. Understanding such variability of fire effects and vegetation in space and time is important for comprehensive understanding of the drivers of natural regeneration and vegetation recovery in post-fire environments (Stevens-Rumann and Morgan, 2019). Our analysis could also help improve the modeling of post-fire recovery pathways by identifying the most important predictors of post-fire recovery and by approximating related thresholds of response. For example, our results suggest a full recovery of LAI in dry, low elevation forest types like Pinyon-Juniper, Ponderosa pine, and Oak within 10 years post-fire when the annual precipitation exceeds the threshold of 500 mm and average summer temperature is ~15-20°C. A quantitative measure of primary controls is needed if efforts to develop realistic post-fire LAI trajectories for ecohydrological modeling studies are to be successful, as suggested by McMichael et al., (2004).

One major significance of our approach and findings is its potential to advance the land surface models (LSMs) embedded in Earth system models (ESMs). Currently, these models lack robust

639   representations of the ecological and biophysical consequences resulting from wildfire events

640   (Lawrence and Chase, 2007; Williams et al., 2009). Modelers could use the pattern of post-fire

641   biophysical dynamics as a function of time since fire, emerged from our data analysis, to inform

642   the LSMs to more accurately represent biophysical and ecological functions of severely disturbed

643   landscapes.

644   **4.5. Implications of Our Research**

645   There is mounting evidence of increased extreme fire incidents in the western US due to ongoing

646   climate change (Westerling et al., 2006; Williams et al., 2014), leading to rapid alteration and

647   considerable uncertainty regarding species composition (McDowell et al., 2015) and ecological

648   dynamics (Johnstone et al., 2016). This study provides an estimate of the effect of the post-fire

649   environment on vegetation and surface albedo balance of the western US. The chronosequence

650   data show clear patterns with time since fire for both biophysical parameters. Our results show that

651   conifer forest ecosystems, particularly Douglas-fir and Ponderosa pine, are slower to recover post-

652   fire, which may indicate they face greater risks from the projected increase in fire severity and

653   frequency as forecasted for drier interiors of the western US (Abatzoglou and Williams, 2016;

654   Littell et al., 2018). The post-fire biophysical changes documented here could be of significance

655   for local to regional climates, potentially eliciting feedbacks that influence regional climate change

656   and needs for adaptation.

657   **Code and Data Availability**

658   All of the research input data and codes supporting the results reported in this paper are available

659   in a repository (https://doi.org/10.5281/zenodo.7927852, Shrestha et al., 2023).

660   **Author Contribution**

661   The first author conceptualized and designed the research, curated data, ran the analysis and wrote

662   a draft. The second author (Dr. Christopher A. Williams) provided substantial input in research

663   conceptualization, research framework, and polishing of the manuscript. Drs. Brendan M. Rogers,

664   John Rogan, and Dominik Kulakowski offered insight into the manuscript's data analysis

665   presentation and contributed to the draft manuscript's finalization.

666   **Conflict of Interest**

667   The authors declare that they have no known competing financial interests or personal

668   relationships that could have appeared to influence the work reported in this paper.

669

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