Reviewer #1

General comments:
The paper "Ecosystem leaf area, gross primary production, and Evapotranspiration Responses to Wildfire in the Columbia River Basin" examines how different vegetation types recovered after a severe fire season during 2015, looking at MODIS LAI, GPP and ET products combined with the MBTS burn serenity classification data. The authors targeted concepts of "resistance" and "resilience" by looking at the difference in LAI, GPP, and ET in years following 2015 compared to the interannual variability of years prior to 2015. The authors then use a random forest feature importance to determine if vapor pressure deficit, precipitation, or burn severity were most important in determining how resilient a vegetation type was. They found that grasses were more resistant and resilient than savannahs and needleleaf evergreen forests, and that LAI was more responsive to burn severity than GPP and ET.

I found this paper to address important scientific concepts. The authors' application of concepts of resilience and resistance was an important and interesting lens to explore how disturbances affect landscapes. I also found the paper to have some major flaws, specifically pertaining to how the authors document uncertainty within their analyses, and the independence of the MODIS LAI, GPP, and ET products. I identified minor flaws in some elements of how the analysis was scoped and discussed.

Notably, the materials I received for review had no supplemental materials, but the paper makes reference in the text to several supplemental elements. The text will need to be edited substantially if the supplement was intentionally excluded.

Major comments:
This paper lacks discussion of uncertainty in interpreting the results presented. For example, in Figure 2 the only delineation of uncertainty is that of interannual variability. It's unclear if that interannual variability is mean to be interpreted as the threshold for "significant difference", and if that is the case it is in contradiction with some of the writing (see comments for line 355). A single number to describe a year gave me pause as a reviewer. Similarly, Figures 3 and figures 4 present single-point comparative data with nothing to contextualize the uncertainty around that single point. This is particularly relevant for figures 3 and 4, because the range in inter-annual resistance and resilience presented in figure 4 is sometimes larger than the differences in resistance and resilience between different vegetation-types. Interpreting if the differences presented are meaningful is left to the reader, undercutting interesting patterns. In the text, discussion of uncertainty only acknowledges limitations of remotely-sensed LAI, and does not discuss the specific uncertainties and limitations unique to the paper itself. While more appropriate to the methods section, the text also does not discuss spatial uncertainty.
Reply: We noticed the relatively low values in both precipitation and temperature in 2019. It is suggested by previous studies that plants adjust the dynamics of stomata to optimally satisfy the trade-off between the amount of carbon assimilated and the amount of water transpired (Cowan and Farquhar, 1977). Thus, vegetation growth and potential photosynthetic carbon (C) uptake or

gross primary production (GPP) are closely related to evapotranspiration (ET; Brümmer et al., 2012), and investigating ET and water use efficiency (WUE; the ratio of GPP to ET) changes is essential to the understanding of their roles in determining the carbon and water variabilities. The variations of ET are usually restricted by both temperature and soil water availability in temperate and high latitudes (Brümmer et al., 2012). For these reasons, we plotted the WUE changes to further understand the carbon and water interactions as a result of the interannual variability of precipitation and temperature (Figure R1).

In 2019, both precipitation and temperature are lower than those in other years during the recovery period (i.e., 2016–2020). The low temperature can reduce ET (e.g., soil evaporation) and maintain relatively high WUE and GPP values as long as the soil water availability is sufficient to support the growth. Compared to other years, 2017 and 2020 have relatively higher precipitation and surface air temperature values, and the annual WUE is lower than that in other years, implying the relative high levels of water usage to maintain the growth. These trends indicate that the interactions between ET and GPP are non-linear and high precipitation and surface air temperature values are not always facilitating high GPP values due to the close connections between ET and GPP (Figure R1). The investigation between ET and GPP across ecosystems is out of the scope of this study.

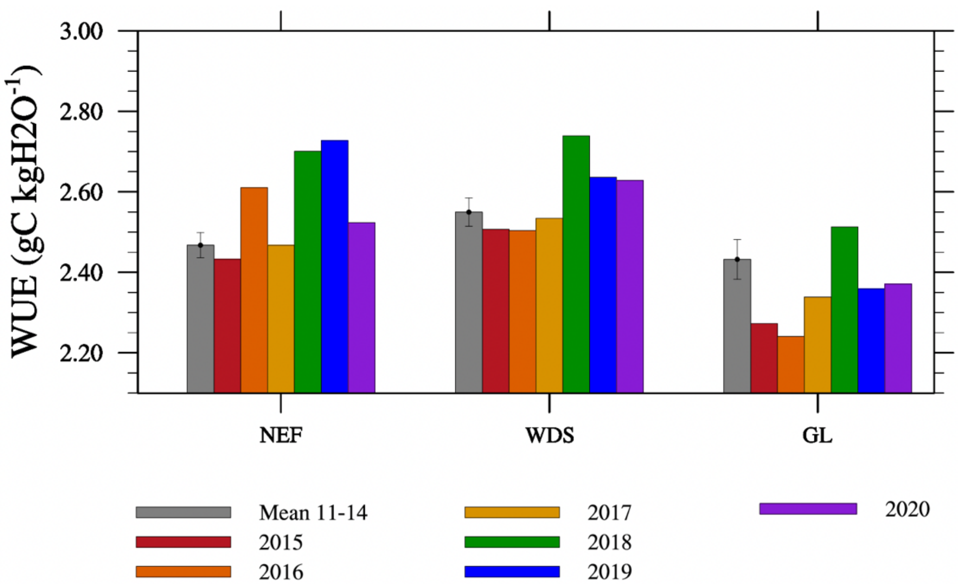

Figure R1. The growing season water use efficiency (WUE) over the three vegetation types with burn severity >3 during 2011–2020.

To address the reviewer's concern regarding the spatial specific uncertainties and spatial variations of the data, we calculated the standard error by using the LAI, GPP, and ET values in data pixels of each vegetation type, and added error bars in Figures 1–3 (newly numbered figures). The implication of the error bars in Figures 1 and S7 is added in Section 3.2. The interannual variation and the variations between vegetation types in terms of resistance and resilience are discussed in the second paragraph of Section 3.3. Overall, the standard errors indicate that LAI and it represented resilience have relatively smaller spatial variations than those of GPP and ET. Woodlands (i.e., NEF and WDS) can have similar resilience values when they are disturbed by severe fires (i.e., $S_{burn} > 3$).

Second, it is unclear if the MODIS LAI, GPP, and ET are independent enough to draw separate conclusions. The authors wisely acknowledge in line 384 that the MODIS GPP and ET products use MODIS LAI as an input, along with meteorological data. However, this does call into question if the finding that LAI responds more to burn severity than GPP or ET, because GPP and ET definitionally contain the same information as the LAI product, plus other variables that don't respond to burn severity. If the GPP and ET product contain information that could respond to burn severity beyond LAI, then that needs to be explicitly stated.
Reply: We agree with the reviewer that GPP and ET indicate some changes that are not closely related to burn severity. LAI is obtained from the MODIS LAI/fraction of photosynthetically active radiation (FPAR) algorithm that consists of a main Look-up-Table (LUT) based procedure, exploiting the spectral information content of the MODIS red and near infrared surface reflectance. For MODIS LAI/FPAR, there is also a back-up algorithm that uses empirical relationships between Normalized Difference Vegetation Index (NDVI) and canopy LAI and FPAR. The estimates of MODIS GPP use the (1) MODIS FPAR, (2) the GMAO/NASA provided photosynthetically active radiation (PAR), and (3) the biome-specific radiation use efficiency parameters that are extracted from the Biome Properties Look-Up Table (BPLUT) and updated by the temperature and vapor pressure deficit scalars. The estimates of MODIS ET use the Penman-Monteith equation, which considers many environmental factors including radiation components, air temperature, and relative humidity. LAI is used to estimate wet canopy resistance to sensible heat and resistance to latent heat transfer, which will be used to calculate evaporation on wet canopy surface. In all the calculations of GPP and ET, the environmental factors will not be responding to burn severity, especially during the recovery years, and have large daily, seasonal, and interannual variabilities. We added the following paragraph in the second paragraph of Section 4.2:

"*Specifically, the MODIS GPP algorithm uses (1) the MODIS fraction of photosynthetically active radiation (FPAR) retrieved at the same time with LAI, (2) the MODIS daily mean Photosynthetically Available Radiation (PAR), (3) the biome-specific radiation use efficiency parameters that are extracted from the Biome Properties Look-Up Table (BPLUT) and adjusted by the temperature and vapor pressure deficit scalars, to estimate GPP (Running and Zhao, 2019). The estimates of MODIS ET use the Penman-Monteith equation, which considers many environmental factors including radiation components, air temperature, and relative humidity. Here, LAI is used to estimate wet canopy resistance to sensible heat and resistance to latent heat transfer, which will be used to calculate evaporation on wet canopy surface (Running et al., 2019). Thus, the recovery of GPP and ET are also affected by post-fire environmental factors, which are not responding to burn severity and have large daily, seasonal, and interannual variabilities.*"

Minor comments:

Methods: Grasses could grow back faster than the “resilience”/ “resistance” increment of 1 year. Is it appropriate to consider grasses’ “resistance” in the first year post fire?

Reply: Figures 1 and S7 show that only when the burn severity is 1, the LAI, GPP, and ET values in 2016 could be higher than that in 2015 or in 2011–2014. In other cases, the values of these three metrics in 2016 are always the smallest, indicating that only when the burn severity is minimum, grasses and other ecosystem types can have a faster growth and recovery to the pre-fire conditions in the first year after fire. That is the higher the burn severity, the lower the values of these three metrics in the first year after fire. Here, we are quantifying resistance and recovery capacity, so use the lowest values that can represent the damage intensity (largest reduction of these variables) given that “*fires happened mid-way through the growing season (Figure S4)*” of 2015 and “*the 2015 values include both pre- and post-fire*” conditions (See Section 2.5). Overall, we comprehensively evaluated different factors and decided to use the values first year after fire for all ecosystem types. We also added the following sentence by the end of Section 4.1:

“*Here, we estimate resistance by using the values of these three metrics in the first post-fire year (i.e., 2016) for all the VTs. When burn severity is 1, some ecosystems, such as grasslands, can recover rapidly, resulting in that values in 2016 may exceed those in 2015 or in 2011–2014 (see Figure S7). These variation (Figures S7c, S7f, and S7i) are primarily influenced by the minimum disturbance intensity, which could facilitate a quick recovery under favorable climate conditions.*”

Line 85- Citation how LAI related to prediction uncertainties of earth system models?

Reply: The citation is added.

Line 160-164 – This seems to contradict methods described in lines 193-195

Reply: We used the method in lines 193–195, and we updated 160-164 to avoid the confusion as “*We use the dominant VT of each fire event, defined as the VT whose area accounts for more than 50% of burned area for that event, to identify the representative landscape type of each fire event (Figure S2b). This analysis aims to comprehend which VT(s) are predominantly affected by fire across the CRB (Figure S2b). However, to precisely estimate the resistance and resilience of different VTs, we explicitly consider the VTs and their changes characterized by LAI, GPP, and ET in each data pixel of each fire event (see more details in Section 2.4).*”

Line 186 - Difficulty understanding the sentence beginning with “Specifically…” What information is applied? Is this referring to MODIS pixels that span multiple fires, or each fire-MODIS pair?

Reply: This sentence is updated as “*Specifically, within each MTBS fire boundary, the MODIS VT information for each data pixel is used to derive different VT determined LAI, GPP, and ET changes in the corresponding MODIS data pixels (Table S1).*”

Line 195 - Table 1 seems more appropriate to a supplement. Perhaps a column indicating the years used in this study?

Reply: Table 1 is moved to Supplement, and an additional column is added.

Line 245 - 248: Citation/discussion for why 100 trained models were sufficient.

Reply: We added citations regarding the 100 trained time simulations. We also performed new simulations by adding the training times to 500, and did not see any changes that affect our conclusions. Thus, we decided keeping the 100 training times in our study.

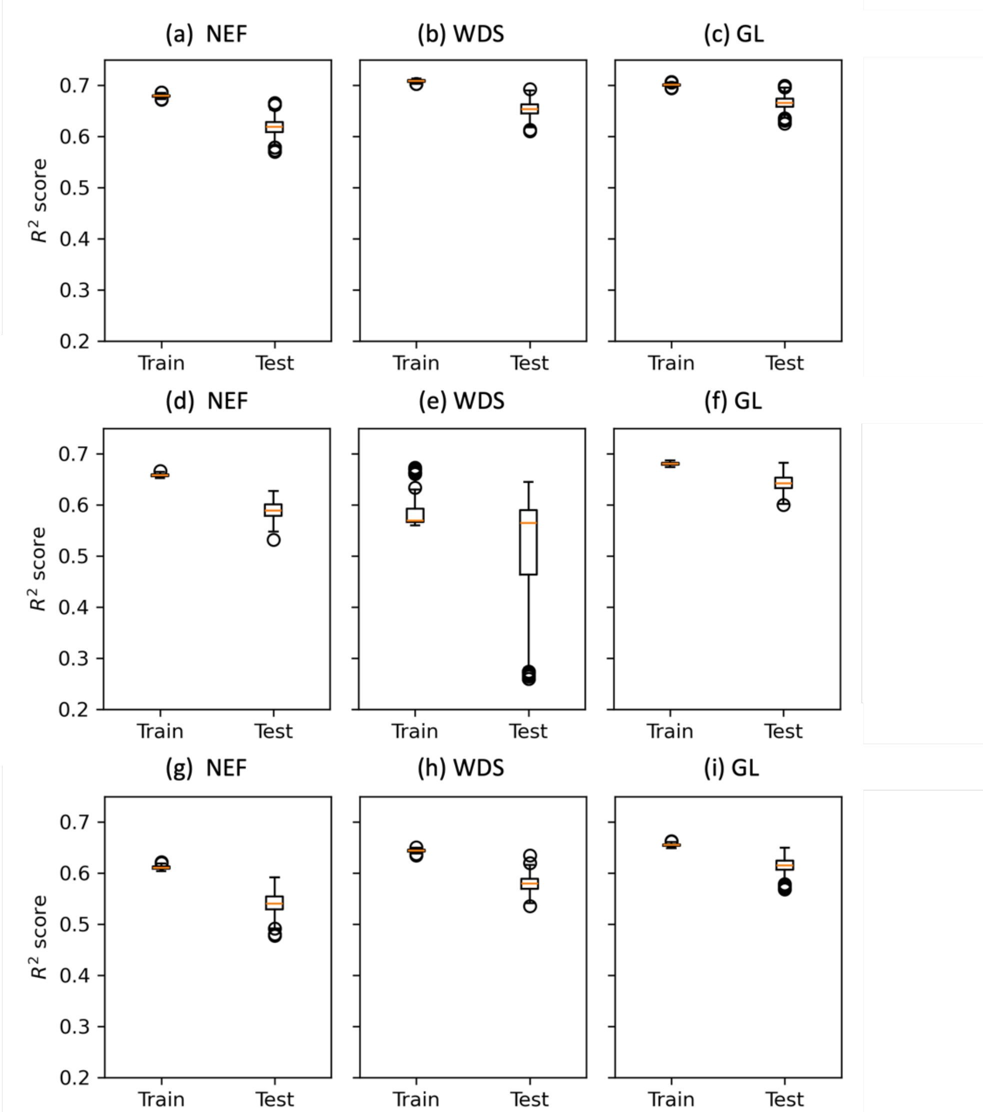

Figure R2. The new simulation with 500 training times. The R^2 scores for the random forest model on train and test datasets for the (a) needleleaf evergreen forest (NEF), (b) woody savanna (WDS), and (c) grassland (GL) VTs represented by LAI, the (d) NEF, (e) WDS, and (f) GL VTs represented by GPP, and for (g) NEF, (h) WDS, and (i) GL VTs represented by ET.

Lines 250-258: This paragraph reads as more relevant to the methods section, and the writing shifts from present tense to past tense.

Reply: The sentence "*During the fire season of 2015, 138 fire events are identified. We also remove the areas that experienced fire in 2011–2014 or in 2016–2020, thus our resistance and resilience* *calculations are not confounded by repeat fires.*" is moved to Section 2.2, and this paragraph is updated as "*The MTBS and VT based analysis shows that August is the month with the highest fire frequency in 2015 with 91 fire events (Figure S2a), where NEF experiences 42, WDS experiences 27, and grassland experiences 67 fire events, respectively (Figures S1 and S2b). There are two fire events in croplands, which were excluded from further analysis.*"

Figure 1 - Also seems more appropriate for a supplement. More discussion/ visual delineation of uncertainty would make this a more powerful figure. For example, why not include error bars for the years themselves? Finally, while the text claims climate variations in years (is that distinct from interanual variability?) are not confounding, 2019 seems to be different than other years compared to the interannual variability of 2001-2014 in precipitation. This is not discussed, and specifically how years are not significantly different is not defined.
Reply: Figure 1 is moved to SI.

Line 355 - Seems to contradict Figure 2 – 2019 is higher than 2020 in GPP. Also, if "Recover" is defined as reaching the same value within the variability of 2011-2014, then many metrics did not "recover" at all.
Reply: This comment is addressed earlier.

Line 321-322 Cite statement about overfitting.
Reply: Yang et al. (2024) and Yildirim et al. (2021) are cited.

443 - The connection between this research and afforestation and sustainable agriculture is unclear in this current writing.
Reply: This sentence is removed from the manuscript.

Conclusions: Potential uses for this research for the calibration of ESM is discussed for the first time in the conclusions.
Reply: We also add discussions of the importance and implications of using ESMs in the last sentence of Section 4.3.

Technical Corrections:
Line 209: - Additional period.
Reply: The period is deleted.

Line 278: "S" denoting severity and "S" denoting supplement both is confusing.
Reply: "S" is updated to "S_{burn}" to represent burn severity in Figures in the main context (e.g., Figure 2) and in Supplementary.

Line 316 important scores -> importance scores
Reply: Updated.

364 - fully – full

Reply: Updated.

395- interacting -> interaction
Reply: Updated.

425 “findings that obtained with” -> findings from, “potential of” -> “potential for”
Reply: Updated.

428 - unclear what is meant by “reasonable data quality controls”
Reply: This sentence is updated as “*Our research affirms the findings from plot-based measurements and shows a strong potential for using satellite observations to investigate ecohydrological processes and resistance and resilience to different types of disturbance in regions with reasonable data quality controls (i.e., with the remote-sensing quality control flags considered).*”

Reference:

Brümmer, C., Black, T. A., Jassal, R. S., Grant, N. J., Spittlehouse, D. L., Chen, B., ... & Wofsy, S. C. (2012). How climate and vegetation type influence evapotranspiration and water use efficiency in Canadian forest, peatland and grassland ecosystems. *Agricultural and Forest Meteorology*, *153*, 14-30.

Cowan, I. R., & GD, F. (1977). Stomatal function in relation to leaf metabolism and environment.

Yang, B., Heagy, L. J., Morgenroth, J., & Elmo, D. (2024). Algorithmic Geology: Tackling Methodological Challenges in Applying Machine Learning to Rock Engineering. Geosciences, 14(3), 67.

Yildirim, M. O., Gok, E. C., Hemasiri, N. H., Eren, E., Kazim, S., Oksuz, A. U., & Ahmad, S. (2021). A machine learning approach for metal oxide based polymer composites as charge selective layers in perovskite solar cells. ChemPlusChem, 86(5), 785-793.