THESIS

EVALUATING THE IMPACTS OF FUEL TREATMENTS ON BURN SEVERITY ACROSS THE FRONT RANGE

Submitted by

Sarah L. Hettema

Department of Forest and Rangeland Stewardship

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Spring 2025

Master's Committee:

Advisor: Camille Stevens-Rumann

Mike Battaglia
Jody Vogeler
Tony Vorster

ABSTRACT

EVALUATING THE IMPACTS OF FUEL TREATMENTS ON BURN SEVERITY ACROSS THE FRONT RANGE

Understanding how wildland fuel treatments interact with more frequent extreme wildfire events is an increasingly pressing issue. Quantifying the effectiveness of fuel treatments is difficult for many reasons including dynamics between treatment type, time since treatment, weather, climate, the fuels present, and topography. This study investigated wildfires along the Front Range from southern Wyoming to northern New Mexico to evaluate under what conditions treatments reduce the ecological impacts of fire, as measured by remotely sensed burn severity. We first evaluated methods and metrics to measure burn severity on the Front Range landscape. We found the Parks et al. (2018) Google Earth Engine (GEE) method and the relativized burn ratio (RBR) to have the highest correlation with field data. Additionally, the GEE method provided the advantage of allowing us to include small wildfires, which have historically been underrepresented in the data. We then determined (1) factors influencing the relationship between treatments and burn severity, (2) how burn severity differed across forest and treatment types, and (3) how extreme fire weather conditions influenced burn severity across treatment types. Across the Front Range, lower elevation forest types burned at lower severities compared to higher elevation forest types. Treatment effects varied across forest types but treatments generally had lower burn severity in lower elevation forest types compared to spruce – fir and lodgepole pine forests. Areas that previously experienced low to moderate severity wildfire had

the lowest burn severity outcomes across forest types and in extreme conditions. Intentional surface fuels reduction treatments (i.e. prescribed fire, removal plus surface fuel reduction, and removal plus fire) had a relatively minor impact across our study area. That said during non-extreme conditions, treatments that included previous fire (prescribed burning or low to moderate severity wildfire) had lower subsequent burn severities. Higher elevation forests (spruce – fir and lodgepole pine) burned at high severity regardless of intentional treatment effect. This better understanding of the outcomes of treatment efforts will help land managers strategically utilize resources and employ adaptive management strategies that account for changing wildfires.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Camille Stevens-Rumann, for her guidance and support. Her expertise has been fundamental in shaping this project, and her mentorship has pushed me to become a better scientist. For that, I am immensely grateful. I also want to thank Tony Vorster for connecting me with this opportunity—his mentorship before and during graduate school was invaluable in shaping my career. His insights have been instrumental to this project. I am deeply grateful to Mike Battaglia for his curiosity, enthusiasm, and guidance, and to Jody Vogeler for providing opportunities to connect with other remote sensing researchers and for valuable feedback. The time and energy my committee invested in me allowed me to do my best work.

Thank you to my Fire Ecology Lab mates for creating an environment of support. I loved learning alongside you all and truly appreciated the feedback you provided throughout my degree. I especially want to thank Hannah Van Dusen for her technical and conceptual help—her contributions were vital to completing this thesis. I am also grateful to the FRS graduate students, especially the F112 office, for their support, advice, and laughter, which made my graduate school experience wonderful. Thank you for making every day in the office a delight.

To my friends and family, thank you for your unwavering support throughout this process. I appreciate your curiosity about my work and for helping me balance work and life. A special thank you to my partner, Brayden, for believing in me and supporting me every step of the way, and to my parents, whose guidance and values have shaped me into the scientist I am today.

Finally, I acknowledge that this project would not have been possible without funding from the USDA Forest Service and the Southwest Climate Adaptation Science Center.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

The compounding effects of fire suppression and climate change have left forested ecosystems in western North America vulnerable to catastrophic wildfire (Abatzoglou & Williams, 2016; Collins, 2014; Hagmann et al., 2021). To combat the wildfire crisis, there is a pressing need to understand how land management activities that modify fuels influence post-fire outcomes (Hessburg et al., 2021). Of the components driving fire behavior, fuel reduction has been shown to be an effective strategy for mitigating wildfire severity (Davis et al., 2024; Kalies & Yocom Kent, 2016; Stephens et al., 2012). However, implementing and assessing the effects of fuels treatments is complex due to the dynamic interactions between treatments, fire behavior, and landscape conditions (Vorster et al., 2024).

Previous studies on treatment effectiveness have found that treatments reducing canopy fuels through thinning and surface fuels through burning are generally successful in moderating subsequent burn severity (Davis et al., 2024; Kalies & Yocom Kent, 2016; Stephens et al., 2012). Much of this research has focused on lower-elevation, dry conifer forests with historically frequent, low severity fire regimes (Davis et al., 2024; Kalies & Yocom Kent, 2016). Less is known about treatment effectiveness in higher elevation forests (Davis et al., 2024). The Front Range of southern Wyoming to northern New Mexico contains a range of bioclimatic conditions resulting in various forest types that are interacting with wildfire.

The overarching goal of this project was to evaluate treatment effects along the Front Range to determine how treatments interact with wildfire on this landscape. To conduct this analysis at a landscape scale, we relied on spatial data to represent factors influencing fire behavior and fuel treatments. Given this approach, we needed to ensure our response variable, burn severity, accurately captured the ecological impacts of wildfire in our study area. While remotely sensed burn severity metrics are widely used to assess fire effects over large spatial extents (Parks et al., 2014), differences in processing methods and burn severity indices can influence how fire impacts are interpreted (Cansler & McKenzie, 2012; Furniss et al., 2020; Kurbanov et al., 2022; Soverel et al., 2010). Thus, before investigating treatment effects in Chapter 3, we first determined the most appropriate method and index for quantifying burn severity on the Front Range.

In Chapter 2, we evaluated different processing methods and burn severity indices to identify the most suitable approach for this landscape. By first ensuring that our burn severity metric was appropriate for our study area, we were able to address our main research questions surrounding treatment effects. Chapter 3 examines how various factors, including fire weather, climatic, topographic, and fuel conditions, interacted with intentional and wildfire treatments to influence burn severity. We assess how treatments modify fire severity across different forest types, the degree to which treatment effects vary under extreme fire weather, and the interactions between treatments and fire behavior variables.

The results of this thesis provide insight into how treatments can mitigate the negative ecological impacts of severe wildfire. By expanding our understanding of treatment effects on the Front Range—a pyro-diverse landscape often overlooked in the literature—we aim to provide more information for land managers. As wildfire activity intensifies, these findings contribute to establishing more resilient, fire-adapted landscapes and communities.

REFERENCES

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, *113*(42), 11770–11775. https://doi.org/10.1073/pnas.1607171113

Cansler, C. A., & McKenzie, D. (2012). How Robust Are Burn Severity Indices When Applied in a New Region? Evaluation of Alternate Field-Based and Remote-Sensing Methods. *Remote Sensing*, *4*(2), 456–483. https://doi.org/10.3390/rs4020456

Collins, B. M. (2014). Fire weather and large fire potential in the northern Sierra Nevada. *Agricultural and Forest Meteorology*, *189–190*, 30–35. https://doi.org/10.1016/j.agrformet.2014.01.005

Davis, K. T., Peeler, J., Fargione, J., Haugo, R. D., Metlen, K. L., Robles, M. D., & Woolley, T. (2024). Tamm review: A meta-analysis of thinning, prescribed fire, and wildfire effects on subsequent wildfire severity in conifer dominated forests of the Western US. *Forest Ecology and Management*, *561*, 121885. https://doi.org/10.1016/j.foreco.2024.121885

Furniss, T. J., Kane, V. R., Larson, A. J., & Lutz, J. A. (2020). Detecting tree mortality with Landsat-derived spectral indices: Improving ecological accuracy by examining uncertainty. *Remote Sensing of Environment*, *237*, 111497. https://doi.org/10.1016/j.rse.2019.111497

Hagmann, R. K., Hessburg, P. F., Prichard, S. J., Povak, N. A., Brown, P. M., Fulé, P. Z., Keane, R. E., Knapp, E. E., Lydersen, J. M., Metlen, K. L., Reilly, M. J., Sánchez Meador, A. J., Stephens, S. L., Stevens, J. T., Taylor, A. H., Yocom, L. L., Battaglia, M. A., Churchill, D. J., Daniels, L. D., … Waltz, A. E. M. (2021). Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. *Ecological*

Applications, *31*(8). https://doi.org/10.1002/EAP.2431

Hessburg, P. F., Prichard, S. J., Hagmann, R. K., Povak, N. A., & Lake, F. K. (2021). Wildfire and climate change adaptation of western North American forests: a case for intentional management. *Ecological Applications*, *31*(8). https://doi.org/10.1002/eap.2432

Kalies, E. L., & Yocom Kent, L. L. (2016). Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. *Forest Ecology and Management*, *375*, 84–95. https://doi.org/10.1016/J.FORECO.2016.05.021

Kurbanov, E., Vorobev, O., Lezhnin, S., Sha, J., Wang, J., Li, X., Cole, J., Dergunov, D., & Wang, Y. (2022). Remote Sensing of Forest Burnt Area, Burn Severity, and Post-Fire Recovery: A Review. *Remote Sensing*, *14*(19), 4714. https://doi.org/10.3390/rs14194714

Parks, S., Dillon, G., & Miller, C. (2014). A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. *Remote Sensing*, *6*(3), 1827–1844. https://doi.org/10.3390/rs6031827

Soverel, N. O., Perrakis, D. D. B., & Coops, N. C. (2010). Estimating burn severity from Landsat dNBR and RdNBR indices across western Canada. *Remote Sensing of Environment*, *114*(9), 1896–1909. https://doi.org/10.1016/j.rse.2010.03.013

Stephens, S. L., Mciver, J. D., Boerner, R. E. J., Fettig, C. J., Fontaine, J. B., Hartsough, B. R., Kennedy, P. L., & Schwilk, D. W. (2012). The Effects of Forest Fuel-Reduction Treatments in the United States. *BioScience*, *62*(6), 549–560. https://doi.org/10.1525/bio.2012.62.6.6

Vorster, A. G., Stevens-Rumann, C., Young, N., Woodward, B., Choi, C. T. H., Chambers, M. E., Cheng, A. S., Caggiano, M., Schultz, C., Thompson, M., Greiner, M., Aplet, G., Addington, R. N., Battaglia, M. A., Bowker, D., Bucholz, E., Buma, B., Evangelista, P., Huffman, D., … West Fordham, A. (2024). Metrics and Considerations for Evaluating How Forest Treatments Alter Wildfire Behavior and Effects. *Journal of Forestry*, *122*(1), 13–30. https://doi.org/10.1093/jofore/fvad036

CHAPTER 2: ASSESSING BURN SEVERITY INDICES AND METHODS ON THE FRONT RANGE

2.1. Introduction

After a wildfire, there is a need to understand ecosystem impacts particularly on vegetation and soils. Burn severity influences key ecological traits and processes, including landscape heterogeneity, soil erosion, nutrient cycling, wildlife habitat, and successional trajectories (McKenzie et al., 2011). By quantifying burn severity, researchers can evaluate the effects of wildfires on ecosystem health and recovery dynamics (Key & Benson, 2006; Keeley, 2009; McKenzie et al., 2011). Understanding burn severity also informs post-fire management decisions, such as erosion control efforts, reforestation strategies, habitat restoration, and implementation of future fuels treatments (Keeley, 2009; Long et al., 2014). Burn severity can be measured through field-based assessments or remote sensing techniques; each method provides advantages for capturing wildfire effects at different scales.

Multispectral-derived burn severity indices are widely used in wildfire research because they can detect wildfire-induced changes over large spatial scales (Parks et al., 2014). The alternative to remotely sensed burn severity data is collecting field-based measurements which is time consuming and costly. The composite burn index (CBI) is a commonly-used field method that measures the average burn conditions of a stand one year post fire (Key & Benson, 2006). CBI measurements account for various aspects of burn severity, including surface fuel consumption, soil char, vegetation mortality, and tree scorching, using a scale of 0 (no fire-related change) to 3 (high fire-related change) (Key & Benson, 2006). Remotely sensed burn severity is typically strongly correlated to these field-based CBI measurements (Holden et al., 2009; Parks et al., 2014; Soverel et al., 2010) allowing researchers to validate remotely sensed data.

In the U.S., wildfire research often relies on the Monitoring Trends in Burn Severity (MTBS) program, which provides a database of burn severity metrics for all wildfires since 1984 larger than 400 hectares (Eidenshink et al., 2007). MTBS metrics are derived by manually selecting one high quality, cloud-free pre-fire and one post-fire Landsat image. Publicly available burn severity indices from MTBS include the normalized burn ratio (NBR), the delta normalized burn ratio (dNBR), and the relativized delta normalized burn ratio (RdNBR) (https://www.mtbs.gov/direct-download). In 2018, Parks et al. released a method to compute Landsat-based fire severity metrics using Google Earth Engine (GEE). GEE is a cloud based geospatial analysis platform that allows users to access and process satellite imagery and geospatial datasets. The Parks et al., (2018) GEE method (hereafter, GEE method) uses a pre-fire and post-fire mean composite of all pixels in a fire season window to derive burn severity metrics. With minor modifications to the GEE script, users can derive NBR, dNBR, RdNBR, and relativized burn ratio (RBR) indices. Users can derive indices for any wildfire, including those less than 400 hectares.

The burn severity metrics dNBR and RBR are widely used in wildfire research; many studies pick one metric over the other because of better correlation with field data (e.g. Fernández-Guisuraga et al., 2023; Prichard et al., 2020) and/or accessibility of data (Finco et al., 2012). dNBR is the difference of pre-fire NBR and post-fire NBR and was developed to detect changes in vegetation and soil conditions following wildfire (Eq. (1); Key & Benson, 2006). RBR was developed to improve upon the relativized delta normalized burn ratio (RdNBR), by addressing some of the issues in the RdNBR equation (Eq. (2); Parks et al., 2014). Both metrics have been criticized, and debate continues over whether relativized indices (e.g., RBR) offer a meaningful improvement over absolute indices (e.g., dNBR) in quantifying burn severity (Cansler & McKenzie, 2012; Furniss et al., 2020; Kurbanov et al., 2022; Soverel et al., 2010). On the Front Range, there are minimal studies and consensus of the strength of using one metric over the other.

$$dNBR = \left(NBR_{pre-fire} - NBR_{post-fire}\right) \times 1000 \tag{1}$$

$$RBR = \frac{dNBR}{(NBR_{pre-fire}+1.001)} \tag{2}$$

Many studies have compared burn severity indices and methods; however, these studies were conducted in regions with different biophysical settings and forest types compared to the Front Range. For example, Fernández-Guisuraga et al. (2023) found that RBR better fit CBI field data in Mediterranean mature broadleaf and conifer forests, as well as shrublands, where fuel continuity and vegetation structure differ from the montane forests of the Front Range. Parks et al. (2014) found that RBR correlated more strongly with CBI data in coniferous and mixed broadleaf-coniferous forests across the western U.S., where fire regimes and moisture availability vary widely. Similarly, Prichard et al. (2020) found that RBR performed best in mixed-conifer forests in north-central Washington State, including Engelmann spruce–subalpine fir, lodgepole pine, moist mixed-conifer, ponderosa pine, and shrubland ecosystems, which differ from the drier, lower-elevation forests of the Front Range. Because the Front Range possesses a unique spread of fire regimes there is a need to determine an appropriate index for a landscape level analysis of the ecological impacts of wildfire. In this study, we aimed to determine the most appropriate method and burn severity metric for studying the ecological impacts of wildfire on the Front Range.

2.2. Methods

We evaluated remotely sensed burn severity methods and metrics for wildfires that occurred from southern Wyoming to northern New Mexico. Using a random selection process, we identified ten wildfires larger than 400 hectares within our study area (Fig. 2.1).

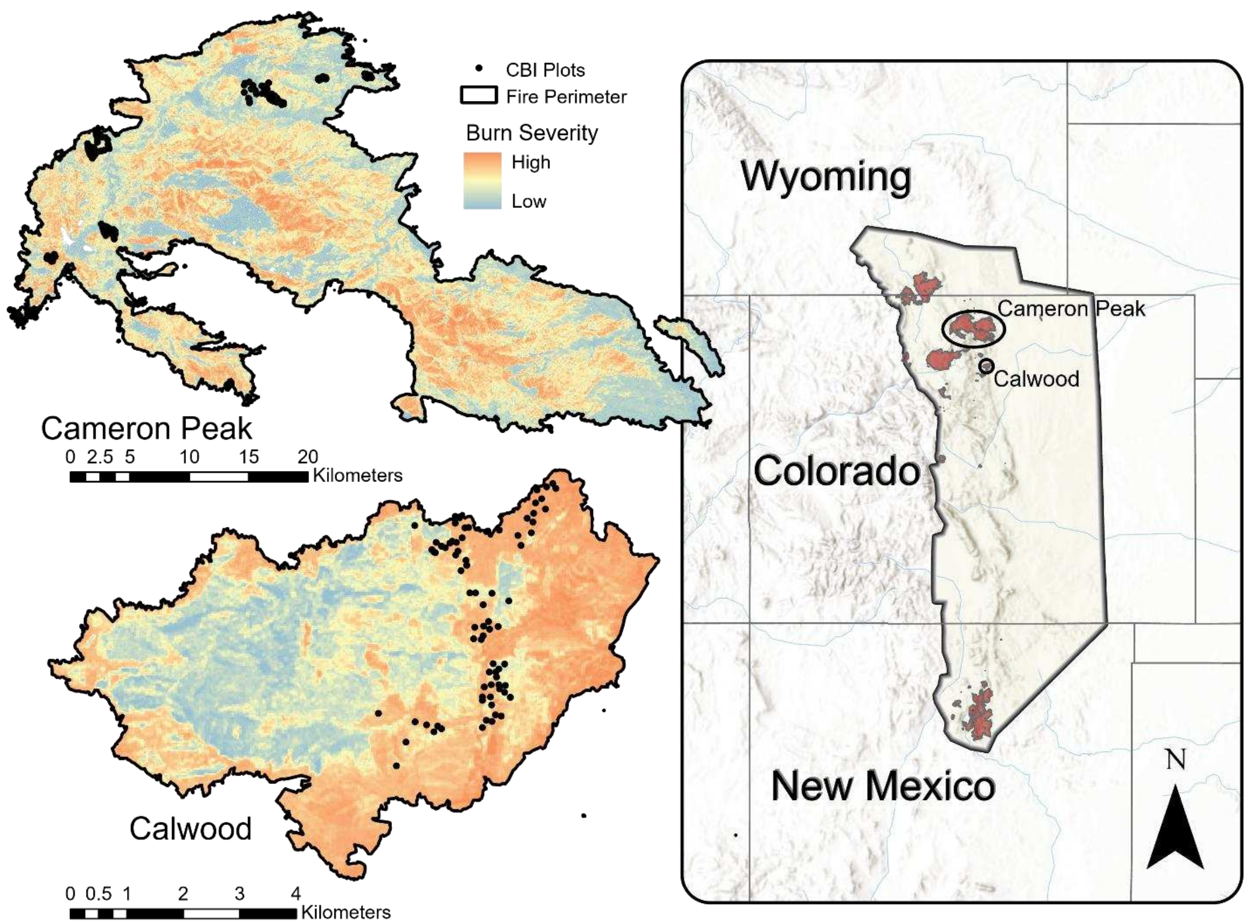

Fig. 2.1. Study area map including wildfires of interest (right), mapped relativized burn ratio (RBR) burn severity, and composite burn index (CBI) points for the Cameron Peak and Calwood fires (left).

For MTBS data, we downloaded individual fire dNBR indices from the MTBS web portal (Eidenshink et al., 2007). For GEE data, we created shapefiles of wildfire perimeters and used a modified GEE script (Parks et al., 2018) to extract dNBR and RBR indices. We did not compare methods to derive RdNBR because the metric was less prevalent in the literature. We set fire season dates to the recommended period for forests in the southern Rockies (Day of Year: 152–258; Parks et al., 2019). Field-based CBI data was collected in the Cameron Peak and Calwood fires for 10 m radius plots during the summer of 2021 (Fig. 2.1; Twaddell, 2023; Vorster et al., 2024). The Cameron Peak data was collected to capture a range of vegetation types, burn severities, and elevations (Vorster et al., 2024), while the Calwood data, collected at lower elevations, focused on paired treated and untreated areas, representing a narrower range of vegetation types and conditions (Twaddell, 2023).

To assess differences between MTBS and GEE derived values, we calculated the percent pixel agreement across the subset of wildfires. Agreement was determined by computing the percent difference between corresponding MTBS and GEE raster values, with pixels considered in agreement if the percent difference was ≤20%. We then calculated the total percentage of pixels within each wildfire perimeter that met this threshold. If ≤80% of pixels in a fire agreed, we classified the difference between MTBS and GEE methods as meaningful.

We compared the distributions of all pixels within the Cameron Peak and Calwood fires by constructing histograms for MTBS dNBR, GEE dNBR, and GEE RBR. To evaluate how well remotely sensed indices correlated with field data, we extracted pixel values at CBI plot coordinates using the extract function in the terra R package (Hijmans, 2024). We then performed linear regressions to assess the relationship between field-measured CBI and remotely sensed burn severity indices. All analyses were performed using R Statistical Software (v4.3.3; R Core Team, 2024).

2.3. Results & Discussion

MTBS and GEE dNBR values were meaningfully different across all randomly selected fires (Table 2.1). The highest percent pixel agreement occurred in the East Troublesome fire, although this was still low (21.4%). Across the ten fires, MTBS dNBR had consistently higher maximum values (8/10 fires) and lower minimum values (10/10 fires) suggesting the MTBS method captured more extreme burn severity values compared to the GEE method. Parks et al. (2018) also concluded that the GEE mean composite method likely reduced pre- and post-fire scene mismatches and image characteristic biases that could result in extreme values.

Table 2.1
Monitoring Trends in Burn Severity (MTBS) and Google Earth Engine (GEE) delta normalized burn ratio (dNBR) value comparisons for ten randomly selected fires.

Fire Name	**Pixel Agreement (%)**	**Minimum Value**		**Maximum Value**	
		MTBS	GEE	MTBS	GEE
East Troublesome	21.4	-969	-284	1181	1217
Hayman	20.4	-1186	-202	1327	1017
Cameron Peak	16.1	-1000	-562	1141	1185
Hayden Pass	14.6	-282	-118	1039	879
Calwood	11.1	-421	-231	1086	976
Pacheco	9.2	-858	-84	1605	1002
Borrego	8.6	-420	-40	991	949
Fourmile Canyon	7.1	-187	-109	947	930
Overland	6.1	-502	-237	1013	832
Big Elk	5.4	-425	-105	1106	933
Wetmore	2.4	-332	-151	867	784

We observed differences in the distributions of MTBS dNBR, GEE dNBR, and GEE RBR values for the Cameron Peak and Calwood fires. The Cameron Peak MTBS dNBR distribution (Fig. 2.2A) has a broader range (Range: -1000 – 1141), with a pronounced peak near zero and more values in the negative range. In contrast, the GEE dNBR distribution (Fig. 2.2B) has a narrower spread (Range: -282 – 1185) and a more even distribution of pixel values across the range, with few values below zero. The GEE RBR distribution (Fig. 2.2C) has a similar range to GEE dNBR (Range: -698 – 708) but shows a higher frequency of values in the moderate severity range.

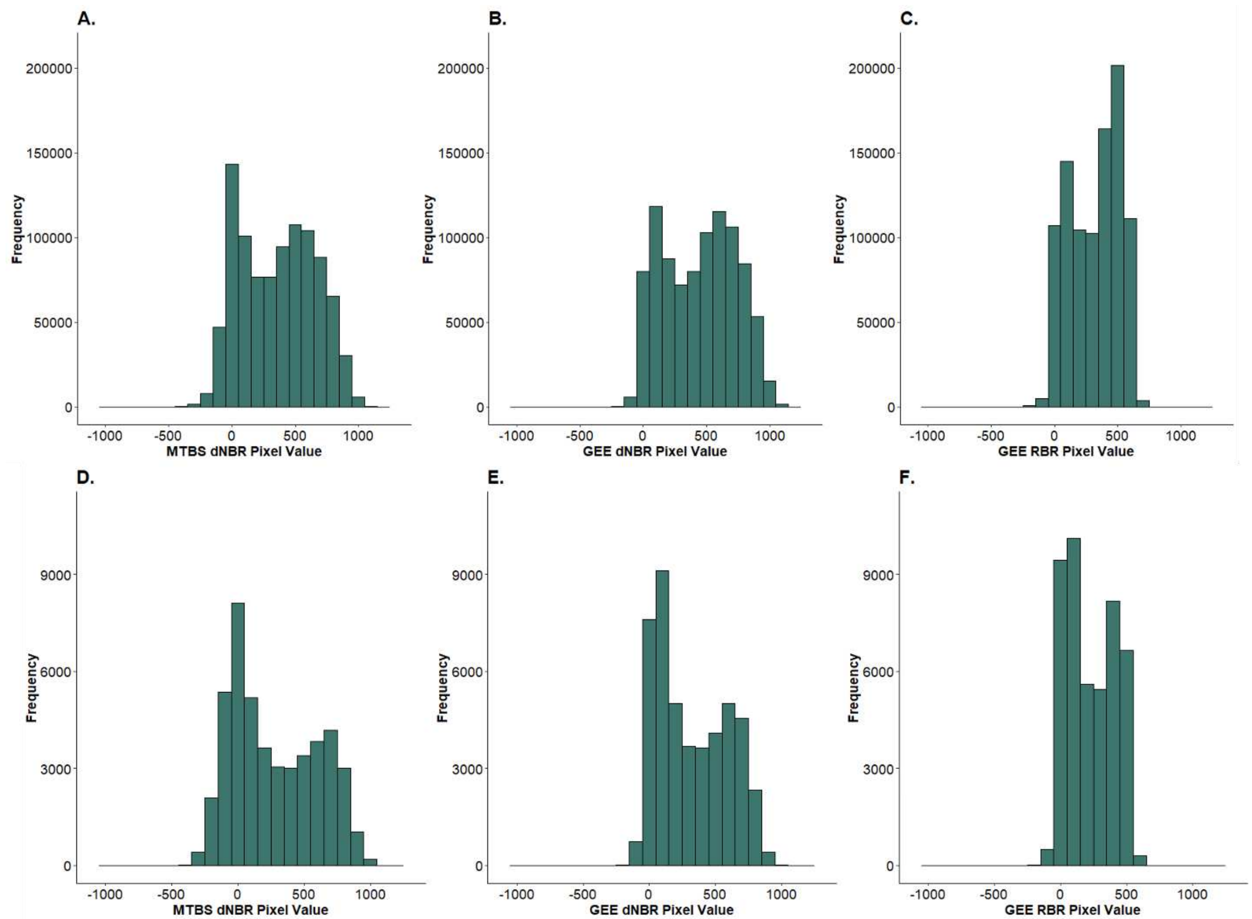

Fig. 2.2. Histograms of all pixel values for burn severity metrics in the Cameron Peak and Calwood fires. (A) Cameron Peak Monitoring Trends in Burn Severity (MTBS) delta normalized burn ratio (dNBR), (B) Cameron Peak Google Earth Engine (GEE) dNBR, (C) Cameron Peak GEE relativized burn ratio (RBR), (D) Calwood MTBS dNBR, (E) Calwood GEE dNBR, and (F) Calwood GEE RBR.

The Calwood MTBS dNBR distribution (Fig. 2.2D) is slightly broader (Range: -421 – 1086), with a more even spread of pixel values across the range, whereas the GEE dNBR distribution (Fig. 2.2E) has a narrower spread (Range: -231 – 976) and a more pronounced peak near zero. In contrast, the GEE RBR distribution (Fig. 2.2F) is even narrower (Range: -199 – 594), with a higher frequency of values in the moderate severity range. Both fires exhibited similar trends in pixel value distributions across the three burn severity metrics. The concentration of GEE RBR values for both fires is likely because the RBR equation does not result in extremely high or low values when pre-fire NBR is near zero and the values are relativized (Parks et al., 2014).

The low agreement percentages and difference in distribution shape and spread suggested that MTBS and GEE dNBR indices may not be interchangeable and highlighted the need to evaluate their performance with field data. We also decided to evaluate RBR because it incorporates the $dNBR_{offset}$, which accounts for differences in pre- and post-fire imagery caused by variations in phenology or precipitation. Previous studies have recommended using metrics that include the $dNBR_{offset}$ when comparing across fires to address these differences (Miller & Thode, 2007; Parks et al., 2014). However, we were unable to compare GEE-derived RBR to MTBS because MTBS does not produce RBR as a data product.

The linear regression models evaluating the relationship between remotely sensed burn severity indices and CBI revealed that the GEE method outperformed the MTBS method. For the Cameron peak fire, MTBS dNBR had a moderate correlation with CBI ($R^2 = 0.55$, RMSE = 0.65; Fig. 2.3A), while GEE dNBR had a stronger correlation with CBI ($R^2 = 0.62$, RMSE = 0.59; Fig. 2.3B). We observed GEE RBR had the strongest correlation with CBI ($R^2 = 0.68$, RMSE = 0.54; Fig. 2.3C). Similarly, in the Calwood fire, MTBS dNBR showed the weakest correlation with CBI ($R^2 = 0.37$, RMSE = 0.54; Fig. 2.3D), while GEE dNBR improved on this relationship ($R^2 = 0.53$, RMSE = 0.47; Fig. 2.3E). Again, GEE RBR had the highest correlation with CBI ($R^2 = 0.56$, RMSE = 0.45; Fig. 2.3F).

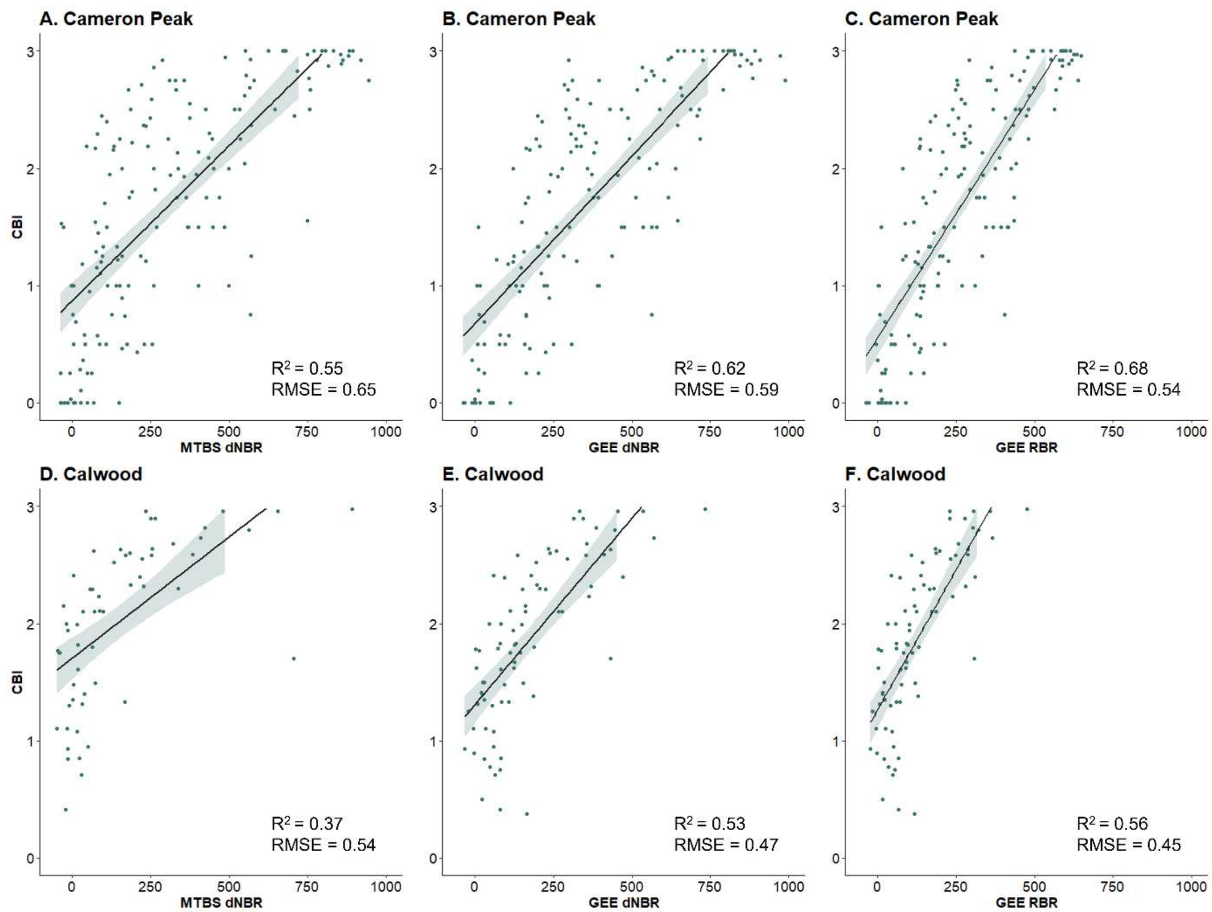

Fig. 2.3. Scatter plots of composite burn index (CBI) versus remotely sensed burn severity indices for the Cameron Peak (n = 169) and Calwood (n = 79) fires. (A) Cameron Peak Monitoring Trends in Burn Severity (MTBS) delta normalized burn ratio (dNBR), (B) Cameron Peak Google Earth Engine (GEE) dNBR, (C) Cameron Peak GEE relativized burn ratio (RBR), (D) Calwood MTBS dNBR, (E) Calwood GEE dNBR, and (F) Calwood GEE RBR.

Overall, these results suggest that the GEE method, particularly RBR, may offer a more accurate representation of burn severity compared to MTBS dNBR. Other studies have also found RBR correlates more strongly with field-based CBI than other remotely sensed burn severity metrics (Fernández-Guisuraga et al., 2023; Parks et al., 2014; Prichard et al., 2020; Vorster et al., 2024) and improves spatial accuracy in areas with low to moderate burn severity (Furniss et al., 2020; Parks et al., 2014). Furniss et al. (2020) found that RdNBR and RBR were not consistently better than dNBR in a singular fire but supported that when applied to a spatial scale with greater variability in biophysical setting the relativized indices likely enhances accuracy.

We adopted the fire season window from Parks et al. (2019) for our study area; however, their study focused on states adjacent to, but not including, Colorado and New Mexico. While there is likely some overlap, the large variety of fire regimes within our study area make it uncertain whether this fire season window is the most appropriate. Future studies could refine this approach by tailoring the fire season window to better reflect regional wildfire patterns when creating image composites.

While the GEE method is relatively user-friendly it requires some proficiency in understanding and modifying code. Users must upload a shapefile in the correct format, modify fire season dates, and make other minor modifications to produce accurate indices. To make the GEE method more accessible, especially for managers with limited capacity to build proficiency in a new platform, the creation of a tutorial or a graphical user interface (GUI) would be beneficial. Additionally, unlike the MTBS method, the GEE method does not have built in data verification or validation, placing the responsibility on the user to understand the code and ensure metrics are accurately produced.

2.4. Conclusion

Overall, we found that MTBS and GEE derived burn severity metrics differed meaningfully across all ten fires we compared, with GEE derived RBR showing the strongest correlation with field data. The GEE method offers greater flexibility, allowing users to generate burn severity maps for fires smaller than 400 hectares, thereby enabling the inclusion of smaller fires in burn severity analyses (Parks et al., 2018). This study provides further support for the GEE compositing method and the use of the $dNBR_{offset}$ in improving correlations with field-based burn severity measurements. While our results were consistent across the Cameron Peak and Calwood fires, researchers should carefully consider the biophysical characteristics of their study area and validate the most appropriate metric for their specific context.

REFERENCES

Cansler, C. A., & McKenzie, D. (2012). How Robust Are Burn Severity Indices When Applied in a New Region? Evaluation of Alternate Field-Based and Remote-Sensing Methods. *Remote Sensing*, *4*(2), 456–483. https://doi.org/10.3390/rs4020456

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.-L., Quayle, B., & Howard, S. (2007). A Project for Monitoring Trends in Burn Severity. *Fire Ecology*, *3*(1), 3–21. https://doi.org/10.4996/fireecology.0301003

Fernández-Guisuraga, J. M., Fernandes, P. M., Marcos, E., Beltrán-Marcos, D., Sarricolea, P., Farris, M., & Calvo, L. (2023). Caution is needed across Mediterranean ecosystems when interpreting wall-to-wall fire severity estimates based on spectral indices. *Forest Ecology and Management*, *546*. https://doi.org/10.1016/j.foreco.2023.121383

Finco, M., Quayle, B., Zhang, Y., Lecker, J., Megown, K. A., & Kenneth Brewer, C. (2012). Monitoring Trends and Burn Severity (MTBS): Monitoring Wildfire Activity for the Past Quarter Century Using Landsat Data. *Moving from Status to Trends: Forest Inventory and Analysis (FIA) Symposium*, *2012*, 4–6. www.mtbs.

Furniss, T. J., Kane, V. R., Larson, A. J., & Lutz, J. A. (2020). Detecting tree mortality with Landsat-derived spectral indices: Improving ecological accuracy by examining uncertainty. *Remo8 te Sensing of Environment*, *237*, 111497. https://doi.org/10.1016/j.rse.2019.111497

Hijmans, R. (2024). terra: Spatial Data Analysis. R package version 1.7-78. https://CRAN.R-project.org/package=terra

Holden, Z. A., Morgan, P., & Evans, J. S. (2009). A predictive model of burn severity based on

20-year satellite-inferred burn severity data in a large southwestern US wilderness area. *Forest Ecology and Management*, *258*(11), 2399–2406. https://doi.org/10.1016/j.foreco.2009.08.017

Keeley, J. E. (2009). Fire intensity, fire severity and burn severity: a brief review and suggested usage. *International Journal of Wildland Fire*, *18*(1), 116. https://doi.org/10.1071/WF07049

Key, C. H., & Benson, N. C. (2006). Landscape Assessment (LA). *FIREMON: Fire Effects Monitoring and Inventory System. Gen. Tech. Rep. RMRS-GTR-164-CD, Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station.*

Kurbanov, E., Vorobev, O., Lezhnin, S., Sha, J., Wang, J., Li, X., Cole, J., Dergunov, D., & Wang, Y. (2022). Remote Sensing of Forest Burnt Area, Burn Severity, and Post-Fire Recovery: A Review. *Remote Sensing*, *14*(19), 4714. https://doi.org/10.3390/rs14194714

Long, J. W., Skinner, C., Charnley, S., Hubbert, K., Quinn-Davidson, L., & Meyer, M. (2014). Post-Wildfire Management. *Science Synthesis to Support Socioecological Resilience in the Sierra Nevada and Southern Cascade Range. Gen. Tech. Rep. PSW-GTR-247. USDA For. Serv., Pacific Southwest Research Station, Albany, CA*, 187-220.

McKenzie, D., Miller, C., & Falk, D. A. (Eds.). (2011). *The Landscape Ecology of Fire*. Springer Science & Business Media.

Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment*, *109*(1), 66–80. https://doi.org/10.1016/j.rse.2006.12.006

Parks, S., Dillon, G., & Miller, C. (2014). A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. *Remote Sensing*, *6*(3), 1827–1844.

https://doi.org/10.3390/rs6031827

Parks, S. A., Holsinger, L. M., Koontz, M. J., Collins, L., Whitman, E., Parisien, M. A., Loehman, R. A., Barnes, J. L., Bourdon, J. F., Boucher, J., Boucher, Y., Caprio, A. C., Collingwood, A., Hall, R. J., Park, J., Saperstein, L. B., Smetanka, C., Smith, R. J., & Soverel, N. (2019). Giving ecological meaning to satellite-derived fire severity metrics across North American forests. *Remote Sensing*, *11*(14). https://doi.org/10.3390/rs11141735

Parks, S., Holsinger, L., Voss, M., Loehman, R., & Robinson, N. (2018). Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. *Remote Sensing*, *10*(6), 879. https://doi.org/10.3390/rs10060879

Prichard, S. J., Povak, N. A., Kennedy, M. C., & Peterson, D. W. (2020). Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. *Ecological Applications*. https://doi.org/10.1002/eap.2104

R Core Team (2024). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Soverel, N. O., Perrakis, D. D. B., & Coops, N. C. (2010). Estimating burn severity from Landsat dNBR and RdNBR indices across western Canada. *Remote Sensing of Environment*, *114*(9), 1896–1909. https://doi.org/10.1016/j.rse.2010.03.013

Twaddell, E. M. N. (2023). *Impacts of Fuel Reduction Treatments and Wildfire on Carbon Stocks of Semi-Arid Pinus ponderosa-Dominant Forests* [Master's thesis, University of Colorado at Denver].

Vorster, A. G., Stevens-Rumann, C., Young, N., Woodward, B., Choi, C. T. H., Chambers, M. E., Cheng, A. S., Caggiano, M., Schultz, C., Thompson, M., Greiner, M., Aplet, G., Addington, R. N., Battaglia, M. A., Bowker, D., Bucholz, E., Buma, B., Evangelista, P., Huffman, D., … West Fordham, A. (2024). Metrics and Considerations for Evaluating How Forest Treatments Alter Wildfire Behavior and Effects. *Journal of Forestry*, *122*(1), 13–30. https://doi.org/10.1093/jofore/fvad036

CHAPTER 3: EVALUATING THE IMPACTS OF FUEL TREATMENTS ON BURN SEVERITY ACROSS THE FRONT RANGE

3.1. Introduction

Contemporary Western North American forested ecosystems have uncharacteristically high fuel loads (Hagmann et al., 2021), warmer and drier climatic conditions that increase fuel aridity (Abatzoglou & Williams, 2016), and increased probability of extreme fire weather conditions (Collins, 2014). Many forests are experiencing shifts in historical fire regimes due to fire suppression policies, land use changes, and/or changing climate (Collins et al., 2019; Fernández-Guisuraga & Fernandes, 2024; Moreira et al., 2020; Tolhurst & McCarthy, 2016; Whitman et al., 2019). To address the wildfire crisis, there are increasing calls to implement proactive management to mitigate the negative effects of recent wildfire events and better prepare landscapes for future wildfires (Hessburg et al., 2021). Forest treatments, including those aimed at restoration or fuels reduction, modify the composition, structure, and distribution of vegetation on the landscape to achieve various management goals. Fuels reduction treatments focus on decreasing the amount and continuity of fuels, whereas, restoration treatments, often including fuel reduction, focus on shifting species composition and spatial patterns to better reflect historical forest structure (Stephens et al., 2020). While objectives between reduction and restoration treatments vary, they include reducing wildfire severity, mitigating infrastructure loss, improving safety in suppression operations, and/or promoting resilient forests on fire adapted landscapes (Davis et al., 2024).

Despite these common goals, details on how land managers should implement treatments to promote the best post-wildfire outcomes for people and forests remains complicated, especially in heterogeneous landscapes. In western North America, the US Forest Service has called for an increase in the pace and scale of wildland fuel treatments (USDA Forest Service, 2022), yet this is a resource intensive, complex task due to the strategic and operational obstacles related to treatment implementation (North et al., 2012; Woolsey et al., 2024). These constraints include lack of infrastructure, funding limitations, and management restrictions (Collins et al., 2010). In addition to implementation challenges, treatments are often designed to mitigate fire effects under specific conditions, such as 95% fire weather, yet many recent wildfires are burning under conditions that exceed what the treatments were designed to handle (Vorster et al., 2024). Furthermore, it is difficult to quantify treatment effectiveness because of dynamics between treatment type, time since treatment, fire weather, climate, the fuels and vegetation present, topography, fire dynamics, suppression actions, and landscape condition.

Although these challenges persist, there is gathering consensus that treatments that focus on reducing canopy fuels through thinning and surface fuels through burning can minimize burn severity under all but the most extreme fire weather conditions (Davis et al., 2024; Kalies & Yocom Kent, 2016; Stephens et al., 2012). In general, studies have found fuel treatments that reduce surface fuels through burning (e.g., past wildfires, prescribed burns and thinning, or clear-cutting with prescribed understory or broadcast burns) are more effective at reducing burn severity compared to treatments that only thin or thin and pile burn (Cansler et al., 2022; Chamberlain et al., 2024; Fulé et al., 2012; Prichard et al., 2020; Stephens et al., 2012). However, there are also many locations where high fuel loads prevent the use of burning without thinning (Addington et al., 2020). The efficacy of the combination of thinning and prescribed burning can be attributed to reducing surface and ladder fuels and intermediate sized trees, reducing the risk of active crown fire (Agee & Skinner, 2005; Stephens et al., 2012).

Management actions have been concentrated in lower elevation, dry forests with historically low and mixed severity fire regimes (Davis et al., 2024; Kalies & Yocom Kent, 2016) but there is an increasing need to understand how fuel treatments impact forests at higher elevations with historically mixed to high severity fire regimes. Common treatments in ponderosa pine (*Pinus ponderosa*) and mixed-conifer forests include mechanical or hand thinning, prescribed burning, pile burning, previous wildfire, and the combination of these prescriptions (Addington et al., 2018). These are often implemented to reduce fuel loads and decrease stand density and basal area to pre-European settlement densities. Treatments in lodgepole pine (*Pinus contorta*) and spruce – fir (i.e. *Picea engelmannii* and *Abies lasiocarpa*) forests are often implemented for other management goals and include clear cuts, patch cuts, group selection, and previous wildfire (Hood et al., 2012). Most treatment effectiveness studies have been conducted in forest types with low to mixed severity fire regimes (Davis et al., 2024). It is unclear if treatments in subalpine forests that remove or rearrange fuel are effective at reducing burn severity, especially since subalpine forests have fewer fire adapted trees, different fuel structures, and different rates of fuel accumulation (Davis et al., 2024).

Fire weather can also impact the effect of a treatment, but knowledge gaps remain in understanding to what degree and under what conditions treatments remain effective. Extreme fire weather—characterized by high wind speeds, elevated temperatures, and low relative humidity—often leads to rapid fire spreading, overwhelming suppression efforts, endangering lives and property, and causing long-term ecological damage (Calkin et al., 2015; Duane et al., 2021; Tedim et al., 2020). Under extreme conditions, studies have found thinning treatments to be less effective compared to treatments that included burning, likely because thinning does not consume surface fuels and covers a smaller area (Chamberlain et al., 2024; Lydersen et al., 2017;

Prichard et al., 2020; Taylor et al., 2022). Studies have also found, treatments that include fire and are sufficiently intense (i.e. reduce basal area and consume surface fuels) are still effective in extreme conditions (Chamberlain et al., 2024; Taylor et al., 2022; Walker et al., 2018). With fires more commonly burning under extreme conditions (Coop et al., 2022), additional research is needed on the impacts of weather conditions on severity and treatment's ability to maintain reductions in burn severity.

Recent wildfires along the Front Range of Colorado and northern New Mexico are increasing in size and severity (Abatzoglou & Williams, 2016; Coop et al., 2022), yielding negative ecological outcomes (Rodman et al., 2022). Some of these large-scale fires with days of extreme fire spread burned through multiple forest types with different treatments, thus there is a need to examine where treatments are being implemented, what kind of treatments are occurring, and how those treatments interact with wildfire. A growing body of work has begun to address treatment effectiveness at the treatment, local, and landscape levels (e.g., Davis et al., 2024; Kalies & Yocom Kent, 2016; Martinson & Omi, 2013); however, studies investigating fire-treatment interactions within the ecologically and pyro-diverse, fire prone Front Range landscape are limited. That said, existing research in this region has found thinning with prescribed fire (Omi & Martinson, 2002; Omi et al., 2006; Petrakis et al., 2018; Vorster et al., 2024), prescribed fire (Arkle et al., 2012), and previous wildfire (Parks et al., 2014a; Petrakis et al., 2018) reduce subsequent fire severity, providing insight into how treatments may perform under varying wildfire conditions.

We investigated wildfires from southern Wyoming to northern New Mexico that burned from 2002-2022 to evaluate under what fire weather, climatic, topographic, and fuel conditions intentional and wildfire treatments reduce the ecological impacts of fire as measured by burn severity. Our research aimed to answer: (1) what factors influence how and when treatments modify burn severity, (2) how do burn severity outcomes differ across forest and treatment types, and (3) how do extreme fire conditions influence burn severity within treatment types?

3.2. Methods

3.2.1. Study area

In this study, we focused on wildfires with treatment interactions along the Front Range of the southern Rocky Mountains from southern Wyoming to northern New Mexico (Fig. 3.1). In 2022, the USDA Forest Service (USFS) identified ten priority landscapes throughout the United States that are experiencing an increased risk of severe fire, negative ecological outcomes, and threats to community infrastructure and property (USDA Forest Service, 2022). The Colorado Front Range and New Mexico Enchanted Circle were identified as two of these landscapes.

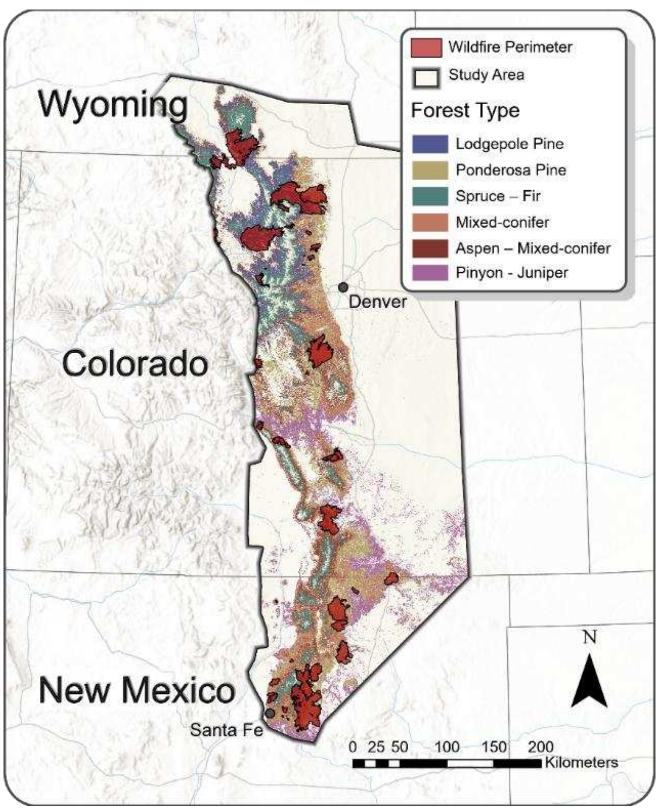

Fig. 3.1. Map of Front Range study area showing wildfires with treatment interactions and dominant forest types.

The forested ecosystems of the Front Range span an elevational gradient of about 5,600 to 11,500 ft with variable bioclimatic and topographic conditions resulting in a range of forest types (Peet et al., 1981). At lower elevations, ponderosa pine and mixed-conifer forests historically experienced low and mixed severity, frequent fire regimes with a fire return interval of 1 to 35 years (McKinney, 2019; Romme et al., 2003; Sherriff & Veblen, 2007). With increasing elevation, mixed-conifer forests experienced longer fire return intervals (20 to > 100 years) and increased severity (i.e. Fulé et al., 2003; Hessburg et al., 2007; Tepley & Veblen, 2015). Spruce – fir and lodgepole pine forests are typically found above 8,000 ft and experienced long fire return intervals and high severity stand replacing fire (Sherriff & Veblen, 2007; Veblen et al., 2000). Spruce – fir experienced fire return intervals of a hundred to several hundred years (e.g. Kipfmueller & Baker, 2000; Veblen et al., 1994; Howe & Baker, 2003; Sibold et al., 2006; Veblen et al., 2000) and slow post-fire regeneration (~100 years) (Pelz, 2016). Whereas, lodgepole pine experienced fire return intervals typically greater than a century (i.e. Veblen et al., 1991; Whitlock et al., 2003) and quickly regenerated post fire (Tower, 1909; Clements, 1910).

Post-fire resilience in forests with high severity fire regimes was historically maintained by landscape heterogeneity (e.g., non-forest and varying stand age) (Prichard et al., 2021) whereas forests with frequent fire maintained lower surface fuel loading resulting in lower severities (Addington et al., 2018). Because of the range of abiotic conditions on the landscape, these forest types and associated fire regimes have established in a patchwork along the Front Range.

3.2.2. Data layers

3.2.2.1. Burn severity

For our burn severity response variable, we evaluated indices from the Monitoring Trends in Burn Severity (MTBS) program (Eidenshink et al., 2007) and the composite Google Earth Engine (GEE) method developed by Parks et al. (2018b). The Parks et al. (2018b) method was better correlated to field based Composite Burn Index (CBI) measurements (Vorster et al., 2024) and offered a flexible approach to deriving burn severity indices for fires less than 400 hectares, allowing us to include small fires in our analysis. We used the Landsat-derived Relativized Burn Ratio (RBR) because it has been shown to correlate more strongly with CBI compared to other remotely sensed burn severity metrics (Parks et al., 2014b), while also improving spatial accuracy in areas with low to moderate burn severity (Furniss et al., 2020; Parks et al., 2014b). For each fire of interest, we derived RBR in GEE using a mean composite of pre- and post-fire images using a modified script from Parks et al. (2018b). To derive the composite image window, we set fire season dates to the recommended period for forests in the southern Rockies (Day of Year: 152–258; Parks et al., 2019).

3.2.2.2. Treatment history

We utilized the common attributes layer from the Forest Service Activity Tracking System (FACTS) database (USDA Forest Service, 2024) and previous wildfire extents from the Colorado Forest Restoration Institute's (CFRI) interagency fire perimeter database (CFRI, 2023; Fig. 3.2). Using FACTS and previous wildfire extents, we identified wildfires from 2002-2022 that burned through a previously treated area. This resulted in 72 wildfires ranging in size from less than one hectare to 138,279 hectares. To account for potential forest change caused by previous wildfires, we derived RBR in GEE (Parks et al., 2018b) then classified the RBR into binary categories, low to moderate (RBR < 298) and high severity (RBR ≥ 298) (Parks et al., 2018a).

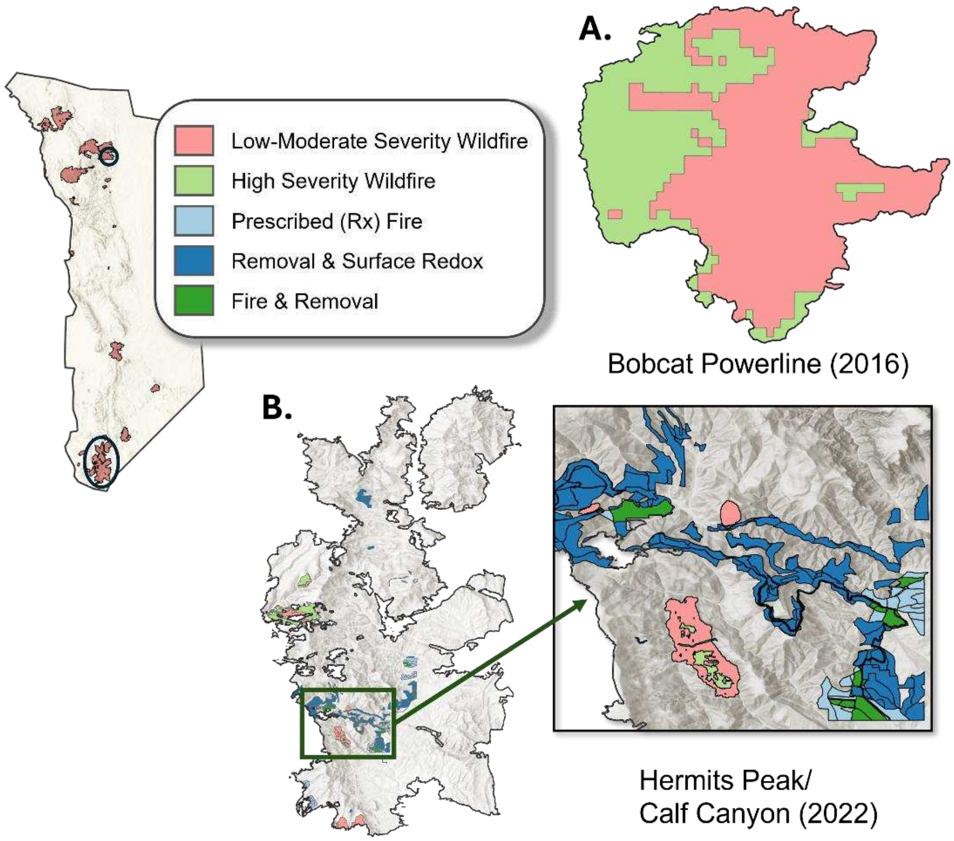

Fig. 3.2. Wildfires demonstrating variability in treatment type and size in the study area. (A) The Bobcat Powerline fire burned entirely within a previous wildfire extent resulting in two treatments. (B) The Hermits Peak/Calf Canyon fire is the largest fire in the study area and demonstrates how treatments are often concentrated in certain areas but can have a wider range of treatment types.

We categorized the combined treatment data into five treatment types: low to moderate severity wildfire, high severity wildfire, prescribed fire, removal and surface fuel reduction, and fire and removal (Table 3.1; Fallon et al., 2024). Overlapping treatments were considered unique treatments and all attributes were combined. Our final treatment variables included treatment type, time since treatment, and treatment size (Table 3.2). Intentional fuels treatments are management actions designed to modify the amount and/or distribution of fuels, including prescribed fire, removal and surface fuel reduction, and fire and removal treatments.

Table 3.1
Treatment type classifications for this study based on original Forest Service Activity Tracking System (FACTS) treatment category and total area (hectares) of final treatment types.

Treatment Category	**Final Treatment Type**	**Area (ha)**
Wildfire	Low to Moderate Severity Wildfire	283,665
Wildfire	High Severity Wildfire	32,563
Prescribed Fire Prescribed Fire & Rearrangement Prescribed Fire & Surface Reduction Prescribed Fire, Rearrangement, & Surface Reduction	Prescribed (Rx) Fire	6,839
Rearrangement & Removal Removal Surface Reduction Rearrangement & Surface Reduction Rearrangement, Removal, & Surface Reduction Removal & Surface Reduction	Removal and/or Surface Fuel Reduction	28,916
Low – Mod Wildfire & Removal Low – Mod Wildfire, Rearrangement, & Removal Low – Mod Wildfire, Removal, & Surface Reduction Low – Mod Wildfire, Rearrangement, Removal, & Surface Reduction Prescribed Fire & Removal Prescribed Fire, Rearrangement, & Removal Prescribed Fire, Removal, & Surface Reduction Prescribed Fire, Rearrangement, Removal, & Surface Reduction	Fire and Removal	1,376

Table 3.2
List of predictor variables for the generalized linear mixed model (GLMM) model with variable name, short description, and data source.

Variable	Description	Source
Treatment		
Time Since Treatment	Fire year minus year treatment was complete (year)	CFRI, 2023; USDA Forest Service, 2024
Treatment Type	Recategorized treatment data (see Table 3.1 for categories)	CFRI, 2023; USDA Forest Service, 2024
Treatment Size	Size of treatment polygon (m^2). Calculated using the expanse() function in the *terra* package	Hijmans, 2024
Topography		
Elevation	Elevation (meters) from USGS digital elevation model (DEM)	U.S. Geological Survey, 2023
Slope	Slope angle of a pixel (degrees). Calculated using the terrain() function in the *terra* package	Hijmans, 2024
Topographic Position Index	Difference between raster cell and neighborhood elevation. Calculated using the terrain() function in the *terra* package	Hijmans, 2024
Topographic Wetness Index	Moisture content of pixel based on topography. Calculated using the wbt_wetness_index() function in the *whitebox* package	Lindsay, 2016; Wu & Brown, 2022
Aspect	Direction of slope face. Calculated using the terrain() function in the *terra* package	Hijmans, 2024
Terrain Roughness	Elevation difference among cells. Calculated using the terrain() function in the *terra* package	Hijmans, 2024
Heat Load Index (HLI)	Measure of solar radiation, accounts for how slope steepness and aspect influence temperature. Calculated using the hli() function in the *spatialEco* package	Evans & Murphy, 2023
Fuel		
Canopy Cover	NLCD vertically projected percent cover of the live canopy layer for a specific area	Housman et al., 2023
Forest Type	Recategorized LANDFIRE Biophysical Setting to treated forest types (see Table 3.3 for categories)	Rollins, 2009
Fire Weather		
Day-of-burning	Day fire burned a given pixel (Julian day)	Parks, 2014
Extreme Condition	Binary extreme (DOB area > 4,127 ha d^{-1} = 1) or not-extreme (DOB area < 4,127 ha d^{-1} = 0) condition	Balik et al., 2024

Wind Speed	Daily wind velocity (meters/second) at 10m from University of Idaho Gridded Surface Meteorological Dataset (GRIDMET)	Abatzoglou, 2013
Max Temperature	Daily maximum temperature (Kelvin) from GRIDMET	Abatzoglou, 2013
Min Relative Humidity	Daily minimum relative humidity (%) from GRIDMET	Abatzoglou, 2013
Fire Weather VPD	Daily mean vapor pressure deficit from GRIDMET	Abatzoglou, 2013
Energy Release Component	Daily modeled mean daily energy release component (NFDRS fire danger index) from GRIDMET	Abatzoglou, 2013
Climate		
Precipitation Anomaly	30 year average precipitation z-score minus fire-year average precipitation z-score	Daly et al., 2008, 2015
Temperature Anomaly (Mean)	30 year average temperature z-score minus fire-year average temperature z-score	Daly et al., 2008, 2015
VPD Minimum Anomaly	30 year average VPD minimum z-score minus fire-year average VPD minimum z-score	Daly et al., 2008, 2015
VPD Maximum Anomaly	30 year average VPD maximum z-score minus fire-year average VPD maximum z-score	Daly et al., 2008, 2015

3.2.2.3. Fuel

To determine potential forest type within fires and treatments, we used the LANDFIRE Biophysical Settings potential vegetation cover dataset (Rollins, 2009). The biophysical setting vegetation layer represents the pre Euro-American reference conditions and acted as a baseline forest type for the range of fire dates (Rollins, 2009). We reclassified these forest types into six categories including non-forest, ponderosa pine, mixed-conifer, aspen – mixed-conifer, lodgepole pine, and spruce – fir (Table 3.3). Fires that contained more than 30% non-forest land were removed from analysis. In addition, we used the National Land Cover Database (NLCD) Tree Canopy Cover layer to account for the year prior to fire canopy cover (Table 3.2; Housman et al., 2023).

Table 3.3
Reclassified forest type categories including original Biophysical Settings (BPS) forest type and treatment specific forest types.

BPS Forest Type	Reclassified Forest Type
Southern Rocky Mountain Ponderosa Pine Savanna (North and South) Southern Rocky Mountain Ponderosa Pine Woodland (North and South)	Ponderosa Pine
Southern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland Southern Rocky Mountain Mesic Montane Mixed Conifer Forest and Woodland	Mixed-conifer
Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland (low and high)	Aspen – Mixed-conifer
Rocky Mountain Lodgepole Pine Forest	Lodgepole Pine
Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland	Spruce – Fir

3.2.2.4. Topography

Topographic variables were derived from a 1/3 arc-second DEM from the USGS 3DEP program (Table 3.2; U.S. Geological Survey, 2023). Slope, aspect, topographic position index, and terrain roughness were calculated using the terrain function in the terra R package (Hijmans, 2024). The topographic wetness index was calculated using the wbt_wetness_index function in the whitebox R package (Lindsay, 2016; Wu & Brown, 2022) and heat load index (HLI) was calculated using the hli function in the spatialEco R package (Evans & Murphy, 2023).

3.2.2.5. Climate

We created climate variables to quantify anomalies between the 30-year climate average and year prior to fire average. For each climate variable, we calculated the 30-year mean and the fire-year mean using PRISM data (4 km resolution; Daly et al., 2008, 2015) in GEE. We then derived z-scores for each variable and computed the difference between the 30-year average and the fire-year average. The climate anomaly variables included monthly total precipitation, mean temperature, minimum vapor pressure deficit (min VPD), and maximum vapor pressure deficit (max VPD) (Table 3.2).

3.2.2.6. Fire weather

For fires greater than 400 hectares, we derived day-of-burning (DOB) maps following the methods developed by Parks (2014). This method maps the most likely day of burning by interpolating VIIRS and MODIS hotspot detections. Because of the resolution limitations of MODIS and VIIRS data (1 km resolution), we used the recorded ignition date as the DOB for smaller fires (< 400 hectares). To account for weather conditions on the DOB, we created mean composites of weather variables based on the day the fire burned through a given area, using data from GridMET (4 km resolution; Abatzoglou, 2013). The GridMET fire weather variables included wind speed, maximum temperature, minimum relative humidity, mean vapor pressure deficit (VPD), energy release component, and extreme condition (Table 3.2). We defined extreme fire weather conditions based on the area burned during daily spread events, using the extreme threshold for the northwestern forested mountains ecoregion: extreme (DOB area > 4,127 ha d^{-1}) and non-extreme (DOB area < 4,127 ha d^{-1}) (Balik et al., 2024).

3.2.3. Statistical analysis

3.2.3.1. Control matching

We matched untreated points to treated areas based on forest type to ensure we made meaningful comparisons between treatments and untreated areas, reducing bias due to differences in biophysical setting and ecology. To create a forest area mask, we used the LANDFIRE existing vegetation type layer (tree = 1, non-tree = 0) (Rollins, 2009) combined with NLCD Tree Canopy Cover layer (≥10% canopy cover = 1, <10% canopy cover = 0) (Housman et al., 2023), classifying forested areas as 1 and non-forested areas as 0. Treatment areas were reclassified into treated (1) and untreated (0). A 100-meter buffer was applied around the treated areas to account for potential treatment shadow. For each treated area, we calculated the percentage of each forest type. Sampling intensity was determined by the size of the treated area; areas <40 acres were assigned 4 sample points, while areas >40 acres were sampled at a rate of 2% of their total area. Sampling points within the treated area were stratified by forest type, proportional to the percentage of each forest type. The same process was applied to the untreated areas. We extracted each predictor variable at each point resulting in 8271 total points for the final model (Table 3.4).

Table 3.4
Sample sizes of points stratified by treatment type and forest type. Summary of sampled points by forest type, showing the number of treated points, total number of points (treated + untreated), percentage of total points, and mean relativized burn ratio (RBR) of all points.

Treatment Type	Ponderosa Pine	Mix-conifer	Aspen - Mix-conifer	Lodgepole Pine	Spruce - Fir
Untreated	1159	894	405	941	365
Low-Mod Wildfire	1170	783	138	26	26
High Wildfire	83	212	12	3	11
Rx Fire	58	52	24	28	0
Removal & Reduction	213	169	268	884	310
Fire & Removal	22	10	5	0	0
Treated Points	1546	1226	447	941	347
Total Points	2705	2120	852	1882	712
Percentage (%)	32.7	25.6	10.3	22.8	8.6
Mean RBR	139	192	240	346	347

3.2.3.2. Modeling

To achieve a model that was sufficiently complex yet interpretable while minimizing overfitting, we first assessed multicollinearity among numeric predictor variables using Spearman's rank correlation. For each highly correlated pair ($r>|0.7|$), we retained the variable with the strongest correlation to RBR values. Energy release component, minimum relative humidity, max temperature, and slope were removed from the final model due to multicollinearity. Next, we implemented a generalized linear mixed model (GLMM) with a Least Absolute Shrinkage and Selection Operator (Lasso) penalty, using the glmmLasso package (Groll, 2023). Lasso is a variable selection and regularization technique designed to reduce model complexity and prevent overfitting by shrinking some coefficients to zero (Groll & Tutz, 2014; Schelldorfer et al., 2014). However, in our analysis, the GLMMLasso did not identify any variables to exclude from the model.

We also considered using variable importance metrics from random forest models to prioritize predictors but opted to retain all non-correlated variables without additional selection. While random forest is an effective tool for capturing nonlinear relationships, variables that perform well in a random forest model do not necessarily translate effectively to a linear framework (Genuer et al., 2010; Grömping, 2009). Given our sample sizes ($n >> p$) and the study's objectives, we determined that retaining all selected predictors was the most appropriate approach.

We fit a GLMM with an identity link using RBR as our response variable (lme4 R package, Bates et al., 2015). Our fixed effects represented aspects of treatment history, fuel, topography, fire weather, and climate. We set individual fire event as a random effect to account for potential spatial autocorrelation between points in individual fires, and variability due to specific pre-fire and burning conditions. We assessed significance at $\alpha = 0.05$ throughout the study. We defined ecological significance as estimate values greater than ± 5 RBR.

Because the homogeneity of variance assumption was not met, we assessed differences in RBR across treatment and forest types using a non-parametric Kruskal-Wallis test, a method for comparing medians among multiple groups (Kruskal & Wallis, 1952). To account for multiple comparisons, we conducted a post-hoc pairwise comparison using Dunn's test with a Bonferroni adjustment (dunn.test R package, Dinno, 2014; Dunn, 1964). This allowed us to identify specific group differences while controlling for Type I error. We replicated this analysis to assess RBR differences across treatment types and extreme fire weather conditions. We considered looking at the pairwise comparison for extreme conditions by forest type but due to sample size limitations, we were unable to compare extreme conditions across forest types. All analyses were performed using R Statistical Software (v4.3.3; R Core Team, 2024).

3.3. Results

3.3.1. Factors influencing treatment effects on burn severity

We began our analysis by visualizing the distributions of select fuel and topographic predictor variables for untreated and treated points (Fig. 3.3). The distribution of canopy cover for both untreated and treated points followed similar bimodal patterns, though certain treatment types showed stronger densities at lower canopy cover values (Fig. 3.3A). Specifically, high severity wildfire, low-to-moderate severity wildfire, and removal & surface reduction treatments had greater density around 10% canopy cover compared to untreated points. HLI had a left-skewed distribution, with prescribed fire and low-moderate severity wildfire treatments exhibiting slightly higher densities at greater HLI values (Fig. 3.3B). The distribution of topographic wetness index was right-skewed, with substantial overlap between untreated and treated points, indicating minimal differences in distributions (Fig. 3.3C). Terrain roughness also displayed a right-skewed distribution, with prescribed fire and low-moderate severity wildfire treatments showing slightly higher densities at lower terrain roughness values (Fig. 3.3D).

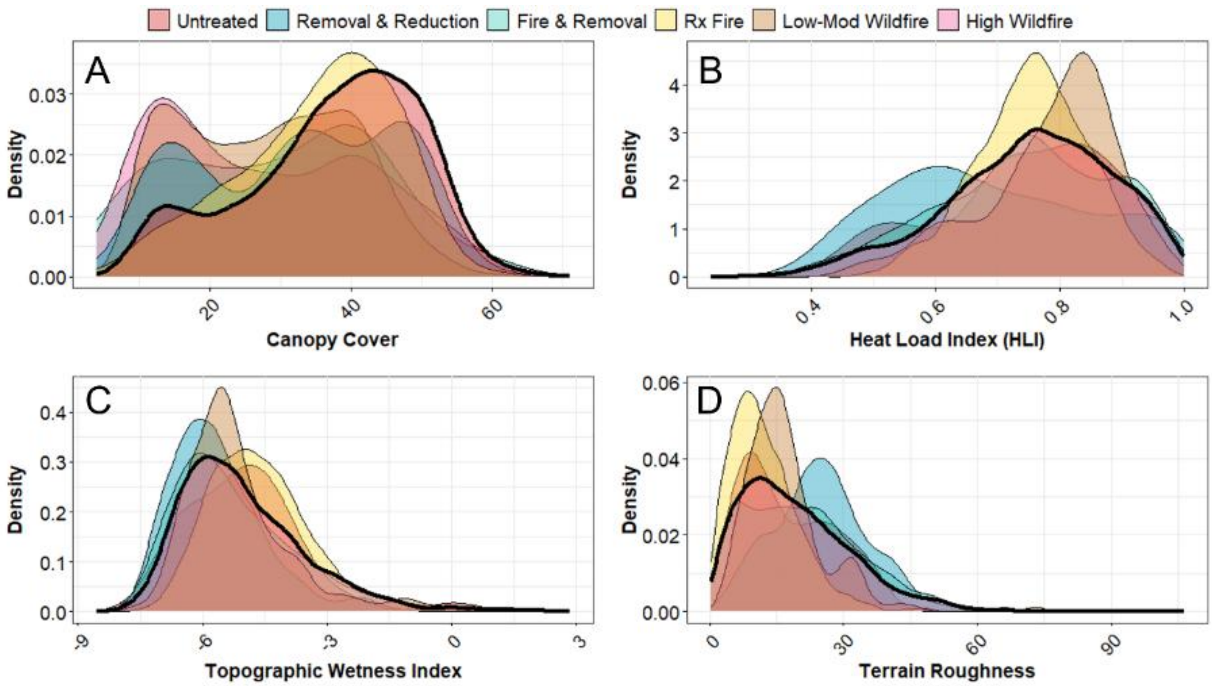

Fig. 3.3. Density plots representing the distribution of fuel (canopy cover) and statistically significant topographic predictor variables (Heat Load Index, Topographic Wetness Index, and Terrain Roughness) for treated and untreated points. The bolded black lines highlight the untreated distributions.

The GLMM showed that forest type, treatments with fire, extreme condition, HLI, temperature anomaly, and VPD max anomaly were ecologically significant predictors of burn severity (Table 3.5). In the model, spruce – fir, mixed-conifer, lodgepole pine, and aspen – mixed-conifer forests all burned more severely on average compared to ponderosa pine, the baseline forest type (Table 3.5). Specifically, lodgepole pine (Mean RBR = 346) and spruce – fir (Mean RBR = 347) had the highest burn severities on average (Table 3.4). Mixed-conifer (Mean RBR = 192) and aspen – mixed-conifer (Mean RBR = 240) had moderate burn severities on average. Whereas ponderosa pine (Mean RBR = 139) had the lowest burn severity on average. Compared to the untreated baseline, low to moderate severity wildfire ($p < 0.001$), prescribed fire ($p = 0.024$), and fire and removal ($p = 0.016$) treatment types had significantly lower burn severity estimates (Table 3.5). High severity wildfire and removal & surface reduction treatments were not significantly different from the untreated baseline.

Table 3.5
Generalized linear mixed model (GLMM) results for predicting burn severity with fixed and random effects. The table shows estimates, standard errors, statistics, and p-values. Positive estimates indicate higher burn severity, while negative estimates suggest lower severity. The random effect included 72 individual fire events. Bolded variables are significant at α = 0.05 and we considered them ecologically significant when estimates were greater than ± 5 relativized burn ratio (RBR). Italicized variables are statistically significant at α = 0.05, but we did not consider them ecologically significant. Variables in regular text are not statistically significant.

	Estimate	Std. Error	Statistic	*P*
(Intercept)	**110.71**	**26.05**	**4.25**	**<0.001**
Canopy Cover	*2.99*	*0.13*	*22.95*	*<0.001*
Forest Type				
Spruce – Fir	**65.65**	**8.09**	**8.12**	**<0.001**
Mixed-conifer	**20.12**	**4.53**	**4.44**	**<0.001**
Lodgepole	**78.14**	**6.9**	**11.33**	**<0.001**
Aspen – Mixed-conifer	**23.88**	**6.67**	**3.58**	**<0.001**
Treatment Type				
Low – Moderate Wildfire	**-66.6**	**6.1**	**-10.92**	**<0.001**
High Wildfire	-0.22	9.51	-0.02	0.982
Prescribed (Rx) Fire	**-29.17**	**12.94**	**-2.25**	**0.024**
Removal & Surface Reduction	-2.44	5.66	-0.43	0.666
Fire & Removal	**-57.45**	**23.78**	**-2.42**	**0.016**
Time Since Treatment	*-1*	*0.42*	*-2.39*	*0.017*
Treatment Size	0.00	0.00	0.97	0.332
Day-of-burning	-0.11	0.07	-1.56	0.120
Extreme Condition	**28.29**	**4.15**	**6.81**	**<0.001**
Fire Weather VPD	0.65	4.42	0.15	0.884
Wind Speed	-0.34	1.04	-0.33	0.741
Aspect	0.03	0.02	1.48	0.138
Heat Load Index (HLI)	**-64.25**	**14.99**	**-4.29**	**<0.001**
Terrain Roughness	*-0.61*	*0.18*	*-3.26*	*0.001*
Topographic Position Index	1.44	0.85	-1.70	0.089
Topographic Wetness Index	*-4.42*	*1.35*	*-3.28*	*0.001*
Precipitation Anomaly	-3.26	6.01	-0.54	0.587
Temperature Anomaly	**-36.49**	**6.94**	**-5.26**	**<0.001**
VPD Maximum Anomaly	**45.03**	**10.54**	**4.27**	**<0.001**
Observations	8271			
AIC	104916.5			

Canopy cover, time since treatment, treatment size, aspect, roughness, topographic position index, topographic wetness index, and precipitation anomaly did not have ecologically significant impacts on burn severity. Contrary to expectations, no fire weather variables, such as day-of-burning, VPD, and wind speed, were significant predictors in the model. HLI had a significant negative effect ($p < 0.001$), mean temperature anomaly had a significant negative effect ($p < 0.001$), and VPD max anomaly had a significant positive effect ($p < 0.001$) in the model (Fig. 3.4).

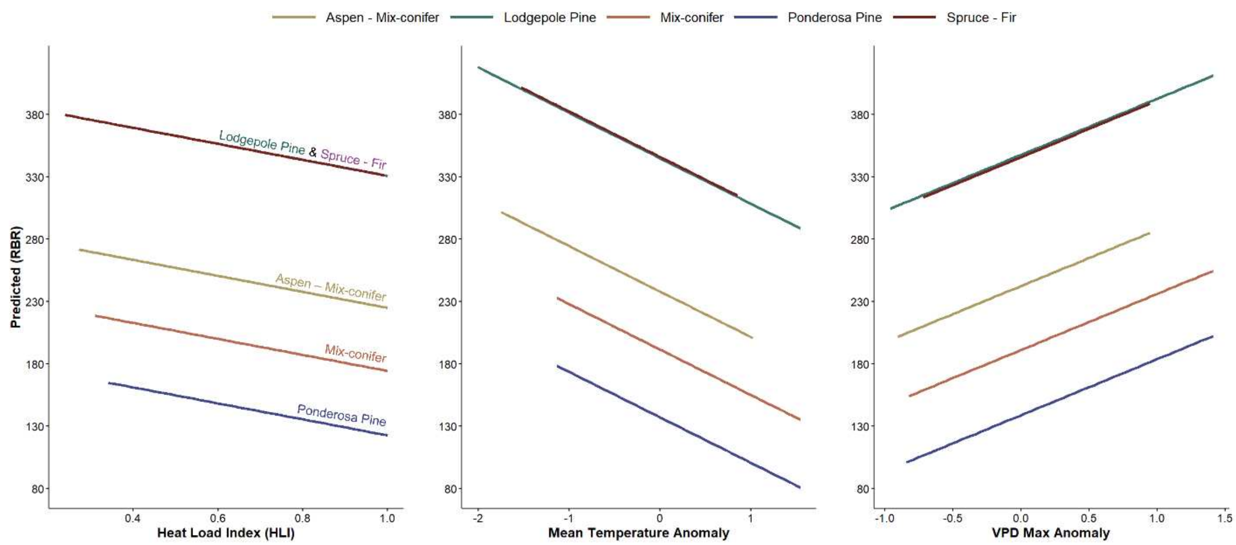

Fig. 3.4. Relationships of predicted burn severity (relativized burn ratio) and ecologically important burn severity variables by forest type: heat load index (HLI; left), mean temperature anomaly (center), and vapor pressure deficit max anomaly (right). Lines represent forest types. Negative temperature anomaly is associated with higher than average fire year temperatures and positive vpd max anomaly is associated with lower than average vpd max values.

3.3.2. Burn severity outcomes across forest and treatment types

The low to moderate severity wildfire treatments had significantly lower burn severities compared to untreated areas across all forest types. There was a significant difference in RBR between different treatment and forest type combinations ($\chi^2 = 2199$, df = 26, $p < 0.001$). A post-hoc Dunn's test indicated that in ponderosa pine forests compared to untreated points, low to moderate severity wildfire ($p < 0.001$), and prescribed fire ($p = 0.01$) had significantly lower mean burn severities; however, high severity wildfire had a significantly higher burn severity ($p < 0.001$) (Fig. 3.5A).

In mixed-conifer forests, fire & removal ($p = 0.02$), high severity wildfire ($p < 0.001$), low to moderate severity wildfire ($p < 0.001$), and prescribed fire ($p < 0.001$) showed significantly lower burn severities compared to untreated (Fig. 3.5B). In aspen – mixed-conifer, low to moderate severity wildfire ($p < 0.001$) and prescribed fire ($p = 0.009$) had significantly lower burn severities compared to untreated (Fig. 3.5C). For lodgepole pine forests, low to moderate severity wildfire ($p = 0.006$), removal & surface reduction ($p < 0.001$), and prescribed fire ($p = 0.01$) had significantly lower burn severities compared to untreated (Fig. 3.5D). In spruce – fir forests, high severity wildfire ($p = 0.003$) and low to moderate severity wildfire ($p < 0.001$) had significantly lower subsequent burn severities compared to untreated (Fig. 3.5E).

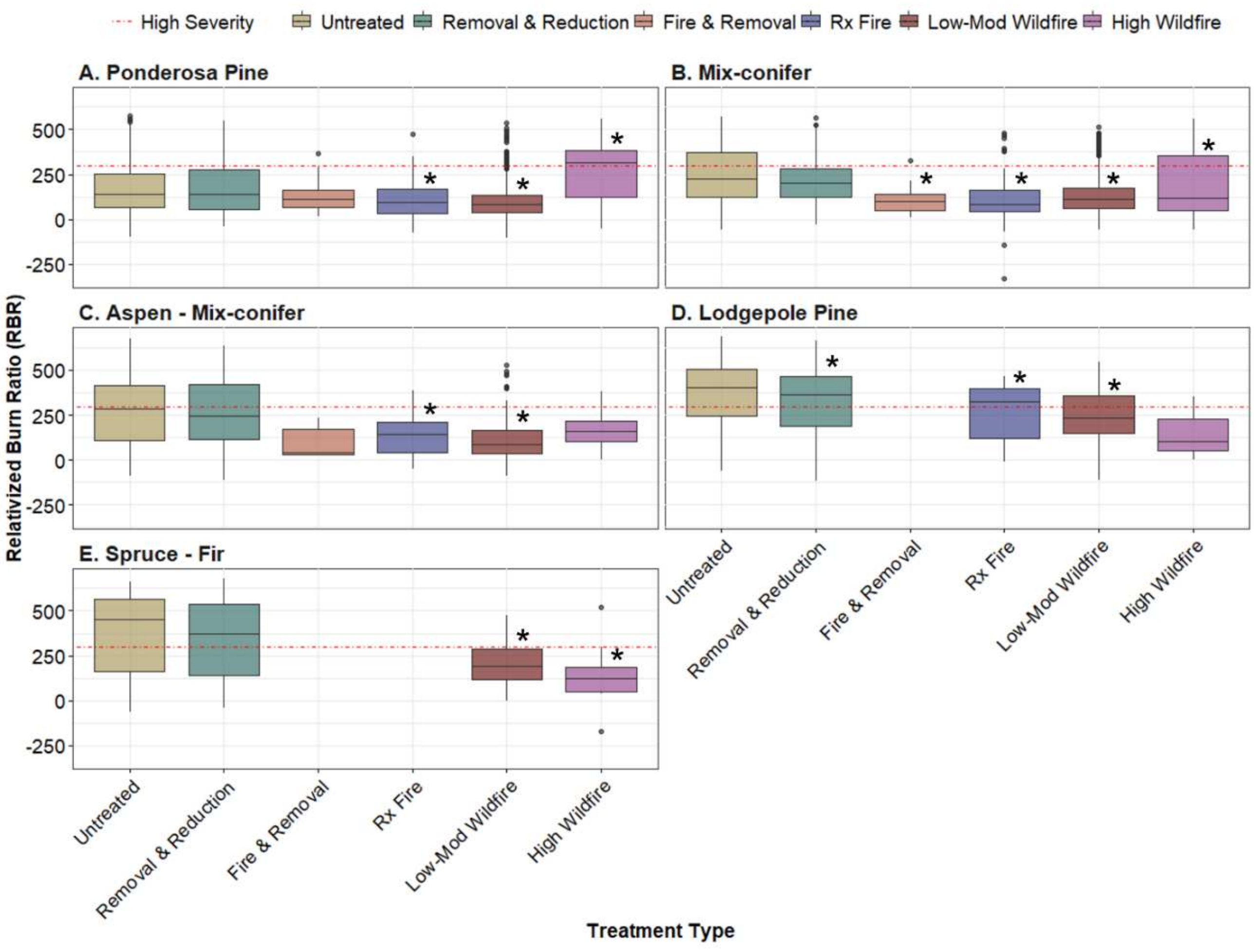

Fig. 3.5. Burn severity differences across treatment types for (A) ponderosa pine, (B) mixed-conifer, (C) aspen – mixed-conifer, (D) lodgepole pine, and (E) spruce – fir. Asterisks represent treatments that were significantly different from the untreated group.

3.3.3. Impact of extreme fire conditions on burn severity within treatment types

Low to moderate severity wildfire and fire & removal were the only treatments to have a lower mean burn severity compared to untreated under both non-extreme and extreme conditions. Areas that burned under extreme conditions were associated with higher burn severities (estimate: 28.29 ± 4.15, $p < 0.001$; Table 3.5). Our Kruskal-Wallis test revealed a significant interaction between treatment type and extreme condition ($\chi^2 = 1682.6$, df = 11, p-value < 0.001) suggesting that burn severity (RBR) varies across combinations of treatment type and extreme conditions. The non-extreme category had 4800 observations whereas the extreme category had 3471 observations (Table 3.6).

Table 3.6
Sample sizes of points stratified by treatment type and extreme condition. Non-extreme had 4800 observations and extreme had 3471 observations.

	Untreated	Low-Mod Wildfire	High Wildfire	Rx Fire	Removal & Reduction	Fire & Removal
Non-extreme	2129	1445	211	136	855	24
Extreme	1635	698	110	26	989	13

In non-extreme conditions, fire & removal ($p < 0.001$), low to moderate severity wildfire ($p < 0.001$), and prescribed fire ($p < 0.001$) had significantly lower burn severity compared to untreated points (Fig. 3.6A). In extreme conditions, fire & removal ($p = 0.04$), high severity wildfire ($p < 0.001$), and low to moderate severity wildfire ($p < 0.001$) had significantly lower burn severities compared to untreated points. However, removal & surface fuel reduction had a significantly higher burn severity compared to untreated points ($p < 0.001$; Fig. 3.6B).

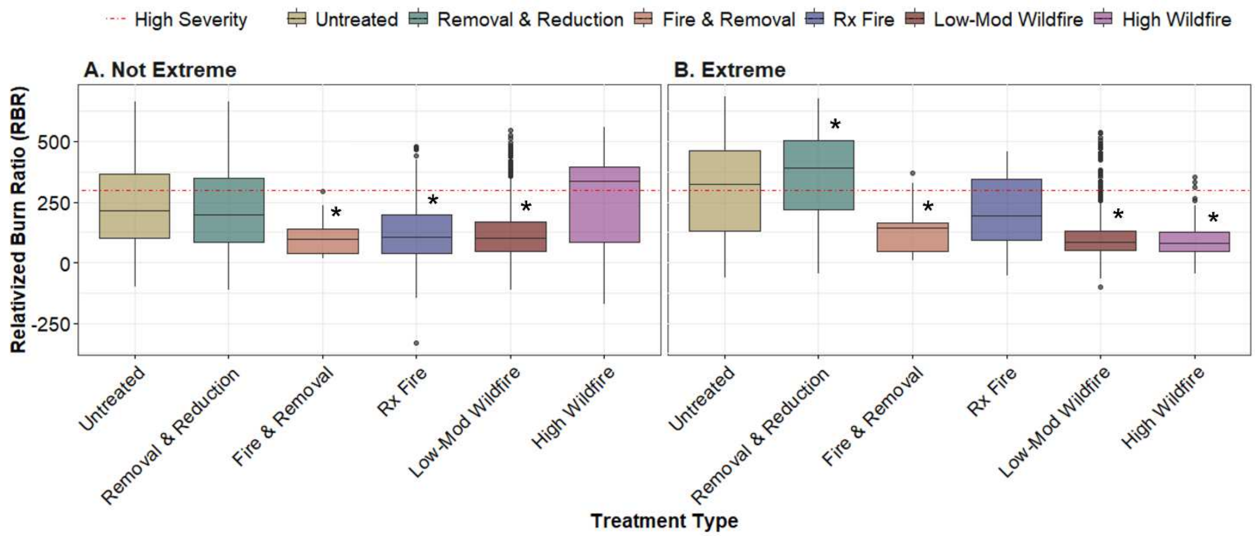

Fig. 3.6. Burn severity differences across treatment types for (A) non-extreme and (B) extreme conditions. Asterisks represent treatments that were significantly different from the untreated group.

3.4. Discussion

Throughout our study, we found intentional fuels treatments have a relatively minor impact on burn severity; however, during non-extreme conditions, treatments with any kind of fire, excluding high severity wildfire, resulted in lower subsequent burn severities. Low to moderate severity wildfire treatments had the lowest mean burn severity outcomes compared to untreated areas across all forest types and this was consistent in extreme and non-extreme conditions. Our results suggest that allowing wildfires to burn under moderate conditions is the most effective management strategy to reduce subsequent burn severity on the pyro-diverse Front Range landscape. We found treatments without fire (removal and surface fuels reduction treatments) have equivalent burn severity to untreated areas across all forest types except lodgepole pine, where burn severity was reduced. Removal and surface fuels reduction treatments even had higher subsequent burn severity during extreme fire conditions, reenforcing the need to address socio-political barriers that currently limit the use of burning as a treatment strategy on this landscape.

3.4.1. Factors influencing treatment effects on burn severity

The relationship between HLI and burn severity highlighted the complexity between solar exposure, fuel availability, and moisture. While the effect of HLI on burn severity may vary by region, our results suggest that within our study area, this relationship was consistent across forest types. HLI, a measure of solar radiation, was the only ecologically significant topographic variable in our model. Our results suggest an inverse relationship, where increased solar exposure and hotter, drier conditions are associated with decreased burn severity (Fig. 3.4). The relationship between HLI and burn severity is mixed in the literature; some studies report higher burn severity in areas with high HLI due to greater evapotranspiration and the drying of surface fuels (Holden et al., 2009; Alexander et al., 2006). These studies evaluated burn severity without specifically focusing on treated areas and were conducted in regions with ponderosa pine, mixed-conifer, Douglas-fir, and hardwood forests. Areas with high HLI values are often water-limited impacting vegetation growth, with slower regeneration rates (He et al., 2017) and increased canopy gap formation after fire (Lorber et al., 2018). Whereas sites with low HLI values often have greater biomass, tend to exhibit larger burned patches (Fang et al., 2015), and burn more severely compared to drier sites with higher solar radiation (Arkle et al., 2012; Prichard et al., 2020).

Of the weather and climate variables, we found temperature anomaly and VPD max anomaly were ecologically significant predictors of burn severity. The negative relationship between temperature anomaly and burn severity suggests that higher temperature anomalies, indicating fire years that are cooler relative to the 30-year average, are associated with a decrease in burn severity (Fig. 3.4). Conversely, warmer fire years result in higher burn severities. Increasing temperature relative to long term climate averages has been linked to increased area burned at high severity (Parks & Abatzoglou, 2020).

The positive relationship between VPD max anomaly and burn severity was unexpected indicating that higher max VPD anomalies, where fire years that are moister relative to the 30-year average, are associated with an increase in burn severity (Fig. 3.4). Past studies have linked high VPD values to increased fire activity and area burned at high severity (Mueller et al., 2020; Seager et al., 2015; Williams et al., 2015). These studies evaluated annual area burned in forested and non-forested ecosystems in southwestern states but did not focus on treated and untreated areas or distinguish between forest types. There is also evidence that wet spring conditions can allow for the accumulation of understory fuels that if followed by a hot, dry summer result in larger fires (Jin et al., 2014; Wasserman & Mueller, 2023). Additionally, areas with increased VPD can experience increased fire frequency and decreased vegetation productivity leading to reduced biomass and lower burn severities (Wasserman & Mueller, 2023). Our study used mean annual VPD values to create VPD max anomaly, which does not include potential changes in VPD across seasons. McEvoy et al. (2019) found 90-day seasonal lag times tend to correlate with decreased summer fuel moisture suggesting that an annual aggregate of anomalous VPD might not capture a season lag relationship. Future studies could benefit from including predictors that capture seasonal differences in VPD.

3.4.2. Treatment effects across forest types and in extreme conditions

Our findings indicate that, on average, all forest types burned at higher severities compared to ponderosa pine (Table 3.5). This demonstrates that even though ponderosa pine forests have experienced infilling and increases in forest density from a century of fire suppression, some legacy of their historical fire regimes of low severity fires are still occurring on some of the landscape. Additionally, lower elevation forest types, such as ponderosa pine, mixed-conifer, and aspen – mixed-conifer, exhibit lower burn severities on average compared to higher elevation forests (Table 3.4). These patterns may reflect differences in fuel load, moisture availability, and fire behavior across elevation gradients, highlighting the need for elevation and forest type specific management strategies (Davis et al., 2024). Management strategies in high elevation forest include increasing landscape heterogeneity through variable-density thinning, creating forest openings, and favoring drought and fire adapted trees, while low elevation forests are generally targeted for small diameter thinning and prescribed fire (Hessburg et al., 2019).

Time since treatment is thought to have an inverse relationship to burn severity, with treatments becoming less effective over time (Dodge et al., 2019; Martinson & Omi, 2013). Our model did not find time since treatment to be an ecologically important predictor of burn severity (Table 3.5), however our approach limits the range of treatment ages considered and recent treatments were more heavily represented in our models. The Front Range is a low productivity system; thus, it is likely that treatments may be effective for longer than treatments that occur in higher productivity systems (i.e. Sierra Nevada, Pacific Northwest, Black Hills; Hunter et al., 2007). Ecosystem productivity is highly site dependent and in less productive areas, treatment maintenance may only be required every 15 – 20 years (Hunter et al., 2007), and our dataset did not capture older treatments. We limited treatment histories to include only treatments that occurred within 20 years pre-fire due to more incomplete treatment records in the past and even with this cut-off, older treatments are not completely represented in treatment databases. Combined, these constraints limit our inference of treatment age.

Low to moderate severity wildfire treatments had significantly lower subsequent burn severities compared to untreated in all forest types (Fig. 3.5). In extreme conditions, previous wildfire of both low to moderate and high severity was effective at reducing burn severity likely because previous wildfires were larger and altered fuel loads compared to intentional treatments (Fig. 3.6). Moreover, there is broad consensus that reburns tend to follow the burn severity patterns of previous wildfires in frequent fire adapted forests (e.g. Grabinski et al., 2017; Harris & Taylor, 2017; Holden et al., 2010; Lydersen et al., 2017; Stevens-Rumann et al., 2016; Taylor et al., 2021). This trend was evident in the ponderosa pine forests, where previous wildfire patterns contributed to lower burn severity outcomes (Fig. 3.5A). In contrast, in ponderosa pine, high severity wildfire treatments exhibited higher subsequent burn severity compared to untreated areas. High severity burns in ponderosa pine forests may be more likely to reburn at high severity due to their biophysical settings and/or resulting vegetation changes (e.g. increased course wood and shrub cover) (Grabinski et al., 2017; Harris & Taylor, 2017; Lydersen et al., 2017; Parks et al., 2014a). However, vegetation changes from high severity reburns may reduce the effectiveness of remotely sensed burn severity metrics, limiting their ability to assess wildfire treatment effects, particularly in non-forest areas where accuracy declines (Morgan et al., 2014). We observed high variability in burn severity outcomes within high severity wildfire treatment observations in both ponderosa pine and mixed-conifer forests (Fig. 3.5).

Our study highlights the need for treatments that include fire, sufficiently reduce surface fuels, and account for historical forest structure (i.e. increased heterogeneity). In non-extreme conditions, treatments with prescribed fire and low to moderate severity wildfire, excluding high severity wildfire, reduced burn severity (Fig. 3.6A). Previous studies have also concluded that treatments with fire result in reduced burn severity compared to controls; this is thought to be because treatments that include fire remove surface fuels, reducing the likelihood of high severity fire (Cansler et al., 2022; Davis et al., 2024; Kalies & Yocom Kent, 2016; Martinson & Omi, 2013; Prichard & Kennedy, 2012; Prichard et al., 2020). However, the intensity of prescribed fire can impact the effects of fuels treatments (Hunter et al., 2011; Kalies & Yocom Kent, 2016). We observed that fire and removal treatments only reduced burn severity in mixed-conifer forests; however, this sample size was small (Fig. 3.5B). Burn severity was similar between fire and removal treatments and untreated areas in ponderosa pine and aspen-mixed conifer forest types, and there was insufficient area of this treatment type in the other forest types (Fig. 3.5). Overall, the sample sizes for fire and removal treatments were small, which may explain the lack of significant effects in other forest types (Table 3.4). Prescribed fire had lower subsequent burn severities in ponderosa pine, mixed-conifer, aspen – mixed-conifer, and lodgepole pine forests; however, in lodgepole pine the mean was still above the high severity threshold (Fig. 3.5).

Removal and surface reduction treatments resulted in higher subsequent burn severity than untreated areas under extreme conditions (Fig. 3.6B) and only had significantly lower subsequent burn severity in lodgepole pine (Fig. 3.5D). Again, in lodgepole pine, the lower removal and surface reduction treatment mean was still high severity. In our study area, most removal and surface reduction treatments were implemented in high-elevation forest types, which historically burned at high severity (Table 3.4). Additionally, treatments that involve thinning alone can be ineffective under extreme conditions (Chamberlain et al., 2024; Lydersen et al., 2017; Prichard et al., 2020) and, when biomass is not removed, may contribute to higher severity outcomes (Omi et al., 2006). Davis et al. (2024) found in some cases thinning-only treatments led to increased burn severity compared to controls. This may be attributed to increased surface fuel loads following treatments, which elevate the likelihood of fire behavior that can result in higher tree mortality (Fulé et al., 2012; Prichard et al., 2010; Stephens et al., 2012).

In some cases, surface fuel reduction treatments may be the only management option, particularly in areas with high fuel loads or near infrastructure. Despite limitations, removal and surface fuels reduction treatments remain an important tool for enhancing forest resistance and resilience to disturbances, including wildfire (Hood et al., 2016; Knapp et al., 2021). We recommend that, when possible, managers leverage multiple treatment strategies to achieve outcomes known to reduce burn severity (i.e. reduction of surface and ladder fuels through a combination of thinning and burning) in frequent fire adapted forests.

We observed that intentional treatments had minimal impact on reducing subsequent burn severity to low or moderate severities in lodgepole pine and spruce – fir forests. As larger wildfire incidents occur, more mid and high elevation forests are affected and frequency in these high elevation forests have increased in the last several decades compared to the previous 2,000 years (Higuera et al., 2021). In the Southern Rockies, higher elevation forests have experienced an increase in burn area, with the area burned in late snow zones during the 2020 fire season exceeding the total area burned over the previous 36 years (Kampf et al., 2022). Our results indicate that intentional treatments are not consistently resulting in low to moderate burn severity in these forest types. Reducing burn severity is not often a management objective for intentional treatments in these forest types, as their fire regimes are climate limited. When fires do occur, they typically burn under more extreme climatic conditions, making it difficult to moderate subsequent burn severity. Previous wildfire reduced subsequent burn severity, suggesting that intentional treatments designed to better emulate wildfire may be a more effective management strategy where the goal is to reduce burn severity.

Our study was limited to federal treatments, and many treatments in lodgepole pine and spruce – fir forests have yet to experience wildfire or were conducted on non-federal land. As additional wildfires occur in these forests, continued research will help determine whether treatments are able to reduce large high severity wildfire. While treatments in ponderosa pine and other low elevation, frequent fire adapted forests are well studied along the Front Range and across western North America, mid to high elevation forests require further research to identify how silvicultural approaches in these forest types interact with wildfire.

3.4.3. Limitations

In our study, we used the FACTS common attributes database, which does not encompass all treatments that alter the amount and distribution of fuels across the landscape. Since the FACTS database was not designed for analyzing treatment effects, we were unable to account for all federal, state, or private fuels treatments. Additionally, the database does not provide information on treatment intensity, or the amount of biomass removed. Current treatment data is limited in its ability to estimate treatment intensity or capture structural differences between treatments. Some studies have addressed this limitation by modeling potential disturbances in Landsat time series to validate and estimate treatment intensity (Knight et al., 2022). Yet utilizing multi-spectral imagery only measures canopy treatment intensity. Below canopy and ladder fuel removal and subsequent biomass generation are poorly captured using these remote sensing techniques. Future research would benefit from incorporating methods to quantify treatment intensity, offering a more nuanced understanding of treatment effects.

Categorizing treatments by the extent to which they modify fuels, rather than relying on broad treatment categories, could enhance our ability to evaluate their impacts.

To make meaningful comparisons across treatments, we sampled untreated areas by matching them to treated areas based on forest type. This approach aimed to control for biophysical differences –for example, ponderosa pine forests typically establish at lower elevation, drier sites, while spruce-fir forests are found at higher elevation, more mesic sites. By ensuring that forest types were represented in both treated and untreated areas, we sought to minimize these differences. However, because forest type was the only criterion used to select untreated points, other factors influencing treatment effects may not have been fully accounted for, such as weather conditions on the day-of-burning or topographic influences not captured by forest type. Additionally, some treatment types had small sample sizes, which may limit our ability to detect significant effects. As a result, the effects of certain treatments on burn severity may be stronger or weaker than we are currently identifying. Similar studies identified treated and untreated controls by either subsampling points and matching bioclimatic settings and fire weather (Cansler et al., 2020) or selecting control units that represent similar site and burning conditions as the treatments (Chamberlain et al., 2024). Despite the potential limitations of our control matching, the distributions of fuel and topographic predictor variables were generally similar between untreated and treated areas (Fig. 3.3).

Outside of our classification of extreme and not extreme conditions, we did not find fire weather to be a significant predictor of burn severity in our study. This contrasts with previous research, which identified fire weather as a key driver of high severity fire (Lydersen et al., 2017; Prichard et al., 2020; Stevens-Rumann et al., 2016). However, under moderate weather conditions, vegetation characteristics have been shown to have a stronger relationship with previous wildfire than fire weather (Grabinski et al., 2017; Harris & Taylor, 2017). Our findings may be influenced by the limitations of GRIDMET data, which provides high temporal resolution (daily images) but coarse spatial resolution (4 km). While daily gridded weather data is useful for understanding broad-scale patterns, many treatments and some fires in our study area were smaller than a single GRIDMET pixel. As a result, significant variability within individual weather pixels likely obscured relationships at the fire or treatment level.

We defined extreme conditions based on fire spread, categorizing a day as extreme if it exhibited significant fire growth. In our dataset, 42% of the sampled pixels met this definition, and we had a sufficient sample size within each treatment category to evaluate the effects of treatments under extreme weather conditions (Table 3.6). However, by defining extreme conditions by fire spread, we may have missed instances of extreme fire behavior that did not result in large spread events. This approach also excludes smaller fires with proportionally large daily spread when using a hectare-based threshold for defining extreme conditions. Other studies have defined extreme conditions as exceeding one (Coop et al., 2022) or two (Balik et al., 2024) standard deviations above the mean daily area burned or have used fire weather indices that capture known drivers of severe fires (Jolly et al., 2019; Rodman et al., 2023). Future research could refine these thresholds by developing region-specific definitions of extreme condition that account for smaller spread events and/or incorporate fire weather indices.

3.4.4. Recommendations

Previous low to moderate severity wildfire was the only treatment to have a lower mean burn severity compared to untreated areas in both non-extreme and extreme conditions and across all forest types. Utilizing managed wildfire under mild to moderate conditions away from communities has been increasingly encouraged as a management tool to expand pace and scale and assist with treatment maintenance (North et al., 2012, North et al., 2024). Conditions are considered moderate when weather and fuel moisture conditions are within a pre-determined range that is likely to result in ecologically beneficial fire (North et al., 2024). Allowing wildfire to burn under moderate conditions is likely to result in low to moderate severities and can modify more fuel on the landscape than prescribed fire alone (Parks et al., 2018a; Prichard et al., 2021). Previous wildfire of low to moderate severity can lower subsequent burn severity and serve as barriers to spread for 10-20 years (Parks et al., 2014a; Rodman et al., 2023) and likely longer along the Front Range. By implementing managed fire, more of the landscape can be treated allowing managers to focus on the strategic placement of treatments in areas that protect people, property, and resources.

Our results suggest that intentional treatments involving fire can reduce subsequent burn severity in certain forest types and under specific wildfire conditions but are less effective under extreme conditions. This highlights the need for more intensive treatments that better mimic the effects of low to moderate severity wildfire. Prescribed fire, removal and surface fuels reduction, and low to moderate severity wildfire have been shown to reduce surface fuels, but wildfire is more efficient at reducing basal area and canopy bulk density (Hunter et al., 2011).

Treatments without fire were largely comparable to untreated areas in our study, underscoring the importance of reducing surface fuels following thinning operations. However, implementing treatments in high elevation forests with high severity, infrequent fire regimes would be for management goals rather than ecological benefit. In landscapes dominated by high elevation forests, strategies such as allowing wildfires to burn under moderate conditions, implementing treatments that restore historic heterogeneity (i.e. varying successional stages and incorporating non-forest patches) (Hessburg et al., 2019; Prichard et al., 2021), or focusing management efforts on mid-elevations to help prevent fire spread into high elevation forests (Remy et al., 2024; Sibold et al., 2006) may be more effective but more research is needed.

3.5. Conclusions

Our results suggest low to moderate severity wildfire reduces burn severity most consistently on the Front Range landscape. It is also the most common fuels modification in this study, accounting for 30% of “treated” areas. While intentional treatments (i.e. prescribed fire, removal and surface fuel reduction, and fire and removal) had less effect than previous wildfire, they still reduced burn severity under certain conditions and in specific forest types. These findings reinforce previous calls to invest in treatments that incorporate fire and mimic the intensity of previous wildfire. Additionally, our results align with prior research on treatments ability to moderate burn severity and underscore the need for further studies in high elevation forests. Understanding where management actions and wildfires are occurring across forest types will help refine future treatment strategies. As wildfires continue to increase in size and severity, investing in treatments that minimize negative ecological outcomes and protect people, property, and resources remains critical.

REFERENCES

Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, *33*(1), 121–131. https://doi.org/10.1002/joc.3413

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, *113*(42), 11770–11775. https://doi.org/10.1073/pnas.1607171113

Addington, R. N., Aplet, G. H., Battaglia, M. A., Briggs, J. S., Brown, P. M., Cheng, A. S., Dickinson, Y., Feinstein, J. A., Pelz, K. A., Regan, C. M., Thinnes, J., Truex, R., Fornwalt, P. J., Gannon, B., Julian, C. W., Underhill, J. L., & Wolk, B. (2018). *Principles and practices for the restoration of ponderosa pine and dry mixed-conifer forests of the Colorado Front Range.* RMRS-GTR-373. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 121 p.

Addington, R. N., Tavernia, B. G., Caggiano, M. D., Thompson, M. P., Lawhon, J. D., & Sanderson, J. S. (2020). Identifying opportunities for the use of broadcast prescribed fire on Colorado's Front Range. *Forest Ecology and Management*, *458*. https://doi.org/10.1016/j.foreco.2019.117655

Agee, J. K., & Skinner, C. N. (2005). Basic principles of forest fuel reduction treatments. *Forest Ecology and Management*, *211*(1–2), 83–96. https://doi.org/10.1016/j.foreco.2005.01.034

Alexander, J. D., Seavy, N. E., Ralph, C. J., & Hogoboom, B. (2006). Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California. *International Journal of Wildland Fire*, *15*(2), 237.

https://doi.org/10.1071/WF05053

Arkle, R. S., Pilliod, D. S., & Welty, J. L. (2012). Pattern and process of prescribed fires influence effectiveness at reducing wildfire severity in dry coniferous forests. *Forest Ecology and Management*, *276*, 174–184. https://doi.org/10.1016/j.foreco.2012.04.002

Balik, J. A., Coop, J. D., Krawchuk, M. A., Naficy, C. E., Parisien, M.-A., Parks, S. A., Stevens-Rumann, C. S., & Whitman, E. (2024). Biogeographic patterns of daily wildfire spread and extremes across North America. *Frontiers in Forests and Global Change*, *7*. https://doi.org/10.3389/ffgc.2024.1355361

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Calkin, D. E., Thompson, M. P., & Finney, M. A. (2015). Negative consequences of positive feedbacks in US wildfire management. *Forest Ecosystems*, *2*(1), 9. https://doi.org/10.1186/s40663-015-0033-8

Cansler, C. A., Kane, V. R., Hessburg, P. F., Kane, J. T., Jeronimo, S. M. A., Lutz, J. A., Povak, N. A., Churchill, D. J., & Larson, A. J. (2022). Previous wildfires and management treatments moderate subsequent fire severity. *Forest Ecology and Management*, *504*, 119764. https://doi.org/10.1016/j.foreco.2021.119764

CFRI (2023). *Interagency Fire Perimeter Database* [Data set]. Colorado Forest Restoration Institute.

Chamberlain, C. P., Meigs, G. W., Churchill, D. J., Kane, J. T., Sanna, A., Begley, J. S., Prichard, S. J., Kennedy, M. C., Bienz, C., Haugo, R. D., Smith, A. C., Kane, V. R., & Cansler, C. A. (2024). Learning from wildfires: A scalable framework to evaluate treatment effects on burn severity. *Ecosphere*, *15*(12). https://doi.org/10.1002/ecs2.70073

Clements, F. E. (1910). *The life history of lodgepole burn forests* (No. 79). US Department of Agriculture, Forest Service.

Collins, B. M. (2014). Fire weather and large fire potential in the northern Sierra Nevada. *Agricultural and Forest Meteorology*, *189–190*, 30–35. https://doi.org/10.1016/j.agrformet.2014.01.005

Collins, L., Bennett, A. F., Leonard, S. W. J., & Penman, T. D. (2019). Wildfire refugia in forests: Severe fire weather and drought mute the influence of topography and fuel age. *Global Change Biology*, *25*(11), 3829–3843. https://doi.org/10.1111/gcb.14735

Collins, B. M., Stephens, S. L., Moghaddas, J. J., & Battles, J. (2010). Challenges and Approaches in Planning Fuel Treatments across Fire-Excluded Forested Landscapes. *Journal of Forestry*, *108*(1), 24–31. https://doi.org/10.1093/jof/108.1.24

Coop, J. D., Parks, S. A., Stevens-Rumann, C. S., Ritter, S. M., & Hoffman, C. M. (2022). Extreme fire spread events and area burned under recent and future climate in the western USA. *Global Ecology and Biogeography*, *31*(10), 1949–1959. https://doi.org/10.1111/geb.13496

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., & Pasteris, P. P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology*, *28*(15), 2031–2064. https://doi.org/10.1002/joc.1688

Daly, C., Smith, J. I., & Olson, K. V. (2015). Mapping Atmospheric Moisture Climatologies across the Conterminous United States. *PLOS ONE*, *10*(10), e0141140. https://doi.org/10.1371/journal.pone.0141140

Davis, K. T., Peeler, J., Fargione, J., Haugo, R. D., Metlen, K. L., Robles, M. D., & Woolley, T.

(2024). Tamm review: A meta-analysis of thinning, prescribed fire, and wildfire effects on subsequent wildfire severity in conifer dominated forests of the Western US. *Forest Ecology and Management*, *561*, 121885. https://doi.org/10.1016/j.foreco.2024.121885

Dinno, A. (2014). dunn.test: Dunn's Test of Multiple Comparisons Using Rank Sums. R package version 1.3.6. https://doi.org/10.32614/CRAN.package.dunn.test

Dodge, J. M., Strand, E. K., Hudak, A. T., Bright, B. C., Hammond, D. H., & Newingham, B. A. (2019). Short- and long-term effects of ponderosa pine fuel treatments intersected by the Egley Fire Complex, Oregon, USA. *Fire Ecology*, *15*(1), 40. https://doi.org/10.1186/s42408-019-0055-7

Duane, A., Castellnou, M., & Brotons, L. (2021). Towards a comprehensive look at global drivers of novel extreme wildfire events. *Climatic Change*, *165*(3–4), 43. https://doi.org/10.1007/s10584-021-03066-4

Dunn, O. J. (1964). Multiple Comparisons Using Rank Sums. *Technometrics*, *6*(3), 241–252. https://doi.org/10.1080/00401706.1964.10490181

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.-L., Quayle, B., & Howard, S. (2007). A Project for Monitoring Trends in Burn Severity. *Fire Ecology*, *3*(1), 3–21. https://doi.org/10.4996/fireecology.0301003

Evans, J. S., & Murphy, M. A. (2023). spatialEco. R package version 2.0-2. https://github.com/jeffreyevans/spatialEco

Fallon, K., Abatzoglou, J. T., Hurteau, M. D., Butz, R. J., Buchanan, B., Pierce, J., McNamara, J., Cattau, M., & Sadegh, M. (2024). *Fuel Treatment Efficacy Across California's Forests: How do Wildfire Covariates Impact the Treatment Outcome?*. ESS Open Archive. 10.22541/essoar.172590227.72370322/v1

Fang, L., Yang, J., Zu, J., Li, G., & Zhang, J. (2015). Quantifying influences and relative importance of fire weather, topography, and vegetation on fire size and fire severity in a Chinese boreal forest landscape. *Forest Ecology and Management*, *356*, 2–12. https://doi.org/10.1016/j.foreco.2015.01.011

Fernández-Guisuraga, J. M., & Fernandes, P. M. (2024). Enhanced post-wildfire vegetation recovery in prescribed-burnt Mediterranean shrubland: A regional assessment. Forest Ecology and Management, 561, 121921. https://doi.org/10.1016/j.foreco.2024.121921

Fulé, P. Z., Crouse, J. E., Heinlein, T. A., Moore, M. M., Covington, W. W., & Verkamp, G. (2003). Mixed-severity fire regime in a high-elevation forest of Grand Canyon, Arizona, USA. *Landscape Ecology*, *18*(5), 465–486. https://doi.org/10.1023/A:1026012118011

Fulé, P. Z., Crouse, J. E., Roccaforte, J. P., & Kalies, E. L. (2012). Do thinning and/or burning treatments in western USA ponderosa or Jeffrey pine-dominated forests help restore natural fire behavior? *Forest Ecology and Management*, *269*, 68–81. https://doi.org/10.1016/j.foreco.2011.12.025

Furniss, T. J., Kane, V. R., Larson, A. J., & Lutz, J. A. (2020). Detecting tree mortality with Landsat-derived spectral indices: Improving ecological accuracy by examining uncertainty. *Remote Sensing of Environment*, *237*, 111497. https://doi.org/10.1016/j.rse.2019.111497

Genuer, R., Poggi, J.-M., & Tuleau-Malot, C. (2010). Variable selection using random forests. *Pattern Recognition Letters*, *31*(14), 2225–2236. https://doi.org/10.1016/j.patrec.2010.03.014

Grabinski, Z. S., Sherriff, R. L., & Kane, J. M. (2017). Controls of reburn severity vary with fire interval in the Klamath Mountains, California, USA. *Ecosphere*, *8*(11).

https://doi.org/10.1002/ecs2.2012

Groll, A. (2023). glmmLasso: Variable Selection for Generalized Linear Mixed Models by L1-Penalized Estimation. R package version 1.6.3. https://CRAN.R-project.org/package=glmmLasso

Groll, A., & Tutz, G. (2014). Variable selection for generalized linear mixed models by L 1-penalized estimation. *Statistics and Computing*, *24*(2), 137–154. https://doi.org/10.1007/s11222-012-9359-z

Grömping, U. (2009). Variable Importance Assessment in Regression: Linear Regression versus Random Forest. *The American Statistician*, *63*(4), 308–319. https://doi.org/10.1198/tast.2009.08199

Hagmann, R. K., Hessburg, P. F., Prichard, S. J., Povak, N. A., Brown, P. M., Fulé, P. Z., Keane, R. E., Knapp, E. E., Lydersen, J. M., Metlen, K. L., Reilly, M. J., Sánchez Meador, A. J., Stephens, S. L., Stevens, J. T., Taylor, A. H., Yocom, L. L., Battaglia, M. A., Churchill, D. J., Daniels, L. D., … Waltz, A. E. M. (2021). Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. *Ecological Applications*, *31*(8). https://doi.org/10.1002/EAP.2431

Harris, L., & Taylor, A. H. (2017). Previous burns and topography limit and reinforce fire severity in a large wildfire. *Ecosphere*, *8*(11). https://doi.org/10.1002/ecs2.2019

He, S., Zhong, Y., Sun, Y., Su, Z., Jia, X., Hu, Y., & Zhou, Q. (2017). Topography-associated thermal gradient predicts warming effects on woody plant structural diversity in a subtropical forest. *Scientific Reports*, *7*(1), 40387. https://doi.org/10.1038/srep40387

Hessburg, P. F., Miller, C. L., Parks, S. A., Povak, N. A., Taylor, A. H., Higuera, P. E., Prichard, S. J., North, M. P., Collins, B. M., Hurteau, M. D., Larson, A. J., Allen, C. D., Stephens,

S. L., Rivera-Huerta, H., Stevens-Rumann, C. S., Daniels, L. D., Gedalof, Z., Gray, R. W., Kane, V. R., … Salter, R. B. (2019). Climate, Environment, and Disturbance History Govern Resilience of Western North American Forests. *Frontiers in Ecology and Evolution*, *7*. https://doi.org/10.3389/fevo.2019.00239

Hessburg, P. F., Prichard, S. J., Hagmann, R. K., Povak, N. A., & Lake, F. K. (2021). Wildfire and climate change adaptation of western North American forests: a case for intentional management. *Ecological Applications*, *31*(8). https://doi.org/10.1002/eap.2432

Hessburg, P. F., Salter, R. B., & James, K. M. (2007). Re-examining fire severity relations in pre-management era mixed conifer forests: inferences from landscape patterns of forest structure. *Landscape Ecology*, *22*(S1), 5–24. https://doi.org/10.1007/s10980-007-9098-2

Higuera, P. E., Shuman, B. N., & Wolf, K. D. (2021). Rocky Mountain subalpine forests now burning more than any time in recent millennia. *Proceedings of the National Academy of Sciences*, *118*(25). https://doi.org/10.1073/pnas.2103135118

Hijmans, R. (2024). terra: Spatial Data Analysis. R package version 1.7-78. https://CRAN.R-project.org/package=terra

Holden, Z. A., Morgan, P., & Evans, J. S. (2009). A predictive model of burn severity based on 20-year satellite-inferred burn severity data in a large southwestern US wilderness area. *Forest Ecology and Management*, *258*(11), 2399–2406. https://doi.org/10.1016/j.foreco.2009.08.017

Holden, Z. A., Morgan, P., & Hudak, A. T. (2010). Burn Severity of Areas Reburned by Wildfires in the Gila National Forest, New Mexico, USA. *Fire Ecology*, *6*(3), 77–85. https://doi.org/10.4996/fireecology.0603085

Hood, S. M., Baker, S., & Sala, A. (2016). Fortifying the forest: thinning and burning increase resistance to a bark beetle outbreak and promote forest resilience. *Ecological*

Applications, *26*(7), 1984–2000. https://doi.org/10.1002/eap.1363

Hood, S. M., Smith, H. Y., Wright, D. K., & Glasgow, L. S. (2012). *Management guide to ecosystem restoration treatments: two-aged lodgepole pine forests of central Montana, USA.* RMRS-GTR-294. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 126 p.

Housman, I. W., Schleeweis, K., Heyer, J. P., Ruefenacht, B., Bender, S., Megown, K., Goetz, W., & Bogle, S. (2023). *National Land Cover Database Tree Canopy Cover Methods v2021.4. GTAC-10268-RPT1*.

Howe, E., & Baker, W. L. (2003). Landscape Heterogeneity and Disturbance Interactions in a Subalpine Watershed in Northern Colorado, USA. *Annals of the Association of American Geographers*, *93*(4), 797–813. https://doi.org/10.1111/j.1467-8306.2003.09304002.x

Hunter, M. E., Iniguez, J. M., & Lentile, L. B. (2011). Short- and Long-Term Effects on Fuels, Forest Structure, and Wildfire Potential from Prescribed Fire and Resource Benefit Fire in Southwestern Forests, USA. *Fire Ecology*, *7*(3), 108–121. https://doi.org/10.4996/fireecology.0703108

Hunter, M. E., Shepperd, W. D., Lentile, L. B., Lundquist, J. E., Andreu, M. G., Butler, J. L., & Smith, F. W. (2007). *A Comprehensive Guide to Fuels Treatment Practices for Ponderosa Pine in the Black Hills, Colorado Front Range, and Southwest.* RMRS-GTR-198. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 93 p.

Jolly, W., Freeborn, P., Page, W., & Butler, B. (2019). Severe Fire Danger Index: A Forecastable Metric to Inform Firefighter and Community Wildfire Risk Management. *Fire*, *2*(3), 47. https://doi.org/10.3390/fire2030047

Kalies, E. L., & Yocom Kent, L. L. (2016). Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. *Forest Ecology and Management*, *375*, 84–95. https://doi.org/10.1016/J.FORECO.2016.05.021

Kampf, S. K., McGrath, D., Sears, M. G., Fassnacht, S. R., Kiewiet, L., & Hammond, J. C. (2022). Increasing wildfire impacts on snowpack in the western U.S. *Proceedings of the National Academy of Sciences*, *119*(39). https://doi.org/10.1073/pnas.2200333119

Kipfmueller, K. F., & Baker, W. L. (2000). A fire history of a subalpine forest in south-eastern Wyoming, USA. *Journal of Biogeography*, *27*(1), 71–85. https://doi.org/10.1046/j.1365-2699.2000.00364.x

Knapp, E. E., Bernal, A. A., Kane, J. M., Fettig, C. J., & North, M. P. (2021). Variable thinning and prescribed fire influence tree mortality and growth during and after a severe drought. *Forest Ecology and Management*, *479*, 118595. https://doi.org/10.1016/j.foreco.2020.118595

Knight, C. A., Tompkins, R. E., Wang, J. A., York, R., Goulden, M. L., & Battles, J. J. (2022). Accurate tracking of forest activity key to multi-jurisdictional management goals: A case study in California. *Journal of Environmental Management*, *302*, 114083. https://doi.org/10.1016/j.jenvman.2021.114083

Kruskal, W. H., & Wallis, W. A. (1952). Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical Association*, *47*(260), 583–621. https://doi.org/10.1080/01621459.1952.10483441

Lindsay, J. B. (2016). Whitebox GAT: A case study in geomorphometric analysis. *Computers & Geosciences*, *95*, 75–84. https://doi.org/10.1016/j.cageo.2016.07.003

Lorber, J., Thomas-Van Gundy, M., & Croy, S. (2018). *Characterizing effects of prescribed fire on forest canopy cover in the George Washington and Jefferson National Forests.* NRS-31. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern

Research Station. 30 p.

Lydersen, J. M., Collins, B. M., Brooks, M. L., Matchett, J. R., Shive, K. L., Povak, N. A., Kane, V. R., & Smith, D. F. (2017). Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. *Ecological Applications*, *27*(7), 2013–2030. https://doi.org/10.1002/EAP.1586

Martinson, E. J., & Omi, P. N. (2013). *Fuel treatments and fire severity: A meta-analysis.* RMRS-RP-103WWW. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 38 p.

McEvoy, D. J., Hobbins, M., Brown, T. J., VanderMolen, K., Wall, T., Huntington, J. L., & Svoboda, M. (2019). Establishing Relationships between Drought Indices and Wildfire Danger Outputs: A Test Case for the California-Nevada Drought Early Warning System. *Climate*, *7*(4), 52. https://doi.org/10.3390/cli7040052

McKinney, S. T. (2019). *Fire regimes of ponderosa pine (Pinus ponderosa) ecosystems in Colorado: a systematic review and meta-analysis*. US Department of Agriculture, Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory. www.fs.usda.gov/database/feis/fire_regimes/CO_ponderosa_pine/all.pdf

Moreira, F., Ascoli, D., Safford, H., Adams, M. A., Moreno, J. M., Pereira, J. M. C., Catry, F. X., Armesto, J., Bond, W., González, M. E., Curt, T., Koutsias, N., McCaw, L., Price, O., Pausas, J. G., Rigolot, E., Stephens, S., Tavsanoglu, C., Vallejo, V. R., … Fernandes, P. M. (2020). Wildfire management in Mediterranean-type regions: paradigm change needed. *Environmental Research Letters*, *15*(1), 011001. https://doi.org/10.1088/1748-9326/ab541e

Morgan, P., Keane, R. E., Dillon, G. K., Jain, T. B., Hudak, A. T., Karau, E. C., Sikkink, P. G., Holden, Z. A., & Strand, E. K. (2014). Challenges of assessing fire and burn severity using field measures, remote sensing and modelling. *International Journal of Wildland Fire*, *23*(8), 1045. https://doi.org/10.1071/WF13058

Mueller, S. E., Thode, A. E., Margolis, E. Q., Yocom, L. L., Young, J. D., & Iniguez, J. M. (2020). Climate relationships with increasing wildfire in the southwestern US from 1984 to 2015. *Forest Ecology and Management*, *460*, 117861. https://doi.org/10.1016/j.foreco.2019.117861

North, M. P., Bisbing, S. M., Hankins, D. L., Hessburg, P. F., Hurteau, M. D., Kobziar, L. N., Meyer, M. D., Rhea, A. E., Stephens, S. L., & Stevens-Rumann, C. S. (2024). Strategic fire zones are essential to wildfire risk reduction in the Western United States. *Fire Ecology*, *20*(1), 50. https://doi.org/10.1186/s42408-024-00282-y

North, M., Collins, B. M., & Stephens, S. (2012). Using Fire to Increase the Scale, Benefits, and Future Maintenance of Fuels Treatments. *Journal of Forestry*, *110*(7), 392–401. https://doi.org/10.5849/jof.12-021

Omi, P. N., & Martinson E. J. (2002). *Effect of fuels treatments on wildfire severity*. Final Report 590 to the Joint Fire Science Program Governing Board.

Omi, P. N., Martinson, E. J., & Chong, G. W. (2006). *Effectiveness of pre-fire fuel treatments.* JFSP Project 03-2-1-07. Joint Fire Science Program Governing Board.

Parks, S. A. (2014). Mapping day-of-burning with coarse-resolution satellite fire-detection data. *International Journal of Wildland Fire, 23*(2), 215–223. https://doi.org/10.1071/WF13138

Parks, S. A., & Abatzoglou, J. T. (2020). Warmer and Drier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017. *Geophysical Research Letters*, *47*(22). https://doi.org/10.1029/2020GL089858

Parks, S. A., Miller, C., Nelson, C. R., & Holden, Z. A. (2014a). Previous Fires Moderate Burn

Severity of Subsequent Wildland Fires in Two Large Western US Wilderness Areas. *Ecosystems*, *17*(1), 29–42. https://doi.org/10.1007/s10021-013-9704-x

Parks, S., Dillon, G., & Miller, C. (2014b). A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. *Remote Sensing*, *6*(3), 1827–1844. https://doi.org/10.3390/rs6031827

Parks, S. A., Holsinger, L. M., Koontz, M. J., Collins, L., Whitman, E., Parisien, M. A., Loehman, R. A., Barnes, J. L., Bourdon, J. F., Boucher, J., Boucher, Y., Caprio, A. C., Collingwood, A., Hall, R. J., Park, J., Saperstein, L. B., Smetanka, C., Smith, R. J., & Soverel, N. (2019). Giving ecological meaning to satellite-derived fire severity metrics across North American forests. *Remote Sensing*, *11*(14). https://doi.org/10.3390/rs11141735

Parks, S. A., Holsinger, L. M., Panunto, M. H., Jolly, W. M., Dobrowski, S. Z., & Dillon, G. K. (2018a). High-severity fire: evaluating its key drivers and mapping its probability across western US forests. *Environmental Research Letters*, *13*(4), 044037. https://doi.org/10.1088/1748-9326/aab791

Parks, S., Holsinger, L., Voss, M., Loehman, R., & Robinson, N. (2018b). Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. *Remote Sensing*, *10*(6), 879. https://doi.org/10.3390/rs10060879

Peet, R. K. (1981). Forest vegetation of the Colorado Front Range. *Vegetatio*, *45*(1), 3–75. https://doi.org/10.1007/BF00240202

Pelz, K. (2016). *Engelmann spruce regeneration following natural disturbances and forest management: A literature and expert-knowledge review focused on southwestern*

Colorado. Colorado Forest Restoration Institute. https://cfri.colostate.edu/wp-content/uploads/sites/22/2017/10/2016-CFRI-Spruce-Regeneration-in-SW-Colorado-compressed.pdf

Petrakis, R. E., Villarreal, M. L., Wu, Z., Hetzler, R., Middleton, B. R., & Norman, L. M. (2018). Evaluating and monitoring forest fuel treatments using remote sensing applications in Arizona, U.S.A. *Forest Ecology and Management*, *413*, 48–61. https://doi.org/10.1016/j.foreco.2018.01.036

Prichard, S. J., Hessburg, P. F., Hagmann, R. K., Povak, N. A., Dobrowski, S. Z., Hurteau, M. D., Kane, V. R., Keane, R. E., Kobziar, L. N., Kolden, C. A., North, M., Parks, S. A., Safford, H. D., Stevens, J. T., Yocom, L. L., Churchill, D. J., Gray, R. W., Huffman, D. W., Lake, F. K., & Khatri-Chhetri, P. (2021). Adapting western North American forests to climate change and wildfires: 10 common questions. *Ecological Applications*, *31*(8). https://doi.org/10.1002/eap.2433

Prichard, S. J., & Kennedy, M. C. (2012). Fuel treatment effects on tree mortality following wildfire in dry mixed conifer forests, Washington State, USA. *International Journal of Wildland Fire*, *21*(8), 1004. https://doi.org/10.1071/WF11121

Prichard, S. J., Peterson, D. L., & Jacobson, K. (2010). Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. *Canadian Journal of Forest Research*, *40*(8), 1615–1626. https://doi.org/10.1139/X10-109

Prichard, S. J., Povak, N. A., Kennedy, M. C., & Peterson, D. W. (2020). Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. *Ecological Applications*. https://doi.org/10.1002/eap.2104

R Core Team (2024). R: A Language and Environment for Statistical Computing. R

Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Remy, C. C., Krofcheck, D. J., Keyser, A. R., & Hurteau, M. D. (2024). Restoring frequent fire to dry conifer forests delays the decline of subalpine forests in the southwest United States under projected climate. *Journal of Applied Ecology*, *61*(7), 1508–1519. https://doi.org/10.1111/1365-2664.14689

Rodman, K. C., Davis, K. T., Chambers, M. E., Chapman, T. B., Fornwalt, P. J., Hart, S. J., Marshall, L. A. E., Rhoades, C. C., Schloegel, C. A., Stevens-Rumann, C. S., & Veblen, T. T. (2022). *The historic 2020 fire year in northern Colorado and southern Wyoming: A landscape assessment to inform post-fire forest management*.

Rodman, K. C., Davis, K. T., Parks, S. A., Chapman, T. B., Coop, J. D., Iniguez, J. M., Roccaforte, J. P., Sánchez Meador, A. J., Springer, J. D., Stevens-Rumann, C. S., Stoddard, M. T., Waltz, A. E. M., & Wasserman, T. N. (2023). Refuge-yeah or refuge-nah? Predicting locations of forest resistance and recruitment in a fiery world. *Global Change Biology*, *29*(24), 7029–7050. https://doi.org/10.1111/gcb.16939

Rollins, M. G. (2009). LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire*, *18*(3), 235. https://doi.org/10.1071/WF08088

Schelldorfer, J., Meier, L., & Bühlmann, P. (2014). GLMMLasso: An Algorithm for High-Dimensional Generalized Linear Mixed Models Using ℓ_1-Penalization. *Journal of Computational and Graphical Statistics*, *23*(2), 460–477. https://doi.org/10.1080/10618600.2013.773239

Seager, R., Hooks, A., Williams, A. P., Cook, B., Nakamura, J., & Henderson, N. (2015). Climatology, Variability, and Trends in the U.S. Vapor Pressure Deficit, an Important

Fire-Related Meteorological Quantity. *Journal of Applied Meteorology and Climatology*, *54*(6), 1121–1141. https://doi.org/10.1175/JAMC-D-14-0321.1

Sherriff, R. L., & Veblen, T. T. (2007). A Spatially-Explicit Reconstruction of Historical Fire Occurrence in the Ponderosa Pine Zone of the Colorado Front Range. *Ecosystems*, *10*(2), 311–323. https://doi.org/10.1007/s10021-007-9022-2

Sibold, J. S., Veblen, T. T., & González, M. E. (2006). Spatial and temporal variation in historic fire regimes in subalpine forests across the Colorado Front Range in Rocky Mountain National Park, Colorado, USA. *Journal of Biogeography*, *33*(4), 631–647. https://doi.org/10.1111/j.1365-2699.2005.01404.x

Stephens, S. L., Battaglia, M. A., Churchill, D. J., Collins, B. M., Coppoletta, M., Hoffman, C. M., Lydersen, J. M., North, M. P., Parsons, R. A., Ritter, S. M., & Stevens, J. T. (2020). Forest Restoration and Fuels Reduction: Convergent or Divergent? *BioScience*, *71*(1), 85–101. https://doi.org/10.1093/biosci/biaa134

Stephens, S. L., Mciver, J. D., Boerner, R. E. J., Fettig, C. J., Fontaine, J. B., Hartsough, B. R., Kennedy, P. L., & Schwilk, D. W. (2012). The Effects of Forest Fuel-Reduction Treatments in the United States. *BioScience*, *62*(6), 549–560. https://doi.org/10.1525/bio.2012.62.6.6

Stevens-Rumann, C. S., Prichard, S. J., Strand, E. K., & Morgan, P. (2016). Prior wildfires influence burn severity of subsequent large fires. *Canadian Journal of Forest Research*, *46*(11), 1375–1385. https://doi.org/10.1139/cjfr-2016-0185

Taylor, A. H., Harris, L. B., & Drury, S. A. (2021). Drivers of fire severity shift as landscapes transition to an active fire regime, Klamath Mountains, USA. *Ecosphere*, *12*(9). https://doi.org/10.1002/ecs2.3734

Taylor, A. H., Harris, L. B., & Skinner, C. N. (2022). Severity patterns of the 2021 Dixie Fire exemplify the need to increase low-severity fire treatments in California's forests. *Environmental Research Letters*, *17*(7). https://doi.org/10.1088/1748-9326/ac7735

Tedim, F., Leone, V., Coughlan, M., Bouillon, C., Xanthopoulos, G., Royé, D., Correia, F. J. M., & Ferreira, C. (2020). Extreme wildfire events. In *Extreme Wildfire Events and Disasters* (pp. 3–29). Elsevier. https://doi.org/10.1016/B978-0-12-815721-3.00001-1

Tepley, A. J., & Veblen, T. T. (2015). Spatiotemporal fire dynamics in mixed-conifer and aspen forests in the San Juan Mountains of southwestern Colorado, USA. *Ecological Monographs*, 85(4), 583–603. https://doi.org/10.1890/14-1496.1

Tolhurst, K. G., & McCarthy, G. (2016). Effect of prescribed burning on wildfire severity: a landscape-scale case study from the 2003 fires in Victoria. *Australian Forestry*, *79*(1), 1–14. https://doi.org/10.1080/00049158.2015.1127197

Tower, G.E., 1909. A study of the reproductive characteristics of lodgepole pine. *Proc. Soc. Am. For.* 4, 84-106.

USDA Forest Service. (2022). *Confronting the Wildfire Crisis: A 10-Year Implementation Plan*.

USDA Forest Service (2024). *FACTS Common Attributes* [Data set]. Washington, DC: USDA Forest Service.

U.S. Geological Survey. (2023). *1/3rd arc-second Digital Elevation Models (DEMs) - USGS National Map 3DEP Downloadable Data Collection: U.S. Geological Survey*.

Veblen, T. T., Hadley, K. S., Nel, E. M., Kitzberger, T., Reid, M., & Villalba, R. (1994). Disturbance Regime and Disturbance Interactions in a Rocky Mountain Subalpine Forest. *The Journal of Ecology*, *82*(1), 125. https://doi.org/10.2307/2261392

Veblen, T. T., Hadley, K. S., & Reid, M. S. (1991). Disturbance and Stand Development of a

Colorado Subalpine Forest. *Journal of Biogeography*, *18*(6), 707. https://doi.org/10.2307/2845552

Veblen, T. T., Kitzberger, T., & Donnegan, J. (2000). Climatic and Human Influences on Fire Regimes in Ponderosa Pine Forests in the Colorado Front Range. *Ecological Applications*, *10*(4), 1178. https://doi.org/10.2307/2641025

Vorster, A. G., Stevens-Rumann, C., Young, N., Woodward, B., Choi, C. T. H., Chambers, M. E., Cheng, A. S., Caggiano, M., Schultz, C., Thompson, M., Greiner, M., Aplet, G., Addington, R. N., Battaglia, M. A., Bowker, D., Bucholz, E., Buma, B., Evangelista, P., Huffman, D., … West Fordham, A. (2024). Metrics and Considerations for Evaluating How Forest Treatments Alter Wildfire Behavior and Effects. *Journal of Forestry*, *122*(1), 13–30. https://doi.org/10.1093/jofore/fvad036

Walker, R. B., Coop, J. D., Parks, S. A., & Trader, L. (2018). Fire regimes approaching historic norms reduce wildfire-facilitated conversion from forest to non-forest. *Ecosphere*, *9*(4). https://doi.org/10.1002/ecs2.2182

Wasserman, T. N., & Mueller, S. E. (2023). Climate influences on future fire severity: a synthesis of climate-fire interactions and impacts on fire regimes, high-severity fire, and forests in the western United States. *Fire Ecology*, *19*(1), 43. https://doi.org/10.1186/s42408-023-00200-8

Whitman, E., Parisien, M.-A., Thompson, D. K., & Flannigan, M. D. (2019). Short-interval wildfire and drought overwhelm boreal forest resilience. *Scientific Reports*, *9*(1), 18796. https://doi.org/10.1038/s41598-019-55036-7

Whitlock, C., Shafer, S. L., & Marlon, J. (2003). The role of climate and vegetation change in shaping past and future fire regimes in the northwestern US and the implications for ecosystem management. *Forest Ecology and Management*, *178*(1–2), 5–21. https://doi.org/10.1016/S0378-1127(03)00051-3

Williams, A. P., Seager, R., Macalady, A. K., Berkelhammer, M., Crimmins, M. A., Swetnam, T. W., Trugman, A. T., Buenning, N., Noone, D., McDowell, N. G., Hryniw, N., Mora, C. I., & Rahn, T. (2015). Correlations between components of the water balance and burned area reveal new insights for predicting forest fire area in the southwest United States. *International Journal of Wildland Fire*, *24*(1), 14. https://doi.org/10.1071/WF14023

Woolsey, G. A., Tinkham, W. T., Battaglia, M. A., & Hoffman, C. M. (2024). Constraints on Mechanical Fuel Reduction Treatments in United States Forest Service Wildfire Crisis Strategy Priority Landscapes. *Journal of Forestry*, *122*(4), 335–351. https://doi.org/10.1093/jofore/fvae012

Wu, Q. & Brown, A. (2022). whitebox: 'WhiteboxTools' R Frontend. R package version 2.2.0. https://CRAN.R-project.org/package=whitebox

CHAPTER 4: CONCLUSIONS

This study examined burn severity outcomes of wildfires interacting with treatments on the Front Range landscape. To address data limitations and ensure our response variable accurately captured the ecological impacts of wildfire, we first determined an appropriate method and index for measuring burn severity. Using the results from Chapter 2, we investigated how treatments influence burn severity across different fire behavior variables, forest types, and extreme conditions.

Our findings broadly support previous research on treatment effectiveness, demonstrating that intentional treatments involving fire are more effective at reducing burn severity under certain conditions and in specific forest types, while removal and surface fuels reduction treatments were largely comparable to untreated areas and even resulted in higher burn severity. Additionally, our results reinforce that low to moderate severity previous wildfire consistently leads to lower burn severity outcomes in our study fires. By focusing on treatment impacts across multiple forest types, our study contributes to the understanding of wildfire treatment interactions in mid to high elevation forests.

While there is strong consensus around effective treatment strategies in low elevation, frequent fire adapted forests, our study provides evidence supporting the use of managed wildfire across forest types. It also highlights the need for additional research evaluating treatment effects on burn severity in higher elevation, infrequent fire adapted forest types. We found that allowing managed wildfires to burn under moderate conditions is likely to reduce future fire severity across the landscape. As conditions for extreme wildfires continue to align across forest types, the use of effective treatments will be vital for mitigating loss.