Dry forest fuel and biodiversity management in the Pacific Northwest

Don Casimir Radcliffe

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington
2024

Reading committee:
Brian J. Harvey, Chair
Jonathan D. Bakker
Sarah J. Converse

Program Authorized to Offer Degree:
School of Environmental and Forest Sciences

Abstract

Dry forest fuel and biodiversity management in the Pacific Northwest

Don Casimir Radcliffe

Chair of the Supervisory Committee:
Brian J. Harvey
School of Environmental and Forest Sciences

Wildfire suppression and exclusion of Indigenous fire have caused profound changes in many historically frequent-fire ecosystems of the world. In dry and historically frequent-fire forests of interior western North America ('dry forests'), fire deficits have led to uncharacteristically high fuel loading and continuity. To address these changes and reduce potential for severe wildfire, managers commonly apply fuel treatments such as thinning and/or prescribed burning. Fuel treatments can reduce the potential for severe wildfire, open stand structure, and improve habitat for open-forest organisms at local spatial scales in years immediately following treatment implementation. However, many key knowledge gaps remain about the long-term (>10 year) dynamics of fuel profiles and stand structures following fuel treatment, and about the spatial impacts of fuel treatments on dry forest biodiversity.

My first chapter is a literature review briefly synthesizing the state of knowledge of long-term treatment effects on fuel profiles and stand structure and exploring opportunities for new research directions. I found that sufficient literature existed to develop general expectations about fuel and stand structural responses 1-2 decades following fuel treatment types of thin-only, burn-

only, and thin-plus-burn. However, I also found several knowledge gaps including: substantial variability of responses reported within treatment types remained largely unexplored and contributed to large statistical uncertainties, the common practice of comparing long-term results against pre-treatment references may not always have reflected management goals, and low sampling frequency in published long-term studies contributed to uncertainty about continuous trajectories of responses. My next two chapters began to address these knowledge gaps. My second chapter used a long-term experimental site to explore the fine-scale (plot-level) drivers of fuel profile and stand structural variation 15 years following burn-only, thin-only, and thin-plus-burn treatments. I found that pre-treatment conditions were positively associated with long-term responses for most studied response variables, and that treatment intensity was negatively associated with long-term basal area, tree density, and potential for active crown fire. My third chapter used a small but intensively sampled dataset to explore trajectories of fuel profiles and stand structure for 15 years following thin-plus-burn treatments. I found that woody surface fuel showed nonlinear patterns of response to treatment, with the post-treatment surface fuel loads often peaking above pre-treatment fuel loads and the timing and magnitude of responses varying with the size of the fuel component. However, basal area and tree density showed sustained reductions relative to pre-treatment values, and sustained increases in among-plot heterogeneity. In my fourth chapter, I focused on songbird responses to thin-plus-burn treatments, exploring edge effects of treatment and landscape contexts of canopy cover. Most songbird species classified as dense-forest favoring showed higher occupancy of interior positions of un-treated stands, and one species classified as open-forest favoring showed higher occupancy of interior positions of treated stands. Songbirds showed a range of magnitudes and directions of responses to landscape context of canopy cover, indicating that no single management strategy is likely to provide habitat for the full range of species. Collectively, this work provides a range of insights for managers interested in dry forest restoration at broad temporal and spatial scales.

Table of Contents

List of Figures

List of Tables

Acknowledgements

This work would not have been remotely possible without substantial support and guidance from many people. Buckle in for a long acknowledgments section!

Brian Harvey, I can't imagine having had a better PhD adviser. There's never any doubt that you care deeply about me as a person and about my development as a scientist. I've seen all the effort you've put in for me over the years, and for all your students, whether in the lab or in classes. Your passion for the work we do is contagious, and I often think about your frequent statements of "I can't believe I get to do this for a living." That's become a mantra of mine that's helped me get through the more trying aspects of graduate school and academia. I'm excited to keep this journey together going into the postdoc and can't wait to see where it takes us!

To my committee members, I can't begin to express how valuable your support has been over the years. Jon Bakker, I'm always impressed by your clarity of thought and your willingness to go into the weeds of analyses for your students and collaborators. Sarah Converse, I'm eternally grateful that you agreed to tag along on my journey to incorporating wildlife responses into my forest ecology work. You've added much rigor to my understanding of how to analyze wildlife data, and you've always been helpful and gentle when I need to be steered in the right direction. Ernesto Alvarado, I'm in awe of your breadth of perspective on fire ecology, and your ability to keep that perspective grounded in the needs of managers and stakeholders. Jessica Lundquist, I appreciate your commitment to ensuring that this process remains fair and equitable.

My list of collaborators is lengthy, and I consider myself extremely lucky to be in that position. Derek Churchill, I'm deeply grateful for your support and guidance throughout this process; I consider you to be my 'unofficial committee member.' I appreciate the pragmatic guidance on how to do this research in a way that best helps the managers, stakeholders, and policy makers who are the ultimate end users, which is crucial to my research philosophy. Dave W. Peterson, thank you for being so helpful in the preparation for re-surveying the Fire and Fire Surrogates site at Mission Creek, both before and during my time in Washington. Karen Kopper, thank you for being so willing to share the National Park Service Fire Effects Monitoring dataset with me, and generous with your time in getting me going with the analyses. Kate Patronik, thanks a ton for your efforts in getting the updated Fire Effects Monitoring analyses going on a tight timeline, I can't begin to express how helpful you've been and how easy you were to work with in a time when I needed it. Dan Donato, thanks for all the support through multiple projects, including our collaboration with the wildlife aspects of my research. I appreciate how your perspective is both extremely broad and grounded, how you give direct, concise, and reasonable feedback, and how fun you are to work with.

A special shoutout goes to Steve Matthews. Thank you first, Steve, for everything you did for me as my master's adviser, building a strong foundation for me to begin a PhD program. Thank you for showing me that it's possible to be a forest ecologist and a wildlife ecologist without compromising on either specialty, and for your perspective that these two fields are so inter-related that they are really one and the same. I hope I can reach that level of Jedi mastery someday. On top of that, you are one of the nicest people I know. I was very excited when it turned out we would have another opportunity to collaborate.

In the Harvey Lab, our lab-mates are also our family, and I can't begin to express all the ways my lab-mates have helped me. Madison Laughlin, it's been a blast to grow together as scientists entering the lab at the same time. I admire how you never hesitate to help with anything, have so much empathy, and retain such a strong curiosity about the natural world around us. Jenna Morris, you are the most organized, thorough, and put-together scientist I know, and one of the most helpful people. Thanks for all the support since my literal first day in Washington. Dr. Michele Buonanduci, I can only hope to someday approach your level of clarity in thinking about ecology, and I appreciate your rapid and helpful responses every time I bug you about statistics. Dr. Michelle Agne, you're the Harvey Lab OG and our undisputed leader, even as you continue through your next career steps. Thanks for letting me know what I was in for, and for all the other mentorship you've provided. Saba Saberi, I appreciate your straightforward approach to life and lack of tolerance for BS, and I can't wait to see where your PhD work is taking you. Liliana Rangel-Parra, big kudos for diving into the lab during the trying time of the pandemic, and still managing to do excellent work. Thank you for all the help in the field, and for being an awesome concert buddy. Sofia Saenz Kruszka, I can't believe how much you've accomplished in the first year of your masters, you're going to be a rock-star. Thanks for being one of the kindest and most helpful people I know. Angie Liotta, thanks for helping fill out the 'eastside side' of the lab, and for relating to the experience of moving programs and advisers between masters and PhD work. Your work ethic is going to take you far!

So many others have been so helpful. Josh Halofsky, I deeply appreciate your support on multiple projects even though we haven't officially collaborated on anything (yet). Your genuine warmth, curiosity, and ability to put others at ease is unrivalled among ecologists I know. Monique Wynecoop and Eric Pfeifer, thank you for being so helpful in tracking down and organizing the Colville National Forest CFLRP monitoring data, and helping me build on that dataset. I'm looking forward to working together on it in the future. Kate Williams, thank you for your enthusiasm during the search for long-term datasets, and for your help and insights during field scouting. Duncan Lutes, thank you for repeatedly helping me troubleshoot my fire models in a timely manner, and helping me understand FFI data entry. James Johnston and Skye Greenler, thank you for helping me make connections in the Blue Mountains when I wanted to conduct research there, and making me feel welcome there. Bob Van Pelt, thank you for the incredible artwork that brought my pipedream of a nine-panel fuel succession figure to life. It was a monumental effort on your part, and I know it's going to inspire new ideas for long-term research in dry forest restoration. Jerry Franklin, thank you for the inspiration and support. You've been my forest ecology hero since I was a college student in Wisconsin, and I still can't believe I had the opportunity to do field work with you and take your ecological forestry class.

None of this work would have been remotely possible without all the field technicians that have made substantial sacrifices to their personal lives to help me collect data in forests far from home. These folks include Michael McNorvell, Hannah Wilson, Hiruni Jayasekera, Sarah Burrington, Nicole Lau, Jocelyn Hernandez, Patrick McGee, Marwa Mahmoud, Marcela Todd, Allison Phillips, Maddy Stone, Sienna Patton, Sam Tharpgeorge, Paige Byassee, Mark Elbrect. I'm eternally grateful to count you among my friends. Special shout-outs to Michael McNorvell for sticking around for multiple seasons and having great taste in music and puns, and to Marwa Mahmoud for lots of post-season help with data management. Thank you Sam Tharpgeorge for leading our Colville National Forest work, and for everything else you've done. Additionally, thanks to Allison Phillips and Mark Elbrect for giving me the opportunity to advise your capstone projects, I surely learned as much as you, and had a great time working with you.

Extra special shoutout to Marwa Mahmoud, Marcela Todd Zaragoza, Michael McNorvell, Maddy Stone, and Sienna Patton for sticking with me during the trying times of the 2020 pandemic field season, when we quarantined together all summer. Holy s***, that was one

of the most intense and sometimes grueling experiences of my life, but I also have some of my best memories from working with y'all: Camas, DodgeGate, Luna Peak, and the once-a-month AirBnb stays. It's safe to say that the surprise half-birthday party was the most unexpected party anyone has ever thrown me, and it was a very thoughtful gesture. Thank you for making that summer bearable and sometimes even fun! After seeing your perseverance that season, I had no doubt about your futures, and it has been immensely gratifying to see each of you follow your ecological passion and become rockstars in your own work.

My work was made possible by a variety of funding sources, for which I am extremely grateful. Thank you first to the University of Washington School of Environmental and Forest Sciences and the College of Environmental for making fellowship offers with my admission, it was deeply appreciated and a major factor in my decision to do my PhD at the University of Washington. Thank you also to the McIntire-Stennis Cooperative Forestry Research Program (USDA-NIFA-10202-MSCFRXXX-18-0002) the Washington Department of Natural Resources (Funding Agreement 93-100144) for additional research assistantship funding supporting with their Graduate Research Innovation Award (Project ID 22-1-01-7), and funded my continuation of long-term treatment research in my upcoming postdoctoral fellowship (Project ID 23-2-01-7).

To my friends in Seattle: thank you so much for being my family away from home. I could have never finished this dissertation without you, and I hope I'll get to see more of you soon than I have in the last few months. Deborah Nemens, thank you for being there from my early days in Seattle, for the countless meals you've cooked me, for the music we've made, and for being generous with your very sweet and *very* crazy dog Palo. I know that I can turn to you whenever I need something, and sometimes that has really saved me. Jake Reny, it feels like we've known each other a lot longer than a couple short years. Thank you for always showing up extraordinarily prepared, whether our day involved an epic experience in the mountains or just having a good time with friends. Anthony Stewart, you're a real one, and I hope we've got at least couple more winters of snow adventures together. I feel bad for missing your wedding for this little ol' defense, and hope to see you and Karen on your home Alaskan turf at another time. James and Jayme Mutchler, thanks for bringing a piece of the Midwest out to Seattle, and for always be willing to geek out on something with me. Let's go on a miserable off-trail slog up a remote choss-pile sometime soon. Bryce-Bartl Geller, thanks for all the adventures, for your openness, and for always pushing me to do harder climbs than I want to attempt. Stuart Illson, I was sad to see you leave for Bellingham so soon after we met, but happy for your life there and grateful we've been able maintain our connection. Thanks for being so genuine, helpful, and knowledgeable, while also being someone I can always just chill with. Kevin Goepp, thank you for being The Great Connector, and for always being willing to help out a friend in need. Doug Chalmers, thanks for all the incredible memories, for taking me into your musical life when I was green, for showing me the true meaning of stage presence, and for teaching Seattle how cool the banjo is. Ed Hou, thank you for being generous in so many ways, and for always knowing just the right amount of feedback to give to help me grow as a musician. Amy Lee, you're one of my favorite musicians ever and coolest people I know, and I feel lucky for so many reasons to count you among my friends. To everyone else: thank you for everything!

To my partner Adrien Owens, thank you for all your love and support through this trying process. I feel incredibly blessed to have a partner who shares a passion for the natural world, has an extremely keen sense of empathy, and makes beautiful art of all kinds. I'm in awe of the music we've been able to make, and can't wait to see where it goes. Mostly, I can't wait for this next chapter in our lives together.

Finally, this PhD work would never have been possible without my family in Wisconsin. To my brother Matt, thanks for having kids so Mom would quit bugging me about it, and for your kind heart. To my sibling Lou, I'm so proud of you for getting through college and becoming an adult through the trying times of the pandemic, and hope you find the next stages of the journey fun and satisfying. To Grandma, thanks for the trips up North, they really helped inspire me to become an ecologist. And a spatial thanks to my parents, Cheryl and Chad Hoff. Thank you for inspiring the fundamental elements of this work from my earliest years and onward: my love of nature, reading, and writing. Thank you for modelling gratitude, recognition, and reciprocity in working with and/or supervising people, these practices have been crucial to so many pieces of my work. Thank you for being there for me as I went down this strange and often confusing career path, and for giving me unconditional support across time zones even when I wasn't sure where this path was headed or too deep into the work to return phone calls often. I dedicate this work to you, Cheryl and Chad.

Published Materials

A portion of the materials presented in this dissertation have been published through the peer-review process. This article is presented in full as Chapter 2 and is reprinted with permission from Elsevier.

Radcliffe, D. C., J. D. Bakker, D. J. Churchill, E. C. Alvarado, D. W. Peterson, M. M. Laughlin, and B. J. Harvey. 2024. How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests? Forest Ecology and Management 553:121594.

Introduction

Wildfire impacts on ecological and social values have increased globally in recent decades (Schoennagel et al. 2017, Moreira et al. 2020, Haque et al. 2021). Wildfire is a natural process that has shaped most terrestrial vegetated ecosystems for millions of years (Pausas and Keeley 2019, McLauchlan et al. 2020), but several factors have recently increased the negative consequences of wildfire relative to those of the last century. These factors include: climate change increasing length and intensity of burn seasons (Liu et al. 2010, Westerling 2016), expanding development increasing negative consequences of fire for humans (Ager et al. 2017, Radeloff et al. 2018), and fire suppression and exclusion of Indigenous fire leading to higher accumulation of fuel (Burrows 2008, Moreira et al. 2020, Hagmann et al. 2021). The relative importance of these factors varies by specific ecological and social context, depending on historical fire regime, seasonal climate variations, human development patterns, and primary ignition sources (Schoennagel et al. 2004, Halofsky et al. 2018).

Forest types that burned frequently before European colonization ('frequent-fire forests') have often missed several fire cycles since colonization. Fire suppression in frequent-fire forests eventually leads to an uncharacteristic fuel accumulation (Agee and Skinner 2005) that makes suppression less feasible over time (Ingalsbee 2017). When wildfires escape containment in fire-suppressed forests, they often cause larger patches of severe wildfire, defined as wildfire with major impacts on ecosystems (Keeley 2009), partially due to escapes being most likely in extreme fire weather conditions (North et al. 2015). Severe wildfire often causes large tree mortality patches (Harvey et al. 2016, Stevens et al. 2017). Large tree mortality patches threaten those frequent-fire forests for which the keystone tree species' reproductive strategy is avoiding topkill through adaptations such as thick bark and self-pruning of branches (Keeley et al. 2011).

Such tree species often have relatively large seeds with short-distance dispersal abilities and cannot disperse in large numbers into uncharacteristically large patches of high-severity wildfire (Haire and McGarigal 2010).

Reducing fuel loads and disrupting continuity of fuel are thus primary goals of many restoration plans in frequent-fire forests (Schoennagel et al. 2004, Franklin and Johnson 2012), to improve the probability that trees survive wildfire (Coop et al. 2020). In the terminology of resilience theory, fuel treatments increase the 'resistance' of fire-tolerant trees, or their ability to withstand disturbance without undergoing major changes in structure and function. Increased resistance confers fire-frequent forests with 'resilience', or the ability to return to similar conditions following disturbance (i.e., wildfire) (Walker et al. 2004).

Managers of frequent-fire forests consider many values other than fuel reduction, and ecological forestry offers a framework with which a holistic suite of values can be addressed (Franklin et al. 2018). Ecological forestry or ecological forest management is a management philosophy that seeks to sustain native biota, diverse ecosystem services, and human communities. Ecological forest management plans start from a model of 'natural' forest development. Ecological forestry regards the future as unpredictable and therefore strives to maximize social, economic, and ecological options for responding to unexpected changes, rather than maximizing any one ecosystem service. Ecological forestry views legitimate management activities as existing along a continuum from intensive economic production areas to 'preserved' areas. Ecological forestry is adaptive, continually incorporating monitoring data, scientific advances, and changing stakeholder and societal preferences (Franklin et al. 2018).

Among many considerations of ecological forest management in frequent-fire forests, three key aspects are managing for fuel profiles, structural heterogeneity, and biodiversity conservation (Franklin and Johnson 2012). My dissertation focused on these aspects following fuel treatments in dry forests in the western United States, with the goal of increasing the breadth of knowledge needed to support ecological forest management. I define 'dry forests' as forests of western North America that experienced frequent low- to moderate-severity fuel-limited wildfire before European colonization. Dry forests are primarily dominated by thick-barked tree species such as ponderosa pine (*Pinus ponderosa*), Jeffrey pine (*Pinus jeffreyi*), and/or Douglas fir (*Psuedotsuga menziesii*) (Stephens and Fulé 2005, Franklin et al. 2018). Fire suppression in dry forests often leads to accumulation of surface fuel, shrubs, and/or tree saplings, leaving dry forests vulnerable to severe wildfires that may cause a change to non-forest conditions (Hagmann et al. 2021).

To address ecological forest management aspects of fuel treatment planning, I used tools and concepts from forest ecology, silviculture, fire ecology, restoration ecology, landscape ecology, and wildlife ecology. I worked closely with collaborators from a range of agencies and academic contexts to ensure that the study questions I asked and the results I presented were relevant to managers, policy makers, and other stakeholders in dry forest restoration. I focused the first three chapters of my dissertation on long-term fuel and stand structure dynamics in fuel treatments, because the Washington Department of Natural Resources and many researchers have identified long-term treatment effects as a key knowledge gap in dry forest restoration planning.

In Chapter 1, I conducted a literature review to briefly synthesize the state of knowledge on long-term treatment effects on fuel profiles and stand structure, and then explored knowledge gaps and opportunities for future research in detail. The synthesis revealed that thin plus burn treatments showed long-term effects on stand structure and canopy fuel across several studies.

Additionally, the research opportunities I identified were: acknowledging inherently high variance and associated statistical challenges, referencing both departure from un-treated conditions and arrival to desired conditions, exploring within-treatment drivers of long-term responses, increasing sampling frequency of post-treatment surveys, and incorporating spatial heterogeneity over time. These research opportunities formed the foundation of the study questions I asked for Chapter 2 and Chapter 3, and will continue to inform my future research. In Chapter 2, I studied 15-year responses to burn-only, thin-only, and thin-plus-burn treatment, exploring the long-term effects of fine-scale drivers such as pre-treatment conditions, treatment intensity, and site productivity, and comparing modelled wildfire behavior with desired treatment outcomes. These analyses revealed the importance of fine-scale drivers like pre-treatment conditions and treatment intensity to long-term responses within a given treatment type. In Chapter 3, I explored trajectories of fuel profile and stand structural responses to treatment over time, harnessing a small but intensively sampled dataset with frequent and consistent monitoring following thin-plus-burn treatments. I found nonlinear trends of surface fuel biomass following treatment, characterized by periods of post-treatment accumulation and followed by decomposition. Collectively, these 3 studies expand the field of long-term treatment effects research in new conceptual directions which will give managers, policy makers, and stakeholders a greater toolset for making decisions about long-term treatment maintenance and dry forest restoration planning.

However, reducing fuel and opening forest conditions is not enough to ‘restore’ a forest, and the history of forestry has many examples of ecosystem homogenization and subsequent loss of resilience from management practices carried out with good intentions (Holling and Meffe 1996). Maintenance of biodiversity is a crucial tenet of ecological forestry, both for the intrinsic value of biodiversity and as an indicator of overall forest ecosystem vitality and adaptive capacity (Franklin et al. 2018). Therefore, I proposed and received funding to study one aspect of biodiversity responses to treatment. Specifically, in Chapter 4, I used a spatially-explicit landscape ecology framework to investigate edge effects of thin-plus-burn treatments and landscape effects of canopy cover on breeding bird occupancy. A key finding was association with interior un-treated forest for 5/8 dense-forest favoring species, and association with interior treated forest for 1/8 open-forest favoring species. While dense-forest patches may be challenging to maintain from a fuel management perspective, Chapter 4 indicates they may have some conservation value even for relatively common songbird species.

References

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Ager, A. A., C. R. Evers, M. A. Day, H. K. Preisler, A. M. G. Barros, and M. Nielsen-Pincus. 2017. Network analysis of wildfire transmission and implications for risk governance. PLOS ONE 12:e0172867.

Burrows, N. D. 2008. Linking fire ecology and fire management in south-west Australian forest landscapes. Forest Ecology and Management 255:2394–2406.

Coop, J. D., S. A. Parks, C. S. Stevens-Rumann, S. D. Crausbay, P. E. Higuera, M. D. Hurteau, A. Tepley, E. Whitman, T. Assal, B. M. Collins, K. T. Davis, S. Dobrowski, D. A. Falk, P. J. Fornwalt, P. Z. Fulé, B. J. Harvey, V. R. Kane, C. E. Littlefield, E. Q. Margolis, M. North, M. A. Parisien, S. Prichard, and K. C. Rodman. Wildfire-driven forest conversion in Western North American landscapes. BioScience 70:659–673.

Franklin, J. F., and K. N. Johnson. 2012. A Restoration Framework for Federal Forests in the Pacific Northwest. Journal of Forestry 110:429–439.

Franklin, J. F., N. K. Johnson, and D. L. Johnson. 2018. Ecological Forest Management. First edition. Waveland Press, Long Grove, IL.

Hagmann, R. K., P. F. Hessburg, S. J. Prichard, N. A. Povak, P. M. Brown, P. Z. Fulé, R. E. Keane, E. E. Knapp, J. M. Lydersen, K. L. Metlen, M. J. Reilly, A. J. S. Meador, S. L. Stephens, J. T. Stevens, A. H. Taylor, L. L. Yocom, M. A. Battaglia, D. J. Churchill, L. D. Daniels, D. A. Falk, P. Henson, J. D. Johnston, M. A. Krawchuk, C. R. Levine, G. W. Meigs, A. G. Merschel, M. P. North, H. D. Safford, T. W. Swetnam, and A. E. M. Waltz. 2021. Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. Ecological Applications e02431.

Haire, S. L., and K. McGarigal. 2010. Effects of landscape patterns of fire severity on regenerating ponderosa pine forests (Pinus ponderosa) in New Mexico and Arizona, USA. Landscape Ecology 25:1055–1069.

Halofsky, J. S., D. C. Donato, J. F. Franklin, J. E. Halofsky, D. L. Peterson, and B. J. Harvey. 2018. The nature of the beast: examining climate adaptation options in forests with stand-replacing fire regimes. Ecosphere 9:e02140.

Haque, Md. K., Md. A. K. Azad, Md. Y. Hossain, T. Ahmed, M. Uddin, Md. M. Hossain, Md. K. Haque, Md. A. K. Azad, Md. Y. Hossain, T. Ahmed, M. Uddin, and Md. M. Hossain. 2021. Wildfire in Australia during 2019-2020, Its Impact on Health, Biodiversity and Environment with Some Proposals for Risk Management: A Review. Journal of Environmental Protection 12:391–414.

Harvey, B. J., D. C. Donato, and M. G. Turner. 2016. Drivers and trends in landscape patterns of stand-replacing fire in forests of the US Northern Rocky Mountains (1984–2010). Landscape Ecology 31:2367–2383.

Holling, C. S., and G. K. Meffe. 1996. Command and control and the pathology of natural resource management. Conservation Biology 10:328–337.

Ingalsbee, T. 2017. Whither the paradigm shift? Large wildland fires and the wildfire paradox offer opportunities for a new paradigm of ecological fire management. International Journal of Wildland Fire 26:557–561.

Keeley, J. E. 2009. Fire intensity, fire severity and burn severity: a brief review and suggested usage. International Journal of Wildland Fire 18:116.

Keeley, J. E., J. G. Pausas, P. W. Rundel, W. J. Bond, and R. A. Bradstock. 2011. Fire as an evolutionary pressure shaping plant traits. Trends in Plant Science 16:406–411.

Liu, Y., J. Stanturf, and S. Goodrick. 2010. Trends in global wildfire potential in a changing climate. Forest Ecology and Management 259:685–697.

McLauchlan, K. K., P. E. Higuera, J. Miesel, B. M. Rogers, J. Schweitzer, J. K. Shuman, A. J. Tepley, J. M. Varner, T. T. Veblen, S. A. Adalsteinsson, J. K. Balch, P. Baker, E. Batllori, E. Bigio, P. Brando, M. Cattau, M. L. Chipman, J. Coen, R. Crandall, L. Daniels, N. Enright, W. S. Gross, B. J. Harvey, J. A. Hatten, S. Hermann, R. E. Hewitt, L. N. Kobziar, J. B. Landesmann, M. M. Loranty, S. Y. Maezumi, L. Mearns, M. Moritz, J. A. Myers, J. G. Pausas, A. F. A. Pellegrini, W. J. Platt, J. Roozeboom, H. Safford, F. Santos, R. M. Scheller, R. L. Sherriff, K. G. Smith, M. D. Smith, and A. C. Watts. 2020. Fire as a fundamental ecological process: Research advances and frontiers. Journal of Ecology 108:2047–2069.

Moreira, F., D. Ascoli, H. Safford, M. A. Adams, J. M. Moreno, J. M. C. Pereira, F. X. Catry, J. Armesto, W. Bond, M. E. González, T. Curt, N. Koutsias, L. McCaw, O. Price, J. G. Pausas, E. Rigolot, S. Stephens, C. Tavsanoglu, V. R. Vallejo, B. W. Van Wilgen, G.

Xanthopoulos, and P. M. Fernandes. 2020. Wildfire management in Mediterranean-type regions: Paradigm change needed. Environmental Research Letters 15:011001.

North, M. P., S. L. Stephens, B. M. Collins, J. K. Agee, G. Aplet, J. F. Franklin, and P. Z. Fulé. 2015. Reform forest fire management. Science 349:1280–1281.

Pausas, J. G., and J. E. Keeley. 2019. Wildfires as an ecosystem service. Frontiers in Ecology and the Environment 17:289–295.

Radeloff, V. C., D. P. Helmers, H. Anu Kramer, M. H. Mockrin, P. M. Alexandre, A. Bar-Massada, V. Butsic, T. J. Hawbaker, S. Martinuzzi, A. D. Syphard, and S. I. Stewart. 2018. Rapid growth of the US wildland-urban interface raises wildfire risk. Proceedings of the National Academy of Sciences115:3314–3319.

Schoennagel, T., J. K. Balch, H. Brenkert-Smith, P. E. Dennison, B. J. Harvey, M. A. Krawchuk, N. Mietkiewicz, P. Morgan, M. A. Moritz, R. Rasker, M. G. Turner, and C. Whitlock. 2017. Adapt to more wildfire in western North American forests as climate changes. Proceedings of the National Academy of Sciences 114:4582–4590.

Schoennagel, T., T. T. Veblen, and W. H. Romme. 2004. The interaction of fire, fuels, and climate across Rocky Mountain forests. BioScience 54:661–676.

Stephens, S. L., and P. Z. Fulé. 2005. Western Pine Forests with Continuing Frequent Fire Regimes: Possible Reference Sites for Management. Journal of Forestry 103:357–362.

Stevens, J. T., B. M. Collins, J. D. Miller, M. P. North, and S. L. Stephens. 2017. Changing spatial patterns of stand-replacing fire in California conifer forests. Forest Ecology and Management 406:28–36.

Walker, B., C. S. Holling, S. R. Carpenter, and A. Kinzig. 2004. Resilience, adaptability and transformability in social-ecological systems. Ecology and Society 9:5.

Westerling, A. L. 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philosophical Transactions of the Royal Society B: Biological Sciences 371:20150178.

Chapter 1: Opportunities to expand understanding of long-term treatment effects in historically frequent-fire forests

Don C. Radcliffe[1*], Jonathan D. Bakker[1], Derek J. Churchill[2], and Brian J. Harvey[1]

[1]University of Washington, School of Environmental and Forest Sciences, Seattle, WA, USA
[2]Washington Department of Natural Resources, Forest Resilience Division, Olympia, WA, USA
*Corresponding author: dradclif@uw.edu

1.1 Abstract

Fuel and restoration treatments ('treatments') have been applied across millions of acres in dry and historically frequent-fire forests of interior western North America ('dry forests') to reduce the potential for severe wildfire that threatens forest resilience. Despite their widespread application, long-term effects of treatments on fuel profiles are not well understood. This knowledge gap could lead to inefficient use of limited resources for treatment, which would hinder long-term dry forest stewardship. New and complementary approaches to studying long-term treatment effects can expand understanding for researchers, managers, policymakers, and other stakeholders. In this synthesis paper, we briefly summarize knowledge on long-term treatment effects, and propose a model of fuel succession following three common treatment types (burn-only, thin-only, and thin-plus-burn). We then propose five opportunities for future research: acknowledging inherently high variance and associated statistical challenges, referencing both departure from un-treated conditions and arrival to desired conditions, exploring within-treatment drivers of long-term responses, increasing sampling frequency of post-treatment surveys, and incorporating spatial heterogeneity over time. Incorporating these opportunities into studies of long-term treatment effects could help managers, policy makers, and other

stakeholders identify more efficient use of limited resources for fuel treatment maintenance and support long-term dry forest stewardship.

1.2 Introduction

More than a century of fire suppression and exclusion of Indigenous fire has led to uncharacteristically high fuel loads in dry and historically frequent-fire forests of interior western North American ('dry forests') (Hagmann et al. 2021). Managers use fuel and forest restoration treatments ('treatments') such as prescribed burning and/or thinning to remove fuel and manipulate stand structure in ways that reduce potential for uncharacteristically severe wildfire (Jain et al. 2012, Stephens et al. 2020, Prichard et al. 2021). Accordingly, treatments have been applied across millions of acres of public and private land in recent decades (Barnett et al. 2016). The short-term effects of these treatments on fuel, forest structure, and wildfire behavior have been extensively studied through observations and models (Agee and Skinner 2005, Schwilk et al. 2009, Stephens et al. 2012b, Prichard et al. 2021). In contrast, relatively few studies have explored long-term treatment effects (e.g., >10 years following implementation) on fuel profiles, stand structure, and potential wildfire behavior. This lack of information may lead to inefficiencies in fuel treatment maintenance planning, and inability to assess tradeoffs between maintaining treated stands and treating previously un-treated stands. Efficiency in treatment planning is crucial for long-term dry forest stewardship, given large treatment deficits (Haugo et al. 2019, Laughlin et al. 2023) and major logistical, political, and budgetary constraints to treatment implementation (Reinhardt et al. 2008, North et al. 2015, Kolden 2019).

Insights from a range of studies suggest that trends in fuel succession may vary among treatment types in relatively consistent general patterns (Fig. 1.1 & Fig. 1.2), with a wide range of variation within treatment types. Among studied treatment types, thinning followed by prescribed burning ('thin-plus-burn treatment') often shows the strongest long-term effects on reducing fuel (Stephens et al. 2012a, Hood et al. 2020, 2024, Morici and Bailey 2021) and wildfire severity (Brodie et al. 2024, Davis et al. 2024). The rapid combination of treatments reduces surface, ladder, and canopy fuels within a short period (Schwilk et al. 2009, Fulé et al. 2012), likely extending treatment longevity for aspects such as canopy-fire potential (Radcliffe et al. 2024, Brodie et al. 2024). Burn-only treatments can reduce some aspects of surface fuel and/or ladder fuel into the long-term, but have less effect on canopy fuel (Keifer et al. 2006, Battaglia et al. 2008, van Mantgem et al. 2016, Busse and Gerrard 2020). Conversely, thin-only treatments can reduce canopy fuel into the long-term, but often increase ladder fuel because saplings that survive initial treatment can respond quickly to canopy openings (Vaillant et al. 2015, Hood et al. 2020, 2024, Radcliffe et al. 2024). Mastication can have variable long-term effects on surface fire potential, depending on decay rates of masticated pieces (Kreye et al. 2014, Reed et al. 2020, Wozniak et al. 2020).

Despite the observations of these general patterns, much variability in long-term responses exists within any given treatment type, suggesting that many knowledge gaps in long-term treatment effects remain. Comparisons among treatment types often contain high variance and correspondingly low statistical power in both the short-term (Agee and Lolley 2006) and long-term (Radcliffe et al. 2024), which may lead to underestimation of fuel treatment longevity. Most studies use pre-treatment conditions as the major point of reference for short-term (Schwilk et al. 2009) and long-term results (van Mantgem et al. 2016, Hood et al. 2020) while comparisons with desired conditions may be more meaningful in many management situations. The effect of factors that may vary within a given treatment type, such as pre-treatment conditions, site productivity, and treatment intensity, has received relatively little attention (Keifer et al. 2006, Stephens et al. 2023). Low frequency of field data collection (Morici and Bailey 2021, Radcliffe et al. 2024) limits inference about the shape and direction of responses to treatment over time. Patterns of heterogeneity in response to treatment remain relatively unexplored in the long-term (Battaglia et al. 2008, Crotteau et al. 2018), despite the possibility of heterogeneity increasing with time since treatment.

Addressing these knowledge gaps can develop further understanding of long-term treatment effects, which may help improve stewardship planning for dry forests on broad spatial and temporal scales. In this synthesis, we propose five opportunities that build on valuable insights gained thus far from experimental and chronosequence study designs:

- Acknowledging inherently high variance and associated statistical challenges
- Referencing both departure from un-treated conditions and arrival to desired conditions
- Exploring within-treatment drivers of long-term responses
- Increasing sampling frequency of post-treatment surveys
- Incorporating spatial heterogeneity over time

These opportunities represent a menu of options for expanding knowledge about long-term treatment effects, to be considered when working with long-term data or designing new studies. Furthermore, questions we explore about statistical inference (Wasserstein et al. 2019), reference points (Durbecq et al. 2020), fine-scale drivers (Graham et al. 2019), sampling frequency (Rasmussen et al. 2013), and heterogeneity of responses (Fraterrigo and Rusak 2008) are common to many fields of ecological research. Therefore, we believe that many of the study design opportunities we highlight may be applicable to a diverse range of ecological contexts.

1.3 Acknowledging inherently high variance and associated statistical challenges

Context

High spatial and temporal heterogeneity of fuel profiles and forest structures is an intrinsic feature of dry forests, leading to challenges that often go unacknowledged with traditional statistical approaches. Most studies have assessed long-term treatment effectiveness using statistical comparisons of treatments with pre-treated or un-treated controls, and often report high variance within each treatment category (e.g., Stephens et al. 2012, Crotteau et al. 2018, Hood et al. 2020, Morici and Bailey 2021, Radcliffe et al. 2024). High variance within and among treatment types likely stems from spatial and temporal heterogeneity in stand structures and fuel profiles, a defining characteristic of dry forests (Keane et al. 2001, Franklin et al. 2012, Hessburg et al. 2015, Vakili et al. 2016). Sources of heterogeneity may include disturbance history and topo-edaphic conditions (Larson and Churchill 2012), intentional creation of heterogeneity in treatment prescriptions (Churchill et al. 2013, Stephens et al. 2020), and/or heterogeneous responses to treatment over time (Radcliffe et al. 2024). High variance increases statistical uncertainty (Lieber 1990, Morrison et al. 2008) and can lead to erroneous declarations of no difference between treatment and control when real differences exist (i.e., a ‘type II error’; Baguley 2004)—potentially leading to underestimates of treatment longevity (Fig. 1.3).

Statistical uncertainty cannot be eliminated (Wasserstein et al. 2019), but uncertainty may be reduced through large sample sizes and/or selective sampling. In high-variance contexts such as treatment studies, large sample sizes may be necessary to increase confidence in results

(Betensky 2019). High sample sizes may not always be feasible, however, because fuel data are labor intensive to collect and funding for long-term monitoring is often limited (Lindenmayer and Likens 2010). Researchers may choose to stratify samples to focus on a specific set of conditions (e.g., mature *Pinus ponderosa* forests on south-facing aspects), which may be useful for reducing variance (Ziliak 2019). However, it may often be infeasible to conduct treatments within a narrow range of environmental parameters, and unexpected sources of variance are common in ecological experiments (Morrison et al. 2008). Furthermore, studies conducted within narrow ranges of conditions may have limited generalizability (Wenger and Olden 2012). Another strategy could be to focus on one treatment type, which could increase sample effort per treatment type given a fixed budget for sampling. Additionally, focusing on one treatment type could allow for greater focus on analyses of continuous variables such as time (Battaglia et al. 2008, van Mantgem et al. 2016, Reed et al. 2020) or treatment intensity (Radcliffe et al. 2024), which inspire conceptual innovations in long-term treatment research.

Opportunities

To address issues with high variance, we suggest-using study designs that reduce statistical uncertainty when possible. However, we also encourage a broader acceptance of uncertainty, interpreting results within the context of prior research, and being mindful of all factors that may affect statistical uncertainty (e.g., variance, sample size, effect size, and alpha value) (Nakagawa and Cuthill 2007, Shieh 2019, Wasserstein et al. 2019). For example, large effect sizes with wide confidence intervals may be common in long-term treatment studies (Radcliffe et al. 2024), and could indicate an interesting effect of the predictor variable with high variance in the response variable and/or low sample size (Nakagawa and Cuthill 2007), potentially justifying increasing sample sizes and/or exploring drivers of variance. Additionally, synthetic analyses and meta-analyses can reduce uncertainty by aggregating data from multiple studies (Arnqvist and Wooster 1995, Lortie 2014), and researchers could strive where possible to facilitate future meta-analyses, by comprehensively reporting point estimates and uncertainty estimates of all response variables collected or modelled in a study (Lortie et al. 2015).

1.4 Referencing both departure from un-treated conditions and arrival to desired conditions

Context

Testing for both departure from un-treated conditions and arrival to desired conditions can increase applicability of long-term study results to diverse management contexts. Treatment longevity is commonly assessed by testing for departure from un-treated conditions (e.g., Hood et al. 2024, Radcliffe et al. 2024), aligning with standard statistical practice emphasizing the importance of statistical controls (Morrison et al. 2008). Testing for departure from un-treated conditions may allow managers to assess whether treatments have any long-term benefit relative to un-treated stands. Thus, un-treated reference data can be useful for managers with limited treatment budgets and large amounts of un-treated and un-disturbed forest under their jurisdiction, which is a common scenario (North et al. 2015). However, un-treated conditions are often not meaningful to restoration goals. Dry forests without recent treatment or disturbance are generally considered to have departed from the historical range of variation and from desired conditions (Hagmann et al. 2021), and may have variable conditions depending on abiotic factors and historical treatment/disturbance history (Hessburg et al. 2015). Therefore, arrival to desired conditions may be a more appropriate reference for high value stands, and a more stable reference over time, relative to un-treated conditions. Desired conditions may also be useful for analyzing effectiveness of maintenance treatments, for which true 'pre-treatment' data may not have been collected or may not be relevant to management goals.

Identification of target outcomes is a very challenging but critical step in quantifying arrival to desired conditions (McIver and Weatherspoon 2010, Ager et al. 2014). Desired conditions may be established from short-term treatment results, data from reference sites, and/or *a priori* determination of management goals. Short-term treatment results are an easy point of comparison for long-term treatment results, when data are collected in the years immediately following treatment. However, using short-term treatment results as a proxy for desired conditions is valid only if a treatment meets restoration goals, and treatment results can be variable (Reinhardt et al. 2008). Reference stands with fire regimes in line with historical range of variation may be used to established desired conditions, especially when forest restoration is a primary goal of fuel treatment (Stephens 2004, Falk 2006, Murphy et al. 2021, Chamberlain et al. 2023). However, fuel data from reference sites in such conditions are relatively scarce, limiting their generalizability (Stephens and Fulé 2005). Additionally, historic and modern ranges of variability in fire regimes may not align with future ranges of variability as climate change and species invasions alter ecosystems (Keane et al. 2009). Therefore, it may be useful (albeit challenging) to define desirable conditions *a priori* based on local management goals, climate context, and/or reference sites, to use as indicators or thresholds in determining long-term treatment effectiveness (Battaglia et al. 2008, Stephens et al. 2023, Radcliffe et al. 2024).

Desired conditions are likely most easily translated to fuel management goals in terms of potential wildfire behavior (Ager et al. 2014), but wildfire modelling requires careful consideration. Specific goals for potential wildfire behavior will vary by socioecological, policy, funding, and management context (Jain et al. 2012, Jewell and Vilsack 2014, Urgenson et al.

2017, 2018, Stephens et al. 2020). Important metrics include wildfire behavior (e.g., surface flame length, rate of spread), indices of critical thresholds in wildfire behavior (e.g., torching index, crowning index), and secondary effects (e.g., tree mortality, smoke emissions) (Agee 1996). Different metrics are valuable to managers in different contexts. For example, wildland firefighters may be interested in a fire behavior metric (e.g., rate of spread) relevant to firefighter safety and feasibility of containment (Cruz et al. 2018), while forest managers may be more interested in an ecological metric (e.g., tree mortality) as an indicator of resilience to fire (Falk et al. 2022). Additional complexity exists because weather parameters strongly affect modelled fire behavior (Penman et al. 2020), and different treatments may be designed to be effective in different weather scenarios depending on how crucial it is that a specific treated area have high resistance to severe wildfire (North et al. 2021).

Opportunities

We suggest testing for both the departure from un-treated conditions and arrival to desired conditions. We suggest evaluating desired conditions using potential wildfire behavior (Ager et al. 2014, Radcliffe et al. 2024), and considering comparison with reference conditions or short-term conditions where they align with management goals. When using potential wildfire behavior, a variety of wildfire model outputs across a variety of weather conditions may be reported, to increase generalizability of study results across diverse management contexts. Analyses referencing desired conditions may be most powerful when researchers choose specific thresholds for potential wildfire behavior based on local weather patterns, management goals, and ecological context, while also reporting enough information so that different stakeholders may evaluate results across diverse management goals. Additionally, researchers may choose to comprehensively report summary statistics of field-collected fuel variables in tabular format, to allow for future revisiting of wildfire models with changes in management goals or advances in wildfire modelling techniques.

1.5 Exploring within-treatment drivers of long-term responses

Context

Drivers of change that vary within a treatment type are a key factor in determining long-term treatment outcomes. High within- and among-stand variability in fuel profiles and stand structure (Hood et al. 2020, Morici and Bailey 2021) suggests opportunities to learn from continuous variables representing fine-scale (e.g., <1 ha) gradients (Radcliffe et al. 2024). Within-treatment drivers offer opportunities to focus on changes in one treatment type over time, which may inspire conceptual innovation because long-term studies have primarily focused on the effect of treatment type. Additionally, exploring within-treatment drivers may increase statistical power, because there is often higher variance within broad treatment types than at a given numerical value of a continuous variable within a treatment type (Radcliffe et al. 2024). Within-treatment drivers can be divided into two categories: inherited factors and treatment regimes (Fig. 1.4).

We define inherited factors as the conditions that exist at a site before treatment, which constrain possible short-term and long-term treatment outcomes. Two important examples of inherited factors are pre-treatment stand conditions and site productivity (Reinhardt et al. 2008). Pre-treatment stand conditions are affected by past management, disturbance, and abiotic conditions, and are likely to affect treatment implementation (Jain et al. 2012, Maher et al. 2019) and fuel responses to treatment over time (Radcliffe et al. 2024). Pre-treatment conditions can be measured as the pre-treatment value of the variable being tested (Radcliffe et al. 2024), or by measuring a stand structure indicator such as canopy cover (Zald et al. 2024). Site productivity affects rates of vegetation growth (McLeod and Running 2011, Zhang et al. 2011) and decomposition (Harmon et al. 1986, Hall et al. 2006). Stands on more productive sites are likely to show faster decomposition and growth rates, and therefore fuel treatments on more productive sites may have less longevity (Jain et al. 2012). However, studies exploring the effects of site productivity on long-term responses to treatment have used varying methods and response variables, and found varying results (Tinkham et al. 2016, Ex et al. 2019, Fialko et al. 2020, Morici and Bailey 2021, Radcliffe et al. 2024). Productivity can be quantified with a variety of methods in dry forests (McLeod and Running 1988), and treatment research would benefit from exploratory analyses investigating which productivity metrics are most strongly related to long-term treatment outcomes.

Treatment regimes include all details of treatment implementation. Treatment category is commonly the focal aspect of the treatment regime in long-term treatment studies, but treatment intensity is another critical factor driving long-term effects of a treatment (Radcliffe et al. 2024). Treatment intensity may be defined broadly as the amount of fuel removed in a treatment. Treatment intensity could be measured as the change from pre-treatment to the immediate post-treatment for some response variable such as canopy cover (Dudney et al. 2021), or measured with a satellite-derived index like relativized differenced normalized burn ratio (RdNBR) when short-term post-treatment data aren’t available (Radcliffe et al. 2024). There may be an inherent tradeoff between treatment intensity and longevity, in which removing more canopy cover and/or fuel in the short-term may result increased rates of vegetation and fuel recovery into the long-term (Jain et al. 2012, Dudney et al. 2021).

Inherited factors and treatment regimes are likely to interact with each other in their effects on long-term treatment outcomes (Fig. 1.4). For example, pre-treatment conditions are likely to affect management decisions, including treatment type and intensity (Dickinson and Cadry 2017, Stephens et al. 2020). Additionally, long-term effects of treatment intensity are likely contingent on site productivity, as vegetation growth and decomposition rates may be constrained on less productive sites (Rossman et al. 2020, Radcliffe et al. 2024). Post-treatment changes in inherited factors such as climate or disturbances will also affect long-term responses to treatment (Crotteau et al. 2018, Hood et al. 2024). To our knowledge, interaction effects among inherited factors, management regimes, and environmental changes have not been studied thoroughly in a long-term treatment context.

Opportunities

We suggest incorporating fine-scale (e.g. plot-level) predictor variables into analyses where feasible, both as predictor variables of interest and as a means of reducing uncertainty associated with high variance within treatment type. Models including plot-level predictors often also include random effects to account for possible correlation among plots within a treatment unit (Radcliffe et al. 2024). Alternatively, focusing a study on the drivers of variation within one treatment type may provide insights by concentrating both conceptual and sampling efforts (Battaglia et al. 2008, van Mantgem et al. 2016, Reed et al. 2020). Researchers may choose to investigate the under-studied treatment intensity-longevity hypothesis (Jain et al. 2012) because of its clear management relevance. Studies investigating potential tradeoffs between treatment intensity and longevity will be even more impactful if they investigate responses over a gradient of site productivity and explicitly test the long-term effects of productivity.

1.6 Increasing sampling frequency in post-treatment surveys

Context

More frequency in measurement of responses to treatment over time is necessary for understanding fuel trajectories following treatment. Many published permanent plot studies contain one treatment period representing ‘long-term’ effects (Hood et al. 2020, Morici and Bailey 2021, Radcliffe et al. 2024), apart from sites receiving repeat treatments (Stephens et al. 2023) or subsequent disturbance (Hood et al. 2024). Studies with low measurement frequency can miss fuel trajectories following treatment (Busse and Gerrard 2020), and different fuel components likely have different trajectories (Fig. 1.5). Fine woody surface fuel is particularly dynamic (Johnston et al. 2021) and likely to show non-linear patterns over time (Fig. 1.5), because of rapid deposition from the canopy of trees injured or killed during treatment (Keane 2015), and high surface area to volume ratio leading to rapid decomposition (Kennedy et al. 2021). Non-linear patterns could include sustained, sigmoidal or convex responses (Fig. 1.5, Fig. 1.6). If such patterns exist, they could change the optimal timing for treatment maintenance to maintain low risk of high severity wildfire. For example, maintenance could be timed to immediately follow periods of rapid fuel accumulation, given a sigmoidal or convex response (Fig. 1.6), thereby minimizing the amount of time a stand is exposed to high surface fire hazard.

Trajectories over time are likely affected by inherited factors. For example, total deposition of surface fuel from the canopy following prescribed burning is likely affected by pre-treatment canopy fuel loads and prescribed burn intensity (Radcliffe et al. 2024). Additionally, decomposition rates of surface fuel inputs are likely affected by site productivity (Hanan et al. 2022). Uncovering the drivers of variation in the shape of trajectories following treatment would require large investments in permanent plot data. However, developing this depth of understanding about long-term treatment effects would be invaluable for modelling responses to treatment over time across diverse management contexts, by allowing more precise prediction of the shape of responses to treatment over time (Fig. 1.6) rather than general patterns.

Opportunities

We suggest measuring post-treatment responses at more frequent intervals when possible. More frequent post-treatment measurement will require greater financial investment in monitoring, which would be worthwhile for developing better understanding of fuel profile trajectories over time. One way to mitigate the total cost of monitoring is to measure response variables of interest in accordance with the expected temporal resolution of change. For example, fine woody surface fuel profiles are likely to be more dynamic within the first ten years of treatment than coarse woody surface fuel profiles (Fig. 1.5), and therefore researchers may choose to measure fine woody surface fuel at finer post-treatment intervals. An analogy may be made with spatial scaling, whereby smaller fuel classes which are expected to vary over finer spatial scales and therefore are sampled over finer spatial scales (Brown 1974, Keane et al. 2012, 2016, Vakili et al. 2016).

1.7 Incorporating spatial heterogeneity over time

Context

Spatial heterogeneity may be an important element of long-term treatment responses, as fuel and vegetation may show increasingly divergent fine-scale responses to treatment over time based on differences in pre-treatment conditions, site productivity, and treatment intensity (Fig 2). Depending on implementation, treatments may increase or decrease spatial heterogeneity of dry forest structure (Churchill et al. 2013, Stephens et al. 2020), which is crucial to study because heterogeneity influences dry forest resilience to a variety of disturbances including wildfire (Larson and Churchill 2012, Koontz et al. 2020, Jeronimo et al. 2020, Ritter et al. 2020, 2023). Fire suppression and exclusion have to relative homogenization of fuel profiles in un-disturbed dry forests, as fire-maintained openings have filled with trees over time (Larson and Churchill 2012, Hagmann et al. 2021). Treatments often create fuel profile heterogeneity in un-disturbed forests by opening gaps in trees and creating patches of low surface and ladder fuel, with the degree of heterogeneity likely depending on pre-treatment conditions, treatment type, treatment intensity, and whether a treatment was designed to create heterogeneity (Churchill et al. 2013, Knapp et al. 2017).

Heterogeneity is challenging to study and has not been used as a focal attribute in ecology as much as central tendency measures (Fraterrigo and Rusak 2008), but methods available to study general patterns of heterogeneity include ordination, coefficient of variation, and spatial statistics. In a multivariate context, ordination can be used to quickly visualize convergence or divergence across all response variables collected in a study, and to visualize variation in plot level responses to treatment over time (Radcliffe et al. 2024). For univariate responses, coefficient of variation (standard deviation divided by mean) is useful because it controls for the positive correlation between variance and mean (Brown 1998), and has been used to evaluate stand-structural heterogeneity in a variety of forest ecology contexts (Kashian et al. 2005, Donato et al. 2013, Harvey and Holzman 2014, Turner et al. 2016, Knapp et al. 2017). Ordination and coefficient of variation are both relatively easy to use in long-term studies because they are often compatible with common plot-based designs meant for use with central tendency measures (Brown 1998, Legendre and Legendre 2012). Spatial statistics such as semivariograms can offer detailed insights into fuel profile spatial heterogeneity, by quantifying the magnitude and range of spatial variation for different fuel components as a continuous measure (Turner et al. 2015a). However, spatial statistics require specialized and relatively intensive sampling protocols to capture the different scales of variation of different fuel components (Keane et al. 2001, 2012, 2016), which could be challenging to fund in repeat-measures contexts.

Aerial LiDAR is well suited to study heterogeneity of stand structure and canopy fuel within and among stands, because it can characterize individual trees (Erdody and Moskal 2010, Jeronimo et al. 2018). For example, the ICO (individuals, trees, openings) method (Churchill et al. 2013) of quantifying stand structural heterogeneity has often been used with aerial LiDAR to study short-term responses of dry forest heterogeneity to treatment and/or disturbance (Jeronimo et al. 2019, Kane et al. 2019, Chamberlain et al. 2023). Surface fuel is more challenging to study at fine scales with aerial LiDAR because of canopy occlusion, inability to measure litter and duff depth, and challenges with field validation, though recent advances have improved the ability of aerial LiDAR to predict surface fuel loads in specific contexts (Bright et al. 2022, Sánchez-López et al. 2023). As aerial LiDAR data availability and repeat flights continue to increase (Wulder et al. 2012, Coops et al. 2021), so may opportunities to study heterogeneity of stand structure and canopy fuel responses to treatments over time, often at broader spatial scales than field data can facilitate (Coops et al. 2021).

Physics-based fire modelling may be the tool with the greatest promise for operationally quantifying the effects of fuel profile heterogeneity on potential wildfire behavior, but heavy computing demands, technical knowledge requirements, and data requirements have thus far limited its use to fine spatial and temporal scales. Studies based on physics-based fire modelling show important effects of heterogeneity in moderating crown fire behavior (Ritter et al. 2020,

2023) and diversifying overall fire behavior (Parsons et al. 2017, Ritter et al. 2022), though there are some confounding effects of fuel heterogeneity and amount (Parsons et al. 2017). Researchers will likely gain more specific, operational understanding of the effects of fuel profile heterogeneity on wildfire behavior as advances continue to be made in computing power and physics-based fire modelling, thereby increasing understanding of long-term treatment effects.

Opportunities

We suggest incorporating heterogeneity as a response of interest in long-term treatment studies, or as the central focus of long-term treatment studies. Heterogeneity can be incorporated into plot-based studies using approaches such as ordination or properties of datasets such as coefficient of variation. Statistical uncertainty is often difficult to quantify with ordination and coefficient of variation, but this should not inhibit reporting and exploration of heterogeneity. Studies that use repeated-measures data to quantify trends in heterogeneity over time could help by reducing spatial variability (Gurevitch and Chester 1986, Green 1993). In addition to plot-based studies, researchers may be alert to opportunities for applying more specialized methods of quantifying heterogeneity in long-term research. These could include taking advantage of repeat aerial LiDAR flights, or resampling datasets designed to inform physics-based fire models or study spatial scaling of fuel profiles.

1.8 Additional Considerations

Our paper has focused on changes of fuel profiles and stand structure following treatment, but many other aspects of dry forest ecology and management are relevant to treatment maintenance planning. These include natural disturbances, observed treatment effects on wildfire, long-term cost-benefit ratios, and additional ecological values. Increasing natural disturbances are becoming increasingly important to dry forest fuel management planning (Laughlin et al. 2023). Natural disturbances can create opportunities for additional fuel reduction and ecological restoration treatments (Churchill et al. 2022, Larson et al. 2022), but similarly to fuel treatments, long-term responses to natural disturbances (Schoennagel et al. 2004, Stevens-Rumann et al. 2012, Dunn and Bailey 2015) and post-disturbance management (Nemens et al. 2019, Leverkus et al. 2021, Cansler et al. 2022a) are not as well studied as short-term responses. Studies that capitalize on opportunities to study long-term effects of treatment on observed wildfire behavior can be highly informative about long-term treatment effects (Cansler et al. 2022b, Davis et al. 2024), especially when there are opportunities to incorporate field data (Brodie et al. 2024). Cost analyses are rarely included in field studies of long-term treatment responses (but see: Stephens et al. 2023), and they would be helpful to include in studies when feasible. Economically efficient treatment planning can increase treated area given fixed budgets (Kreitler et al. 2019), and treatment longevity is a major determinate of the long-term cost to benefit ratio over the lifespan of a treatment (Finney et al. 2007, Jain et al. 2012, Barnett et al. 2016, Hunter and Taylor 2022). Many ecological values and services other than fuel reduction are important for treatment planning, potentially including biodiversity, carbon, soil, water, food, timber, aesthetics, spirituality, and more (Franklin et al. 2018). Factors not directly affecting potential wildfire behavior are generally understudied in fuel treatment research (Kalies and Yocom Kent 2016), especially in the context of long-term responses to treatment, and merit further research. Finally, there is more to be gained from long-term treatment studies in ecosystems other than dry forests (Hutchinson et al. 2012, Iverson et al. 2017, Morris et al. 2022), which we did not focus on in this paper.

1.9 Conclusions

Innovations in research about long-term treatment maintenance may increase the ability of managers and policy makers to efficiently plan treatment maintenance over a broad range of contexts. Given limited resources for treatment, efficient treatment maintenance is a crucial component of restoring historically frequent-fire dry forests and in maintaining the broad suite of ecological values and services these forests provide. Our hope is to inspire more long-term thinking about dry forest restoration and management, ultimately with the goal of increasing dry forest resilience to climate change and wildfire.

1.10 Figures

Figure 1.1: Hypothetical pre-treatment conditions for the fuel succession model displayed in Fig. 1.2. The stand represented experienced some high-grade logging around the early 20th century, and has not been disturbed or treated since. It is likely that if a wildfire occurred in this stand, it would burn with high intensity and severity. Painting by Robert Van Pelt.

		Short-term (e.g., 0-3 years post-treatment)	Medium-term (e.g., 3-10 years post-treatment)	Long-term (e.g. 10-20 years post-treatment)
Burn-only	Fine woody surface fuel	Decreased relative to pre-treatment	Increased relative to pre-treatment due to canopy deposition following burn damage	Roughly equivalent to pre-treatment levels after some decomposition
	Coarse woody surface fuel	Slightly decreased relative to pre-treatment	Slightly increased relative to pre-treatment	Locally increased in areas of higher intensity burn
	Litter and duff	Decreased relative to pre-treatment	Some re-accumulation after burning, still less than pre-treatment	Roughly equivalent to pre-treatment levels
	Shrubs	Decreased relative to pre-treatment	Some shrubs in limited areas of canopy opening	Locally well developed in areas of higher intensity burn
	Ladder fuel	Decreased relative to pre-treatment	Some tree seedling regeneration in limited areas of canopy opening	Locally developing in areas of higher intensity burn
	Canopy fuel	Not affected in most areas, localized reductions in areas of higher intensity burn	Canopy is mostly closed except for localized areas of higher intensity burn	Canopy closed for the most part
Thin-only	Fine woody surface fuel	Increased relative to pre-treatment	Roughly equivalent to pre-treatment after some decomposition of activity fuel	Slightly lower than pre-treatment, due to decreased rate of canopy deposition
	Coarse woody surface fuel	Slightly increased relative to pre-treatment	Slightly increased relative to pre-treatment	Roughly equivalent to pre-treatment
	Litter and duff	Locally affected by incidental logging activity such as skidding	Relatively similar to pre-treatment	Roughly equivalent to pre-treatment
	Shrubs	Slightly decreased by intentional removal of large shrubs and incidental logging activity	Growing in response to canopy opening	Well-developed
	Ladder fuel	Decreased by intentional removal, but seedlings and some saplings remain	Seedlings and saplings that escaped thinning responding to canopy opening	Well-developed, has reached canopy base height in many areas
	Canopy fuel	Reduced relative to pre-treatment	Reduced relative to pre-treatment	Reduced relative to pre-treatment
Thin-plus-burn	Fine woody surface fuel	Decreased relative to pre-treatment	Slightly increased relative to pre-treatment, especially in areas of higher intensity burn	Decreased relative to pre-treatment following decomposition of activity fuel
	Coarse woody surface fuel	Roughly equivalent to pre-treatment	Slightly increased relative to pre-treatment	Slightly increased relative to pre-treatment, localized in areas of higher intensity burn
	Litter and duff	Decreased relative to pre-treatment	Some re-accumulation after burning, still less than pre-treatment	Slightly decreased relative to pre-treatment
	Shrubs	Decreased relative to pre-treatment	Growing in response to canopy opening	Well developed and forming some areas of continuous shrub fuel
	Ladder fuel	Decreased relative to pre-treatment	Some seedlings appearing	Slightly decreased relative to pre-treatment, but developing
	Canopy fuel	Decreased relative to pre-treatment	Decreased relative to pre-treatment	Decreased relative to pre-treatment

Figure 1.2: Conceptual model of fuel succession patterns following thin-only, burn-only, and thin-plus-burn treatments, showing short-term (e.g. 0-3 year), medium-term (e.g., 3-10 year), and long-term (e.g., 10-20 year) responses of stand structure and fuel profiles. Burn-only treatment represents a prescribed low intensity broadcast burn. Thin-only treatment represents a thin from below without follow-up slash management. Thin-plus-burn treatment represents a thin from below followed one year later by a prescribed broadcast burn of low intensity. The model ends 20 years following treatment because few data exist to inform longer time-scales, but this does not imply that treatments cease to meaningfully affect forests 20 years after treatment. The model is meant as a heuristic starting point for understanding fuel succession following treatment implementation, but outcomes of specific treatments will depend on a variety of factors including pre-treatment conditions, site productivity, treatment intensity, treatment implementation details, and more. Additionally, responses are likely to be heterogeneous on fine spatial scales (e.g. <1 ha). See Figure 1 for pre-treatment conditions. This table is a stand-in for a painting being developed by Robert Van Pelt.

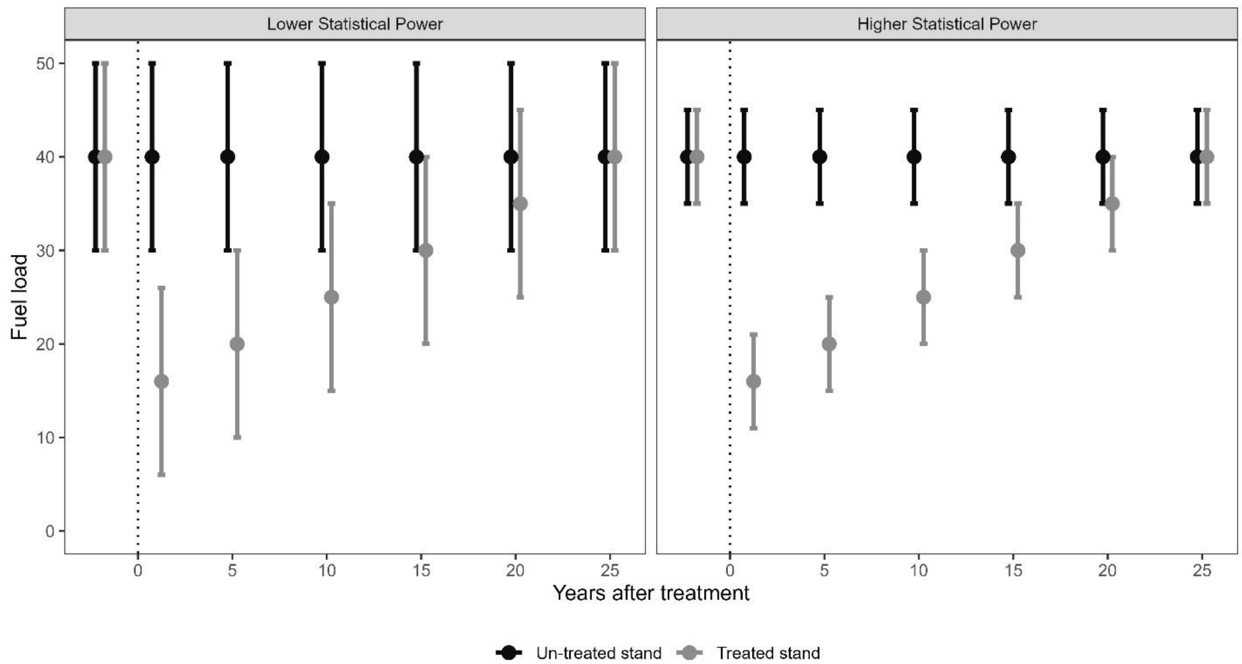

Figure 1.3: Hypothetical example of the effect of statistical power on fuel treatment longevity estimation using statistical comparisons of treated and un-treated stands. Factors affecting statistical power include effect size, sample size, alpha level, and variance (Lieber 1990, Greenland et al. 2016). Graphs represent a treatment that caused an initial decrease in fuel, followed by a simple linear increase over time. Different panels represent different levels of statistical uncertainty in mean fuel loads over time. Dots represent mean fuel loads, lines bounded by ticks represent confidence intervals reflecting a researcher-chosen alpha level. If fuel treatment longevity were determined by statistical significance, and the confidence interval overlap are seen as the determinant of statistical significance (e.g. an 83% confidence interval for an alpha level of 0.05), 5 years would be considered the end of a treatment's lifespan given the lower statistical power scenario, and 15 years would be considered the end of the treatment's lifespan given the higher statistical power scenario. These wide differences in longevity estimates exist despite the mean responses being the same, and the time required for the means to converge being 25 years. This is a simplified hypothetical example, but highlights a possible bias towards under-estimation of longevity in the prevailing method studying long-term treatment effects. The bias may increase with statistical uncertainty. The same pattern may work in reverse; if reference conditions or desired conditions were the point of reference, statistical uncertainty could lead to overestimation of treatment effects.

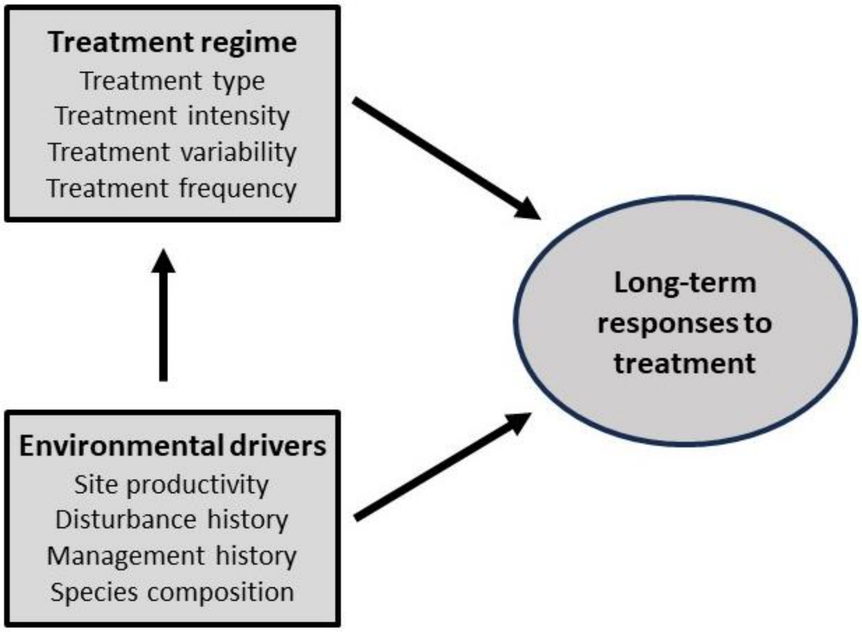

Figure 1.4: Simple conceptual model of interaction between inherited factors and treatment regime in affecting long-term treatment responses. Inherited factors are those factors that exist at a site before treatment and constrain possible outcomes, including site level abiotic characteristics and legacies of past disturbances or treatment. Treatment regime includes details of treatment implementation, and decisions about the treatment regime may or may not be affected by inherited factors. Ultimately, long-term fuel profile responses to treatment are determined by the interaction of inherited factors and treatment regime in determining short-term treatment responses, and by any changes to inherited factors or treatment regime following initial treatment.

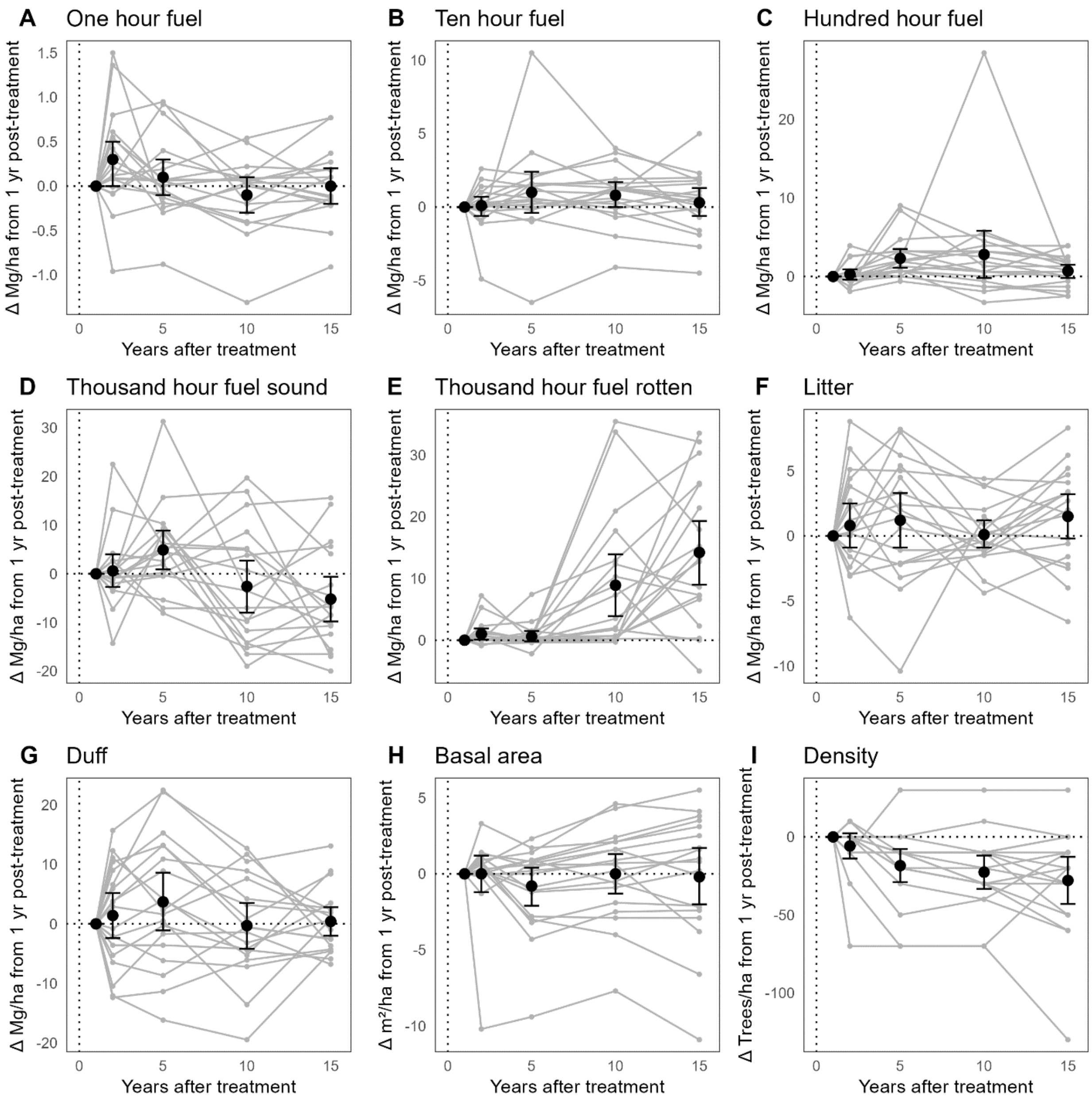

Figure 1.5: Fuel profiles and stand structure trajectories over time relative to immediate post-treatment outcomes (horizontal dotted lines), from 19 permanent plots sampled at 1, 2, 5, 10, and 15 years after thin-plus-burn treatments on National Park Service Fire Effects Monitoring Sites in Washington State (Chapter 3). Black dots represent means within time periods, black bars represent 95% confidence intervals around those means. Gray lines represent plot level trajectories, and while lines are shown to display these trajectories, they do not necessarily indicate linear change between the sample periods. Vertical dotted lines represent the time of burn implementation in the 'thin-plus-burn' sequence.

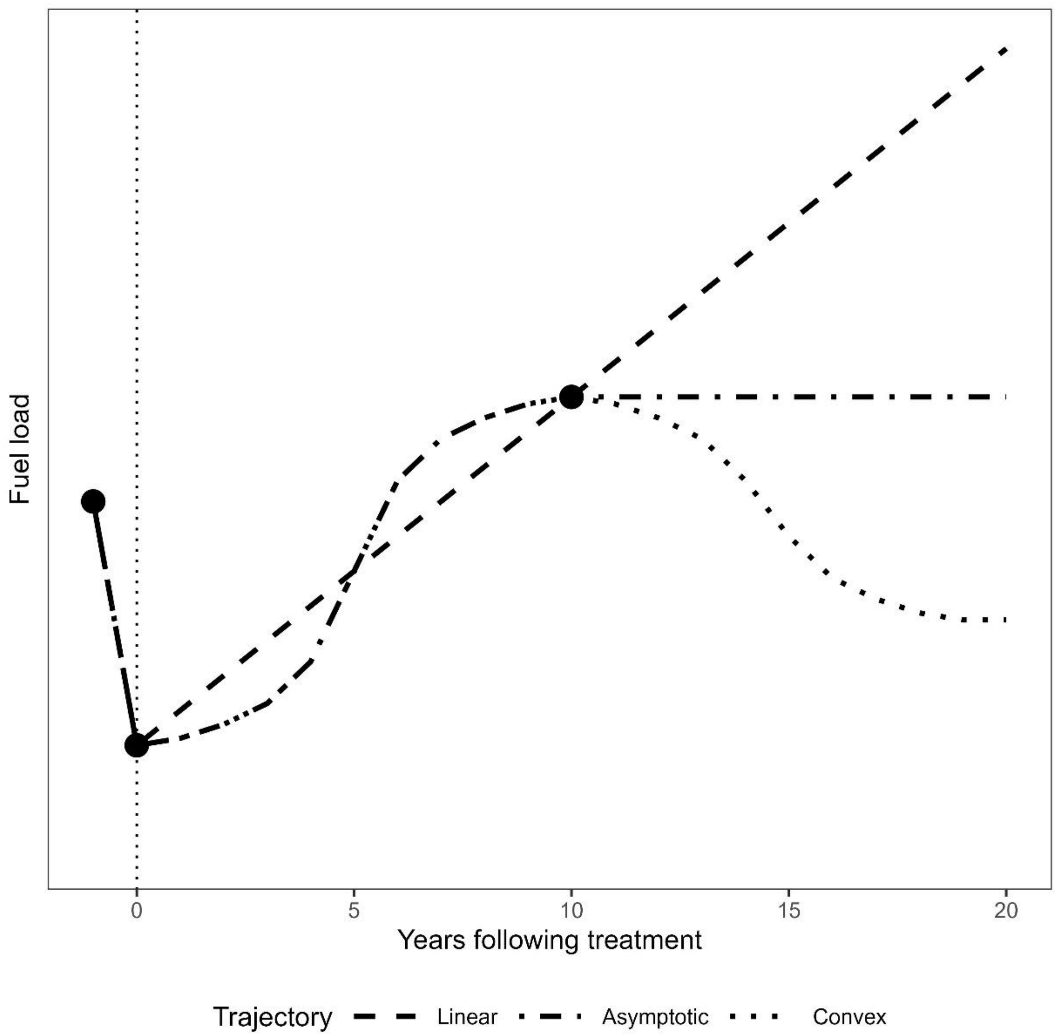

Figure 1.6: Possible trajectory shapes of fuel profile and stand structure responses to treatment over time. The x axis represents time since treatment, with the dashed vertical line representing the time of treatment implementation. The y axis represents loading of a fuel profile or stand structure category of interest. The dot represents a point in time in which a sample would represent the same 'long-term' result across several types of trajectories, potentially misleading researchers about long-term effects in subsequent years if the trajectory is unknown. Note that the asymptotic and convex trajectories show the same trend until diverging after 10 years following treatment. Different fuel profile components are likely to show different trajectories: Fig. 1.5 is an example of woody surface fuel showing reverse parabolic trajectories and stand structure showing (mostly) sustained effects over a 15-year time-scale. Additionally, different variables showing the same shape of trajectory over time since treatment may have different magnitudes of response and timing of peaks, such as the different woody surface fuel components in Fig. 1.5. In practice, sustained effects and asymptotes are unlikely over long time scales, but they may be useful heuristics for the decadal time scales that long-term treatment studies typically address.

1.11 Boxes

Box 1.1

Treatment longevity vs. long-term treatment effects: a note on terminology

We believe the phrase 'treatment longevity' implies the lifespan of usefulness for a treatment unit within the context of management goals for that unit. Therefore, we propose that the phrase 'long-term treatment effects' is often more appropriate for framing research findings, while 'treatment longevity' may be used in reference to factors that may affect the lifespan of treatment usefulness in the context of a management goal. We believe that few if any published studies can make precise estimations of treatment longevity, for two major reasons. First, long-term treatment studies often lack the sampling frequency to precisely estimate trajectories over time. Second, management goals are context dependent and therefore cannot be precisely quantified by researchers.

1.12 References

Agee, J. K. 1996. Fire Ecology of Pacific Northwest Forests. First edition. Island Press, Washington D.C.

Agee, J. K., and M. R. Lolley. 2006. Thinning and Prescribed Fire Effects on Fuels and Potential Fire Behavior in an Eastern Cascades Forest, Washington, USA. Fire Ecology 2:3–19.

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Ager, A. A., M. A. Day, C. W. McHugh, K. Short, J. Gilbertson-Day, M. A. Finney, and D. E. Calkin. 2014. Wildfire exposure and fuel management on western US national forests. Journal of Environmental Management 145:54–70.

Arnqvist, G., and D. Wooster. 1995. Meta-analysis: synthesizing research findings in ecology and evolution. Trends in Ecology & Evolution 10:236–240.

Barnett, K., S. A. Parks, C. Miller, and H. T. Naughton. 2016. Beyond Fuel Treatment Effectiveness: Characterizing Interactions between Fire and Treatments in the US. Forests 7:237.

Battaglia, M. A., F. W. Smith, and W. D. Shepperd. 2008. Can prescribed fire be used to maintain fuel treatment effectiveness over time in Black Hills ponderosa pine forests? Forest Ecology and Management 256:2029–2038.

Betensky, R. A. 2019. The *p*-Value Requires Context, Not a Threshold. The American Statistician 73:115–117.

Bright, B. C., A. T. Hudak, T. R. McCarley, A. Spannuth, N. Sánchez-López, R. D. Ottmar, and A. J. Soja. 2022. Multitemporal lidar captures heterogeneity in fuel loads and consumption on the Kaibab Plateau. Fire Ecology 18:1–16.

Brodie, E. G., E. E. Knapp, W. R. Brooks, S. A. Drury, and M. W. Ritchie. 2024. Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. Fire Ecology 20:17.

Brown, C. E. 1998. Coefficient of Variation *in* Applied Multivariate Statistics in Geohydrology and Related Sciences. 155–157. 1st edition. Springer-Verlag Berlin Heidelburg. Berlin.

Brown, J. 1974. Handbook for inventorying downed woody material. Gen. Tech. Rep. INT-16. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 24 p. 016.

Busse, M., and R. Gerrard. 2020. Thinning and Burning Effects on Long-Term Litter Accumulation and Function in Young Ponderosa Pine Forests. Forest Science 66:761–769.

Cansler, C. A., V. R. Kane, B. N. Bartl-Geller, D. J. Churchill, P. F. Hessburg, N. A. Povak, J. A. Lutz, J. Kane, and A. J. Larson. 2022a. Postfire treatments alter forest canopy structure up to three decades after fire. Forest Ecology and Management 505:119872.

Cansler, C. A., V. R. Kane, P. F. Hessburg, J. T. Kane, S. M. A. Jeronimo, J. A. Lutz, N. A. Povak, D. J. Churchill, and A. J. Larson. 2022b. Previous wildfires and management treatments moderate subsequent fire severity. Forest Ecology and Management 504:119764.

Chamberlain, C. P., G. R. Cova, C. A. Cansler, M. P. North, M. D. Meyer, S. M. A. Jeronimo, and V. R. Kane. 2023. Consistently heterogeneous structures observed at multiple spatial scales across fire-intact reference sites. Forest Ecology and Management 550:121478.

Churchill, D. J., S. M. A. Jeronimo, P. F. Hessburg, C. A. Cansler, N. A. Povak, V. R. Kane, J. A. Lutz, and A. J. Larson. 2022. Post-fire landscape evaluations in Eastern Washington, USA: Assessing the work of contemporary wildfires. Forest Ecology and Management 504:119796.

Churchill, D. J., A. J. Larson, M. C. Dahlgreen, J. F. Franklin, P. F. Hessburg, and J. A. Lutz. 2013. Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring. Forest Ecology and Management 291:442–457.

Coops, N. C., P. Tompalski, T. R. H. Goodbody, M. Queinnec, J. E. Luther, D. K. Bolton, J. C. White, M. A. Wulder, O. R. van Lier, and T. Hermosilla. 2021. Modelling lidar-derived estimates of forest attributes over space and time: A review of approaches and future trends. Remote Sensing of Environment 260:112477.

Crotteau, J. S., C. R. Keyes, S. M. Hood, D. L. R. Affleck, and A. Sala. 2018. Fuel dynamics after a bark beetle outbreak impacts experimental fuel treatments. Fire Ecology 14:13.

Cruz, M. G., M. E. Alexander, A. L. Sullivan, J. S. Gould, and M. Kilinc. 2018. Assessing improvements in models used to operationally predict wildland fire rate of spread. Environmental Modelling & Software 105:54–63.

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

Dickinson, Y. L., and J. D. Cadry. 2017. An evaluation of tree marking methods for implementing spatially heterogeneous restoration. Journal of Sustainable Forestry 36:47–64.

Donato, D. C., B. J. Harvey, W. H. Romme, M. Simard, and M. G. Turner. 2013. Bark beetle effects on fuel profiles across a range of stand structures in Douglas-fir forests of Greater Yellowstone. Ecological Applications 23:3–20.

Dudney, J., R. A. York, C. L. Tubbesing, A. T. Roughton, D. Foster, S. L. Stephens, and J. J. Battles. 2021. Overstory removal and biological legacies influence long-term forest management outcomes on introduced species and native shrubs. Forest Ecology and Management 491:119149.

Dunn, C. J., and J. D. Bailey. 2015. Temporal fuel dynamics following high-severity fire in dry mixed conifer forests of the eastern Cascades, Oregon, USA. International Journal of Wildland Fire 24:470.

Durbecq, A., R. Jaunatre, E. Buisson, A. Cluchier, and A. Bischoff. 2020. Identifying reference communities in ecological restoration: the use of environmental conditions driving vegetation composition. Restoration Ecology 28:1445–1453.

Erdody, T. L., and L. M. Moskal. 2010. Fusion of LiDAR and imagery for estimating forest canopy fuels. Remote Sensing of Environment 114:725–737.

Ex, S. A., J. P. Ziegler, W. T. Tinkham, and C. M. Hoffman. 2019. Long-Term Impacts of Fuel Treatment Placement with Respect to Forest Cover Type on Potential Fire Behavior across a Mountainous Landscape. Forests10:438.

Falk, D. A. 2006. Process-centred restoration in a fire-adapted ponderosa pine forest. Journal for Nature Conservation 14:140–151.

Falk, D. A., P. J. van Mantgem, J. E. Keeley, R. M. Gregg, C. H. Guiterman, A. J. Tepley, D. JN Young, and L. A. Marshall. 2022. Mechanisms of forest resilience. Forest Ecology and Management 512:120129.

Fialko, K., S. Ex, and B. H. Wolk. 2020. Ecological niches of tree species drive variability in conifer regeneration abundance following fuels treatments. Forest Ecology and Management 476:118475.

Finney, M. A., R. C. Seli, C. W. McHugh, A. A. Ager, B. Bahro, and J. K. Agee. 2007. Simulation of long-term landscape-level fuel treatment effects on large wildfires. International Journal of Wildland Fire 16:712.

Franklin, J. F., N. K. Johnson, and D. L. Johnson. 2018. Ecological Forest Management. First edition. Waveland Press, Long Grove, IL.

Fraterrigo, J. M., and J. A. Rusak. 2008, July 1. Disturbance-driven changes in the variability of ecological patterns and processes. Ecology Letters 11:756–70.

Fulé, P. Z., J. E. Crouse, J. P. Roccaforte, and E. L. Kalies. 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.

Graham, L. J., R. Spake, S. Gillings, K. Watts, and F. Eigenbrod. 2019. Incorporating fine-scale environmental heterogeneity into broad-extent models. Methods in Ecology and Evolution 10:767–778.

Green, R. H. 1993. Application of repeated measures designs in environmental impact and monitoring studies. Australian Journal of Ecology 18:81–98.

Greenland, S., S. J. Senn, K. J. Rothman, J. B. Carlin, C. Poole, S. N. Goodman, and D. G. Altman. 2016. Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. European Journal of Epidemiology 31:337–350.

Gurevitch, J., and S. T. Chester. 1986. Analysis of repeated measures experiments. Ecology 67:251–255.

Hagmann, R. K., P. F. Hessburg, S. J. Prichard, N. A. Povak, P. M. Brown, P. Z. Fulé, R. E. Keane, E. E. Knapp, J. M. Lydersen, K. L. Metlen, M. J. Reilly, A. J. S. Meador, S. L. Stephens, J. T. Stevens, A. H. Taylor, L. L. Yocom, M. A. Battaglia, D. J. Churchill, L. D. Daniels, D. A. Falk, P. Henson, J. D. Johnston, M. A. Krawchuk, C. R. Levine, G. W. Meigs, A. G. Merschel, M. P. North, H. D. Safford, T. W. Swetnam, and A. E. M. Waltz. 2021. Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. Ecological Applications e02431.

Hall, S. A., C. Burke, and N. T. Hobbs. 2006. Litter and dead wood dynamics in ponderosa pine forests along a 160-year chronosequence. Ecological Applications 16:2344–2355.

Hanan, E. J., M. C. Kennedy, J. Ren, M. C. Johnson, and A. M. S. Smith. 2022. Missing Climate Feedbacks in Fire Models: Limitations and Uncertainties in Fuel Loadings and the Role of Decomposition in Fine Fuel Accumulation. Journal of Advances in Modeling Earth Systems 14:e2021MS002818.

Harmon, M. E., J. F. Franklin, F. J. Swanson, P. Sollins, S. V. Gregory, J. D. Lattin, N. H. Anderson, S. P. Cline, N. G. Aumen, J. R. Sedell, G. W. Lienkaemper, K. Cromack, and K. W. Cummins. 1986. Ecology of Coarse Woody Debris in Temperate Ecosystems. Advances in Ecological Research 15:133–302.

Harvey, B. J., and B. A. Holzman. 2014. Divergent successional pathways of stand development following fire in a California closed-cone pine forest. Journal of Vegetation Science 25:88–99.

Haugo, R. D., B. S. Kellogg, C. A. Cansler, C. A. Kolden, K. B. Kemp, J. C. Robertson, K. L. Metlen, N. M. Vaillant, and C. M. Restaino. 2019. The missing fire: quantifying human exclusion of wildfire in Pacific Northwest forests, USA. Ecosphere 10:e02702.

Hessburg, P. F., D. J. Churchill, A. J. Larson, R. D. Haugo, C. Miller, T. A. Spies, M. P. North, N. A. Povak, R. T. Belote, P. H. Singleton, W. L. Gaines, R. E. Keane, G. H. Aplet, S. L. Stephens, P. Morgan, P. A. Bisson, B. E. Rieman, R. B. Salter, and G. H. Reeves. 2015. Restoring fire-prone Inland Pacific landscapes: seven core principles. Landscape Ecology 30:1805–1835.

Hood, S. M., J. S. Crotteau, and C. C. Cleveland. 2024. Long-term efficacy of fuel reduction and restoration treatments in Northern Rockies dry forests. Ecological Applications:e2940.

Hood, S. M., C. R. Keyes, K. J. Bowen, D. C. Lutes, and C. Seielstad. 2020. Fuel Treatment Longevity in Ponderosa Pine-Dominated Forest 24 Years After Cutting and Prescribed Burning. Frontiers in Forests and Global Change 3:78.

Hunter, M. E., and M. H. Taylor. 2022. The Economic Value of Fuel Treatments: A Review of the Recent Literature for Fuel Treatment Planning. Forests 13:2042.

Hutchinson, T. F., R. P. Long, J. Rebbeck, E. K. Sutherland, and D. A. Yaussy. 2012. Repeated prescribed fires alter gap-phase regeneration in mixed-oak forests. Canadian Journal of Forest Research 42:303–314.

Iverson, L. R., T. F. Hutchinson, M. P. Peters, and D. A. Yaussy. 2017. Long-term response of oak-hickory regeneration to partial harvest and repeated fires: influence of light and moisture. Ecosphere 8:e01642.

Jain, Theresa B., Mike A. Battaglia, Han-Sup. Han, Russell T. Graham, Christopher R. Keyes, Jeremy S. Fried, and Jonathan E. Sandquist. 2012. A comprehensive guide to fuel management practices for dry mixed conifer forests in the northwestern United States Gen Tech Rep RMRS-GTR-292, 331. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Jeronimo, S. M. A., V. R. Kane, D. J. Churchill, J. A. Lutz, M. P. North, G. P. Asner, and J. F. Franklin. 2019. Forest structure and pattern vary by climate and landform across active-fire landscapes in the montane Sierra Nevada. Forest Ecology and Management 437:70–86.

Jeronimo, S. M. A., V. R. Kane, D. J. Churchill, R. J. McGaughey, and J. F. Franklin. 2018. Applying LiDAR Individual Tree Detection to Management of Structurally Diverse Forest Landscapes. Journal of Forestry 116:336–346.

Jeronimo, S. M. A., J. A. Lutz, V. R. Kane, A. J. Larson, and J. F. Franklin. 2020. Burn weather and three-dimensional fuel structure determine post-fire tree mortality. Landscape Ecology:1–20.

Jewell, S., and T. Vilsack. 2014. The National Cohesive Wildland Fire Management Strategy. Washington DC. 93p.

Johnston, J. D., J. H. Olszewski, B. A. Miller, M. R. Schmidt, M. J. Vernon, and L. M. Ellsworth. 2021. Mechanical thinning without prescribed fire moderates wildfire behavior in an Eastern Oregon, USA ponderosa pine forest. Forest Ecology and Management 501:119674.

Kalies, E. L., and L. L. Yocom Kent. 2016. Tamm review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. Forest Ecology and Management 375:84–95.

Kane, V. R., B. N. Bartl-Geller, M. P. North, J. T. Kane, J. M. Lydersen, S. M. A. Jeronimo, B. M. Collins, and L. Monika Moskal. 2019. First-entry wildfires can create opening and tree clump patterns characteristic of resilient forests. Forest Ecology and Management 454:117659.

Kashian, D. M., M. G. Turner, W. H. Romme, and C. G. Lorimer. 2005. Variability and convergence in stand structural development on a fire-dominated subalpine landscape. Ecology 86:643–654.

Keane, R. E., Y. Bergeron, and S. Gauthier. 2016. Spatiotemporal Variability of Wildland Fuels in US Northern Rocky Mountain Forests. Forests 7:129.

Keane, R. E., R. Burgan, and J. Van Wagtendonk. 2001. Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling. International Journal of Wildland Fire 10:301–319.

Keane, R. E., K. Gray, V. Bacciu, and S. Leirfallom. 2012. Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA. Landscape Ecology 27:1213–1234.

Keane, R. E., P. F. Hessburg, P. B. Landres, and F. J. Swanson. 2009. The use of historical range and variability (HRV) in landscape management. Forest Ecology and Management 258:1025-1037.

Keifer, M., J. W. van Wagtendonk, and M. Buhler. 2006. Long-term surface fuel accumulation in burned and unburned mixed-conifer forests of the Central and Southern Sierra Nevada, CA (USA). Fire Ecology 2:53–72.

Kennedy, M. C., M. C. Johnson, and S. C. Harrison. 2021. Model Predictions of Postwildfire Woody Fuel Succession and Fire Behavior Are Sensitive to Fuel Dynamics Parameters. Forest Science 67:30–42.

Knapp, E. E., J. M. Lydersen, M. P. North, and B. M. Collins. 2017. Efficacy of variable density thinning and prescribed fire for restoring forest heterogeneity to mixed-conifer forest in the central Sierra Nevada, CA. Forest Ecology and Management 406:228–241.

Kolden, C. A. 2019. We're Not Doing Enough Prescribed Fire in the Western United States to Mitigate Wildfire Risk. Fire 2:30.

Koontz, M. J., M. P. North, C. M. Werner, S. E. Fick, and A. M. Latimer. 2020. Local forest structure variability increases resilience to wildfire in dry western U.S. coniferous forests. Ecology Letters 23:483–494.

Kreitler, J., M. P. Thompson, N. M. Vaillant, and T. J. Hawbaker. 2019. Cost-effective fuel treatment planning: a theoretical justification and case study. International Journal of Wildland Fire 29:42–56.

Kreye, J. K., N. W. Brewer, P. Morgan, J. M. Varner, A. M. S. Smith, C. M. Hoffman, and R. D. Ottmar. 2014. Fire behavior in masticated fuels: A review. Forest Ecology and Management 314:193–207.

Larson, A. J., and D. Churchill. 2012. Tree spatial patterns in fire-frequent forests of western North America, including mechanisms of pattern formation and implications for designing fuel reduction and restoration treatments. Forest Ecology and Management 267:74–92.

Larson, A. J., S. M. A. Jeronimo, P. F. Hessburg, J. A. Lutz, N. A. Povak, C. A. Cansler, V. R. Kane, and D. J. Churchill. 2022. Tamm Review: Ecological principles to guide post-fire forest landscape management in the Inland Pacific and Northern Rocky Mountain regions. Forest Ecology and Management 504:119680.

Laughlin, M. M., J. D. Bakker, D. J. Churchill, M. J. Gregory, T. DeMeo, E. C. Alvarado, and B. J. Harvey. 2023. Trends in forest structure restoration need over three decades with increasing wildfire activity in the interior Pacific Northwest US. Forest Ecology and Management 527:120607.

Legendre, P., and L. Legendre. 2012. Numerical Ecology. Third edition. Elsevier. Oxford.

Leverkus, A. B., B. Buma, J. Wagenbrenner, P. J. Burton, E. Lingua, R. Marzano, and S. Thorn. 2021. Tamm review: Does salvage logging mitigate subsequent forest disturbances? Forest Ecology and Management 481:118721.

Lieber, R. L. 1990. Statistical significance and statistical power in hypothesis testing. Journal of Orthopaedic Research 8:304–309.

Lindenmayer, D. B., and G. E. Likens. 2010. The science and application of ecological monitoring. Biological Conservation 143:1317–1328.

Lortie, C. J. 2014. Formalized synthesis opportunities for ecology: systematic reviews and meta-analyses. Oikos 123:897–902.

Lortie, C. J., G. Stewart, H. Rothstein, and J. Lau. 2015. How to critically read ecological meta-analyses. Research Synthesis Methods 6:124–133.

Maher, C. T., E. Oja, A. Marshall, M. Cunningham, L. Townsend, G. Worley-Hood, L. R. Robinson, T. Margot, D. Lyons, S. Fety, E. E. Schneider, S. M. A. Jeronimo, D. J. Churchill, and A. J. Larson. 2019. Real-Time Monitoring with a Tablet App Improves Implementation of Treatments to Enhance Forest Structural Diversity. Journal of Forestry 117:280–292.

van Mantgem, P. J., L. B. Lalemand, M. B. Keifer, and J. M. Kane. 2016. Duration of fuels reduction following prescribed fire in coniferous forests of U.S. national parks in California and the Colorado Plateau. Forest Ecology and Management 379:265–272.

McIver, J. D., and C. P. Weatherspoon. 2010. On conducting a multisite, multidisciplinary forestry research project: Lessons from the national fire and fire surrogate study. Forest Science 56:4–17.

McLeod, S. D., and S. W. Running. 2011. Comparing site quality indices and productivity in ponderosa pine stands of western Montana. Canadian Journal of Forest Research 18:346–352.

Morici, K. E., and J. D. Bailey. 2021. Long-Term Effects of Fuel Reduction Treatments on Surface Fuel Loading in the Blue Mountains of Oregon. Forests 12:1306.

Morris, J. E., M. S. Buonanduci, M. C. Agne, M. A. Battaglia, B. J. Harvey, M. S. Buonanduci, M. C. Agne, M. A. Battaglia, and B. J. Harvey. 2022. Does the legacy of historical thinning treatments foster resilience to bark beetle outbreaks in subalpine forests? Ecological Applications 32:e02474.

Morrison, M. L., W. M. Block, M. D. Strickland, B. A. Collier, and M. J. Peterson. 2008. Wildlife Study Design. Second edition. Springer. New York.

Murphy, J. S., R. York, H. Rivera Huerta, and S. L. Stephens. 2021. Characteristics and metrics of resilient forests in the Sierra de San Pedro Martír, Mexico. Forest Ecology and Management 482:118864.

Nakagawa, S., and I. C. Cuthill. 2007. Effect size, confidence interval and statistical significance: a practical guide for biologists. Biological Reviews 82:591–605.

Nemens, D. G., J. M. Varner, and M. C. Johnson. 2019. Environmental effects of postfire logging: an updated literature review and annotated bibliography. Gen. Tech. Rep. PNW-GTR-975. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

North, M., A. Brough, J. Long, B. Collins, P. Bowden, D. Yasuda, J. Miller, and N. Sugihara. 2015. Constraints on Mechanized Treatment Significantly Limit Mechanical Fuels Reduction Extent in the Sierra Nevada. Journal of Forestry 113:40–48.

North, M. P., R. A. York, B. M. Collins, M. D. Hurteau, G. M. Jones, E. E. Knapp, L. Kobziar, H. McCann, M. D. Meyer, S. L. Stephens, R. E. Tompkins, and C. L. Tubbesing. 2021. Pyrosilviculture Needed for Landscape Resilience of Dry Western United States Forests. Journal of Forestry 119:520–544.

Parsons, R., R. Linn, F. Pimont, C. Hoffman, J. Sauer, J. Winterkamp, C. Sieg, and W. Jolly. 2017. Numerical Investigation of Aggregated Fuel Spatial Pattern Impacts on Fire Behavior. Land 6:43.

Penman, T. D., D. A. Ababei, J. G. Cawson, B. A. Cirulis, T. J. Duff, W. Swedosh, and J. E. Hilton. 2020. Effect of weather forecast errors on fire growth model projections. International Journal of Wildland Fire 29:983–994.

Prichard, S. J., P. F. Hessburg, R. K. Hagmann, N. A. Povak, S. Z. Dobrowski, M. D. Hurteau, V. R. Kane, R. E. Keane, L. N. Kobziar, C. A. Kolden, M. North, S. A. Parks, H. D. Safford, J. T. Stevens, L. L. Yocom, D. J. Churchill, R. W. Gray, D. W. Huffman, F. K. Lake, and P. Khatri-Chhetri. 2021. Adapting western North American forests to climate change and wildfires: 10 common questions. Ecological Applications 31:e02433.

Radcliffe, D. C., J. D. Bakker, D. J. Churchill, E. C. Alvarado, D. W. Peterson, M. M. Laughlin, and B. J. Harvey. 2024. How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests? Forest Ecology and Management 553:121594.

Rasmussen, C., Y. L. Dupont, J. B. Mosbacher, K. Trjøelsgaard, and J. M. Olesen. 2013. Strong Impact of Temporal Resolution on the Structure of an Ecological Network. PLOS ONE 8:e81694.

Reed, W. P., J. M. Varner, E. E. Knapp, and J. K. Kreye. 2020. Long-term changes in masticated woody fuelbeds in northern California and southern Oregon, USA. International Journal of Wildland Fire 29:807–819.

Reinhardt, E. D., R. E. Keane, D. E. Calkin, and J. D. Cohen. 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. Forest Ecology and Management 256:1997–2006.

Ritter, S. M., C. M. Hoffman, M. A. Battaglia, and T. B. Jain. 2022. Restoration and fuel hazard reduction result in equivalent reductions in crown fire behavior in dry conifer forests. Ecological Applications 32:e2682.

Ritter, S. M., C. M. Hoffman, M. A. Battaglia, R. Linn, and W. E. Mell. 2023. Vertical and Horizontal Crown Fuel Continuity Influences Group-Scale Ignition and Fuel Consumption. Fire 6:321.

Ritter, S. M., C. M. Hoffman, M. A. Battaglia, C. S. Stevens-Rumann, and W. E. Mell. 2020. Fine-scale fire patterns mediate forest structure in frequent-fire ecosystems. Ecosphere 11: e03177.

Rossman, A. K., J. D. Bakker, D. W. Peterson, and C. B. Halpern. 2020. Long-term effects of fuels treatments, overstory structure, and wildfire on tree regeneration in dry forests of Central Washington. Forests 11:888.

Sánchez-López, N., A. T. Hudak, L. Boschetti, C. A. Silva, K. Robertson, E. L. Loudermilk, B. C. Bright, M. A. Callaham, and M. K. Taylor. 2023. A spatially explicit model of tree leaf litter accumulation in fire maintained longleaf pine forests of the southeastern US. Ecological Modelling 481:110369.

Schoennagel, T., T. T. Veblen, and W. H. Romme. 2004. The interaction of fire, fuels, and climate across Rocky Mountain forests. BioScience 54:661–676.

Schwilk, D. W., J. E. Keeley, E. E. Knapp, J. McIver, J. D. Bailey, C. J. Fettig, C. E. Fiedler, R. J. Harrod, J. J. Moghaddas, K. W. Outcalt, C. N. Skinner, S. L. Stephens, T. A. Waldrop, D. A. Yaussy, and A. Youngblood. 2009. The national Fire and Fire Surrogate study: effects of fuel reduction methods on forest vegetation structure and fuels. Ecological Applications 19:285–304.

Shieh, G. 2019. Effect size, statistical power, and sample size for assessing interactions between categorical and continuous variables. British Journal of Mathematical and Statistical Psychology 72:136–154.

Stephens, S. L. 2004. Fuel loads, snag abundance, and snag recruitment in an unmanaged Jeffrey pine–mixed conifer forest in Northwestern Mexico. Forest Ecology and Management 199:103–113.

Stephens, S. L., M. A. Battaglia, D. J. Churchill, B. M. Collins, M. Coppoletta, C. M. Hoffman, J. M. Lydersen, M. P. North, R. A. Parsons, S. M. Ritter, and J. T. Stevens. 2020. Forest Restoration and Fuels Reduction: Convergent or Divergent? BioScience 71:85–101.

Stephens, S. L., B. M. Collins, and G. Roller. 2012a. Fuel treatment longevity in a Sierra Nevada mixed conifer forest. Forest Ecology and Management 285:204–212.

Stephens, S. L., D. E. Foster, J. J. Battles, A. A. Bernal, B. M. Collins, R. Hedges, J. J. Moghaddas, A. T. Roughton, and R. A. York. 2023. Forest restoration and fuels reduction work: Different pathways for achieving success in the Sierra Nevada. Ecological Applications:e2932.

Stephens, S. L., and P. Z. Fulé. 2005. Western Pine Forests with Continuing Frequent Fire Regimes: Possible Reference Sites for Management. Journal of Forestry 103:357–362.

Stephens, S. L., J. D. McIver, R. E. J. Boerner, C. J. Fettig, J. B. Fontaine, B. R. Hartsough, P. L. Kennedy, and D. W. Schwilk. 2012b. The Effects of Forest Fuel-Reduction Treatments in the United States. BioScience 62:549–560.

Stevens-Rumann, C. S., C. H. Sieg, and M. E. Hunter. 2012. Ten years after wildfires: How does varying tree mortality impact fire hazard and forest resiliency? Forest Ecology and Management 267:199–208.

Tinkham, W. T., C. M. Hoffman, S. A. Ex, M. A. Battaglia, and J. D. Saralecos. 2016. Ponderosa pine forest restoration treatment longevity: Implications of regeneration on fire hazard. Forests 7:137.

Turner, M. G., R. H. Gardner, M. G. Turner, and R. H. Gardner. 2015. Spatial Statistics. Pages 143–174. Landscape Ecology in Theory and Practice. Springer New York.

Turner, M. G., T. G. Whitby, D. B. Tinker, and W. H. Romme. 2016. Twenty-four years after the Yellowstone Fires: Are postfire lodgepole pine stands converging in structure and function? Ecology 97:1260–1273.

Urgenson, L. S., C. R. Nelson, R. D. Haugo, C. B. Halpern, J. D. Bakker, C. M. Ryan, A. E. M. Waltz, R. T. Belote, and E. Alvarado. 2018. Social perspectives on the use of reference conditions in restoration of fire-adapted forest landscapes. Restoration Ecology 26:987–996.

Urgenson, L. S., C. M. Ryan, C. B. Halpern, J. D. Bakker, R. T. Belote, J. F. Franklin, R. D. Haugo, C. R. Nelson, and A. E. M. Waltz. 2017. Visions of Restoration in Fire-Adapted Forest Landscapes: Lessons from the Collaborative Forest Landscape Restoration Program. Environmental Management 59:338–353.

Vaillant, N. M., E. K. Noonan-Wright, A. L. Reiner, C. M. Ewell, B. M. Rau, J. A. Fites-Kaufman, and S. N. Dailey. 2015. Fuel accumulation and forest structure change following hazardous fuel reduction treatments throughout California. International Journal of Wildland Fire 24:361–371.

Vakili, E., C. M. Hoffman, R. E. Keane, W. T. Tinkham, Y. Dickinson, E. Vakili, C. M. Hoffman, R. E. Keane, W. T. Tinkham, and Y. Dickinson. 2016. Spatial variability of surface fuels in treated and untreated ponderosa pine forests of the southern Rocky Mountains. International Journal of Wildland Fire 25:1156–1168.

Wasserstein, R. L., A. L. Schirm, and N. A. Lazar. 2019. Moving to a World Beyond "p < 0.05." The American Statistician 73:1-19.

Wenger, S. J., and J. D. Olden. 2012. Assessing transferability of ecological models: an underappreciated aspect of statistical validation. Methods in Ecology and Evolution 3:260–267.

Wozniak, S. S., E. K. Strand, T. R. Johnson, A. Hulet, B. A. Roundy, K. Young, C. : Wozniak, E. K. Strand, T. R. Johnson, A. Hulet, B. A. Roundy, and K. Young. 2020. Treatment longevity and changes in surface fuel loads after pinyon–juniper mastication. Ecosphere 11:e03226.

Wulder, M. A., J. C. White, R. F. Nelson, E. Næsset, H. O. Ørka, N. C. Coops, T. Hilker, C. W. Bater, and T. Gobakken. 2012. Lidar sampling for large-area forest characterization: A review. Remote Sensing of Environment 121:196–209.

Zald, H. S. J., C. J. May, A. N. Gray, M. P. North, and M. D. Hurteau. 2024. Thinning and prescribed burning increase shade-tolerant conifer regeneration in a fire excluded mixed-conifer forest. Forest Ecology and Management 551:121531.

Zhang, J., W. W. Oliver, and M. D. Busse. 2011. Growth and development of ponderosa pine on sites of contrasting productivities: relative importance of stand density and shrub competition effects. 36:2426–2438.

Ziliak, S. T. 2019. How Large Are Your G-Values? Try Gosset's Guinnessometrics When a Little "p" Is Not Enough. The American Statistician 73:281–290.

Chapter 2: How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests?

Don C. Radcliffe[1*], Jonathan D. Bakker[1], Derek J. Churchill[2], Ernesto C. Alvarado[1], David W. Peterson[3], Madison M. Laughlin[1], and Brian J. Harvey[1]

[1]University of Washington, School of Environmental and Forest Sciences, Seattle, WA, USA
[2]Washington Department of Natural Resources, Forest Resilience Division, Olympia, WA, USA
[3]United States Forest Service, PNW Research Station, Wenatchee, WA, USA
*Corresponding author: dradclif@uw.edu

This Chapter is published in a peer-reviewed journal:

Radcliffe D.C., Bakker J.D., Churchill D.J., Alvarado E.C., Peterson D.W., Laughlin M.M., Harvey B.J. 2024. How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests? *Forest Ecology and Management*: 553, 121594.

2.1 Abstract

Fuel treatments are commonly applied to increase resilience to wildfire in dry and historically frequent-fire forests of western North America. The long-term effects of fuel treatments on forest structure, fuel profiles (amount and configuration of fuels), and potential wildfire behavior are not well known relative to short-term effects. Additionally, long-term treatment effects have rarely been compared to the effects of pre-treatment conditions, treatment intensity, and site productivity on the long-term development of stand structure and fuel profiles. In this study, we addressed these knowledge gaps by resurveying 204 permanent plots at the Northeastern Cascades site of the Fire and Fire Surrogates study 13-18 years ('long-term') after burn-only, thin-only, and thin-plus-burn treatment, and comparing results to pre-treatment and un-treated

controls. Methods included ordinations, generalized linear mixed models, and fire models. All treatments shifted long-term average stand structure toward lower tree density, basal area, and crown fire potential, with thin-plus-burn treatments showing the highest magnitude of effects for most variables. However, the direction and magnitude of trajectories among plots within treatment types were highly variable. Long-term responses of stand structure, fuel profiles, and modelled fire behavior were positively correlated with their pre-treatment values. Treatment intensity strongly affected long-term stand structure and canopy fuel loads. By ~15 years post-treatment and under 80th percentile fire weather conditions, most plots in all treatments and un-treated controls failed to meet target thresholds for surface flame length, basal area mortality, and torching index, while most plots met thresholds for crowning index. However, live stand structure following simulated wildfire under 80th percentile conditions was characterized by lower stand density and a shift toward dominance by large-diameter and fire-resistant trees, suggesting that treated stands may be resilient to wildfires occurring under moderate weather. Our study suggests that understanding fuel treatment efficacy and longevity may be improved in future studies by incorporating fine-scale (i.e., plot-level) drivers of variability in stand structure, fuel profiles, and modelled fire behavior, and by using multiple methods of evaluating treatment effectiveness. Thin-plus-burn treatments and intensely applied burn-only and thin-only treatments can reduce basal area and potential for crown-fire for more than a decade. Additional maintenance treatments may be needed by 15 years after initial treatment, to further reduce potential for severe surface fire and high tree mortality in subsequent wildfire.

2.2 Introduction

Ecological and social impacts of wildfires have increased globally in recent decades (Schoennagel et al. 2017, Moreira et al. 2020, Haque et al. 2021). In western North America, many forests that burned frequently before European colonization (‘frequent-fire forests’) have missed multiple fire cycles since the late 1800s because of fire suppression and exclusion of Indigenous fire (Hessburg and Agee 2003). The resulting fuel accumulation, combined with a warming and drying climate, increases potential for large and severe fires that are likely outside the range of the historical fire regime (Abatzoglou and Williams 2016, Hagmann et al. 2021). Reducing fuel loads is therefore a major component of many forest management plans to restore low and mixed-severity fire regimes (Hessburg et al. 2021).

Fuel treatment types vary in their effects on stand structure, fuel profiles (amount and configuration of fuels), and potential fire behavior (Schwilk et al. 2009, Stephens et al. 2012b). For example, in the short-term (<5 years post-treatment), prescribed burning (‘burn-only’ treatment) tends to reduce surface fuel (e.g., dead woody material and leaf litter on the forest floor) but usually has relatively little effect on canopy fuel in the mild weather conditions in which prescribed burning often takes place (Schwilk et al. 2009). Thinning (‘thin-only’ treatment) often reduces canopy fuel by selectively removing smaller trees, but can increase surface fuel via transport of fuel from the canopy to the forest floor, unless additional fuel management practices such fuel piling, burning, and/or whole tree harvest are implemented (Schwilk et al. 2009). Thinning followed by burning (‘thin-plus-burn’ treatment) tends to reduce both surface and canopy fuel profiles (Schwilk et al. 2009, Fulé et al. 2012, Stephens et al. 2012b). Each of the above fuel treatments can reduce wildfire severity, most often measured by tree mortality, though effects are typically strongest in burn-only and especially thin-plus-burn treatments (Prichard et al. 2010, 2020, Kalies and Yocom Kent 2016, Cansler et al. 2022b).

Vegetation conditions and fuel profiles change with time since treatment, and the long-term dynamics of treatment have been studied less than short-term effects (Kalies and Yocom Kent 2016, Urza et al. 2023). Vegetation conditions and fuel profiles are often statistically indistinguishable from untreated areas and/or pre-treatment values by 5-15 years after treatment, often with high variability among sample plots and correspondingly low statistical power (Battaglia et al. 2008, Chiono et al. 2012, Stephens et al. 2012a, van Mantgem et al. 2016, Crotteau et al. 2018, Hood et al. 2020, Rossman et al. 2020, Morici and Bailey 2021). Among treatment types, thin-plus-burn treatments likely have the strongest long-term effects (Stephens et al. 2012a, Hood et al. 2020, Morici and Bailey 2021) because of near-simultaneous short-term reductions in surface, ladder, and canopy fuels (Schwilk et al. 2009). However, many key mechanisms affecting treatment longevity are not well understood, including long-term dynamics of tree regeneration (Tinkham et al. 2016, Rossman et al. 2020, Zald et al. 2024), understory vegetation growth (Rossman et al. 2018, Dudney et al. 2021), delayed tree mortality (Hood et al. 2018), surface fuel deposition (Harris et al. 2016), and surface fuel decomposition (Kennedy et al. 2021, Hanan et al. 2022).

Long-term effects of treatments on fuel profiles may be influenced by factors that vary within and among stands, such as pre-treatment stand structure, site productivity, and treatment intensity (Jain et al. 2012). Pre-treatment stand conditions are legacies of past management and disturbance, and constrain potential treatment outcomes (Reinhardt et al. 2008, Zald et al. 2024). For example, stands consisting solely of smaller fire-intolerant trees will take longer to build resistance to fire when treated than stands containing relatively larger, fire-resistant trees

(Hessburg et al. 2015). Site productivity drives vegetation growth and decomposition rates, with vegetation in more productive forests likely to grow more rapidly after treatment (Jain et al. 2012, Ex et al. 2019) and activity fuel (i.e., fuel inputs associated with treatment) likely to decompose more rapidly after treatment. However, studies of the effects of productivity on treatment longevity have had variable results (Tinkham et al. 2016, Morici and Bailey 2021), potentially because of different methods and response variables among studies. For example, Tinkham et al. (2016) analyzed the effect of productivity on longevity through modelling development of canopy and ladder fuel, and Morici and Bailey (2021) analyzed the effects of productivity through field measurements of surface fuel changes over time. Treatment intensity, broadly defined here as the change in vegetation and fuel profiles caused by treatment, varies widely within and among treatments and is likely to affect the duration of fuel treatment effectiveness (Jain et al. 2012). By definition, greater treatment intensity leads to greater short-term reductions in fuel, but long-term effects are less clear. It is plausible that greater treatment intensity may stimulate vegetation development in more productive sites, and thus increase fuel profiles in the long-term (Jain et al. 2012).

We addressed the above knowledge gaps by analyzing long-term (~15-year post-treatment) stand structure and fuel profile responses to control, burn-only, thin-only, and thin-plus-burn treatments, while accounting for plot-level differences in pre-treatment condition, treatment intensity, and site productivity. We used field data from the Northeastern Cascades site of the US Fire and Fire Surrogates (FFS) study (McIver and Weatherspoon 2010) to ask:

1) How are long-term stand structure and fuel profiles affected by pre-treatment forest condition, treatment type, treatment intensity, and site productivity?

2) How are expected fire behavior and severity affected by pre-treatment forest condition, treatment type, treatment intensity, and site productivity?
3) Does modelled wildfire behavior meet desired target metrics for surface flame length, basal area mortality, torching index, and crowning index ~15 years after treatment?

2.3 Methods

Study Area

The Northeastern Cascades site of the FFS study is in central Washington (USA) on the forested mid-slopes between the sagebrush steppe and the alpine crest of the Cascade Mountains, and is characteristic of dry forests of the interior Columbia River basin (Agee and Lehmkuhl 2009). Forest structure and composition are heavily influenced by moisture dynamics, and therefore, elevation and topographic position (Agee and Lehmkuhl 2009). The tree layer is dominated by ponderosa pine (*Pinus ponderosa*) and Douglas fir (*Pseudotsuga menziesii*), with much smaller components of western larch (*Larix occidentalis*) and grand fir (*Abies grandis*) (Rossman et al. 2020). The precolonial (before settlement of non-Indigenous peoples, ca. 1850s) fire return interval was between 6 and 21 years (Agee and Lehmkuhl 2009). In the 20th century, fire suppression and exclusion of Indigenous burning resulted in fuel accumulation and increased density of shade-tolerant, fire-intolerant tree species, and high-grade logging (i.e., selectively cutting the largest trees) caused a deficit of large, fire-resistant trees (Hessburg and Agee 2003).

Treatment selection and implementation

The FFS study was a coordinated distributed experiment initiated in the late 1990s and early 2000s across US forests. It was designed to experimentally test the effects of three common fuel treatments (mechanical thinning [thin-only], prescribed burning [burn-only], and mechanical thinning followed by prescribed burning [thin-plus-burn]) along with an un-treated control. A wide range of response variables were measured, so FFS sites were designed to have fewer and larger experimental units than would generally be used for studies focusing solely on fuel or stand structure (McIver and Weatherspoon 2010). Treatment implementation details were decided by site managers so that treatments would accurately reflect local ecological conditions and management practices. The common goal of each FFS site was to treat forests so that 80% of the remaining basal area would survive a fire that occurred during 80th percentile fire weather conditions (McIver and Weatherspoon 2010).

Planning at the Northeastern Cascades site began in the late 1990s. In accordance with FFS protocols, 30 candidate units of 10 ha or larger were identified. Twelve experimental units were randomly selected from the set of 30 candidates, and three units were randomly assigned to each treatment type. Units were required to be approximately rectangular in shape, have slopes averaging less than 26.5 degrees, and be 90% forested with the overstory dominated by Douglas-fir and/or ponderosa pine. Thinning was implemented in 2002 and 2003 and was designed to be spatially clumpy, reducing average stand basal area to 10-14 m^2 per hectare. Yarding was done by helicopter, and most snags were felled due to safety concerns (Harrod et al. 2009). Some units were burned in 2004 and others in 2006. Burns implemented in 2004 were of lower intensity and severity than prescribed due to an early spring green up, while those implemented in 2006 met intensity and severity goals but were patchy (Agee and Lehmkuhl 2009).

In 2012, a wildfire (the Poison Fire, part of the Wenatchee Complex) burned two control units, a thin-only unit, and a burn-only unit (Fig. 2.A.1). These four units were omitted from our analyses, along with three wildfire-burned plots in a thin-plus-burn unit that was otherwise not affected by wildfire (Tripp, the unit immediately north of the wildfire in Fig. 2.A.1). As a result, the long-term experimental design consists of three thin-plus-burn units, two thin-only units, two burn-only units, and one control unit (Rossman et al. 2018). The un-treated control unit remaining after the wildfire is at a relatively low elevation and represents relatively arid and low productivity conditions within the scale of the study.

Data collection

Each experimental unit contains up to 40 sample plots on which fuel profiles and stand structure were measured. Plots were arranged on a 40-meter grid system within units. These plots were measured in 2000-2001 (pre-treatment) and again in 2004-2006 (short-term post-treatment). We resampled 204 permanent plots in 2019 and 2020 (71 plots from three thin-plus-burn units, 58 plots from two burn-only units, 52 plots from two thin-only units, and 24 plots from one untreated control unit). The protocols detailed below match those followed in pre-treatment surveys (Agee and Lolley 2006, Agee and Lehmkuhl 2009), except where noted.

At each plot, we re-measured surface fuel in two planar intercept transects (Brown 1971) at the same locations as were measured during pre-treatment. The surface fuel transects radiated from plot center with the first transect oriented towards a random azimuth and the second oriented randomly within the range of possible azimuths at least 90 degrees from the first azimuth. In each surface fuel transect, we counted 1-hour fuel for 2 m, 10-hour fuel for 3 m, 100-hour fuel for 5 m, and 1000-hour fuel for 20 m. Differences in inclusion of bark pieces in the fuel transects necessitated subsequent calibration and correction for the contribution of bark to 1-, 10-, and 100- hour fuels; see Appendix 2.2 for details. For 1000-hour fuel, the diameter, decay class, and species of each piece were also recorded. Litter depth, duff depth, and woody fuel height were measured at three points per transect.

The protocol for determining tree plot size was different for pre-treatment surveys than for our survey, though measurements on individual trees were the same (Agee and Lolley 2006, Agee and Lehmkuhl 2009). Pre-treatment surveys used variable rectangular plots with coarser size increments than in our survey. We measured overstory structure with a circular adjustable radius design. Specifically, we used one radius for ‘smaller trees’ (≥0.1 cm diameter at breast height [dbh] and <30 cm dbh), and another radius for ‘larger trees’ (≥30 cm dbh), to avoid the possibility of sapling clumps causing under-sampling of larger, more fire-resistant trees. We customized each plot radius to sample at least ten trees per plot, at least five of which had to be larger trees. The maximum allowable plot radius was 18 m. Radii were adjustable in meter increments. The smaller tree plot could have an equal or lesser area than the larger tree plot, but not greater. For each tree, we recorded species, dbh, total height, and height to base of live crown.

Fuel profiles and stand structure were measured during the pre-treatment and soon after treatments were implemented (Agee and Lolley 2006), but we could not locate detailed short-term post-treatment data in either paper or digital format. Therefore, all analyses in this manuscript compare only pre-treatment and long-term data collection periods. Although more plots were measured in the pre-treatment and short-term post-treatment measurements, all analyses and summaries reported here are based on the 204 plots we resampled in the long-term. Data from the Mission Creek FFS site addressing stand structure (Harrod et al. 2009), tree regeneration (Rossman et al. 2020), and understory plants (Rossman et al. 2018) are from a separate network of 20x50 m plots within the experimental units.

Because we did not have access to short-term post-treatment field data on treatment outcomes for each plot, we estimated treatment intensity using the satellite-derived relativized differenced normalized burn ratio (RdNBR) as an indicator of vegetation change caused by treatment (Knipling 1970, Knight et al. 2022). We calculated RdNBR without offsets from Landsat 7 imagery with 30-m resolution, using Google Earth Engine and Python code modified from (Parks et al. 2021) to gather composite imagery from the growing season. In calculating RdNBR, we used the 2001 growing season as the base year to reduce interannual bias among units and the growing season after treatment as the post-treatment reference. For example, RdNBR was calculated for units burned in 2006 by comparing the growing seasons of 2001 and 2007.

Modelling potential fire behavior

We modelled surface flame length, total flame length, torching probability, torching index, and crowning index using the Forest Vegetation Simulator Fire and Fuels Extension (FVS-FFE) (Reinhardt and Crookston 2003) version 20220311, East Cascades variant (Rebain et al. 2010), and modelled tree mortality as a proportion of density and basal area using the First Order Fire Effects Model (FOFEM) (Reinhardt et al. 1997) version 6.7. We entered inputs and generated outputs at the plot level to visualize distributions and to use model outputs in the same analyses as field variables. To model diameter distributions following wildfire, we implemented the FOFEM equations from Lutes (2020) in statistical program R, which allowed us to efficiently obtain estimates of mortality probability for individual trees.

In FVS-FFE, we used field-measured fuel and stand structural inputs to represent surface fuel profiles and as the base inputs for indicators of ladder fuel and canopy fuel profiles (e.g., canopy base height, canopy bulk density, torching index, and crowning index). We allowed FVS-FFE to assign the fuel model automatically based on our field-measured fuel and stand structural data (Rebain et al. 2010), using a hierarchical decision process tuned for the East

Cascades model variant. Automatic fuel model assignment eliminated the potential for bias in fuel model assignment between field crews from different years; see Fig. 2.A.2 for average fuel model weighting by period and treatment. In our model implementation, fuel model assignment did not affect fuel profiles, but affected estimated surface area to volume ratio of some fuel classes, dead fuel extinction moisture, and fuelbed depth (Rebain et al. 2010).

In FOFEM, we used field-measured species, dbh, height, and live crown ratio inputs along with predictions of surface flame length from FVS-FFE. FOFEM crown scorch equations use these inputs to estimate bark thickness and percentage of crown scorched as independent predictor variables of tree mortality. FOFEM does not account for delayed mortality, torching, or crown fire, and therefore is a conservative estimate of tree mortality, particularly when crown fire is likely (Lutes 2020).

We modelled fire behavior using three weather scenarios, “mild”, “moderate”, and “severe.” For tree mortality models we added a fourth “null” scenario. To determine parameters for each weather scenario, we used Fire Family Plus (Bradshaw and McCormick 2000) version 5 to gather weather and fuel moisture data from the nearby Swauk and Dry Creek Remote Automated Weather Stations (Agee and Lolley 2006). Fuel moisture, temperature, and windspeed parameters were selected so that the mild and moderate scenarios corresponded to the 60^{th} and 80^{th} percentiles of daily average fire season conditions and the severe scenario corresponded to the 97^{th} percentile of daily maximum fire season conditions. The severe scenario used daily maximum temperatures and windspeeds to reflect an extreme fire weather event. In tree mortality models, we applied the FVS-FFE default 1.22 m (four foot) flame length to plots in the ‘null’ condition, to isolate the effect of tree size from those of fuel profiles and wind friction. The reference climate window was 2002-2017; this interval likely reflects warmer and drier conditions than were considered in the original FFS study design. We defined the fire season as June 15 through September 15. For each fire weather and fuel moisture parameter, we calculated values for each weather station and then used the average values as model inputs. See Table 2.A.1 for fuel moisture and fire weather parameters.

Statistical analyses

We addressed Q1 (stand structure and fuel profiles) and Q2 (potential fire behavior and severity) with nonmetric-multidimensional scaling (NMDS) and generalized linear mixed models (GLMMs). NMDS was used to assess general changes at the plot and treatment scale among the 204 plots and two sample periods (i.e., 408 total plot measurements). We scored plots based on all response variables, including fuel, stand structure, and modelled fire behavior variables. Modelled fire behavior variables were obtained from the moderate weather scenario as this best reflects FFS design for 80th percentile fire weather (McIver and Weatherspoon 2010). We relativized each variable by its maximum before calculating the Euclidean distance matrix. We chose the fewest number of axes that produced a stress below 0.20 (McCune and Grace 2002). The final solution contained three axes and a stress of 0.11. We ran one ordination with all plot measurements but graphed each sample period separately. To represent the location of the predictors in ordination space, we calculated the weighted average value for each predictor in ordination space, using the 'wascores()' function in R package vegan (Oksanen et al. 2023). We also graphed the trajectory of each plot by translating its coordinates so that its pre-treatment value was at the centroid and its long-term location the same distance and direction from there as in the original ordination space.

We used GLMMs to test potentially significant drivers of variation for each response variable in the long-term period on a fine-scale (e.g., plot-level). Fixed effects included pre-treatment condition, topographic wetness index (TWI), heat load index (HLI), treatment type, and the nested effect of treatment intensity (RdNBR) within treatment type (see Table 2.1 for more information on collection and use of these variables). We included the experimental unit as a random intercept term to allow for plot-level analysis while accounting for potential within-unit correlation and within-unit variability that we were unable to account for with fixed effects (Zuur et al. 2009, Bolker et al. 2009). We used the same model structure and set of predictors for every response variable so that effect sizes could be directly compared between models (Zuur et al. 2009). Models included a gamma distribution of errors with a log link function, and continuous variables were scaled by their standard deviation (Zuur et al. 2009). We generated models with the 'glmer()' function in the R package lme4 (Bates et al. 2019). Models were screened for collinearity of fixed effects using a threshold of 0.7. We generated confidence intervals by bootstrapping with replacement, using 1000 iterations of each model including random effects. We used the function 'confint.merMod()' in R package lme4 (Bates et al. 2019) to generate confidence intervals of fixed effects parameter estimates, and the function 'bootMer()' in R package lme4 (Bates et al. 2019) to generate confidence intervals of predicted values for marginal effects plots.

To test whether modelled fire behavior met target metrics reflecting low severity wildfire effects (Q3), we used threshold analyses for surface flame length, basal area mortality, torching index, and crowning index. Target metrics were selected to reflect FFS goals and thus were based on the moderate weather scenario, corresponding to 80^{th} percentile fire weather (McIver and Weatherspoon 2010). The threshold for basal area mortality was 20 percent, directly taken from FFS study goals (McIver and Weatherspoon 2010). The surface flame length threshold was 1.2 m, which represents a relatively low severity fire that most trees above 12.7 cm can survive

(Ryan and Noste 1985), and that is usually manageable by hand crews of wildland firefighters (Alexander and Cruz 2019). The threshold for torching and crowning indices (i.e., the windspeeds that would support passive and active crown fire, respectively) was 28 km per hour. This threshold was based on wind gusts likely to be encountered at nearby RAWS stations under 80th percentile fire weather conditions, determined with the same methods used to select weather and fuel moisture parameters for fire modelling. We reported results in terms of the percentage of plots that met the thresholds within each combination of treatment, period, and metric.

Finally, to assess the resultant stand structure from the effects of treatments (Q1) and modelled wildfire 15-years post-treatment (Q3), we present diameter distributions of live trees across each of the treatment and control conditions at each relevant point in time.

2.4 Results

Question 1: Long-term effects of fuel treatments on fuel profiles and stand structure

All fuel treatments had long-term effects on stand structure and canopy fuel profiles. Thin-plus-burn treatment had the strongest long-term effects relative to pre-treatment conditions, with a 40% reduction of basal area, 64% reduction of tree density, 55% reduction in canopy bulk density, 98% increase in canopy base height, and 53% increase in quadratic mean tree diameter (Table 2.2). Trees in the smallest diameter classes are important components of ladder fuel, and were reduced most strongly following burn-only and thin-plus-burn treatments; conversely, trees of the smallest diameter classes increased in thin-only treatments (Fig. 2.1, far-left and middle-left columns). Quadratic mean diameter and woody surface fuel increased long-term in all treatments and the un-treated control (Table 2.2). Trends among plots within treatment types were highly variable in the direction and magnitude of change in ordination space, with thin-plus-burn as the primary exception where plots trended consistently toward lower basal area, density, and canopy fuel loads (Fig. 2b-e). Untreated controls and thin-only treatments had the most varied effects on stand conditions, shifting plots in many directions in ordination space (Fig. 2.2b & Fig. 2.2e).

Treatment intensity affected long-term stand structure and canopy fuel loads for all treatment types (Fig. 2.3, Fig. 2.4). Greater treatment intensity generally produced greater long-term reductions in stand density, basal area, and canopy bulk density, with large effect sizes but wide confidence intervals for treatment-level predictions. The thin-plus-burn treatment produced the greatest reductions in basal area, density, and canopy bulk density across most of the treatment intensity spectrum, although trends were within the confidence intervals of other treatments (Fig. 2.4h, Fig. 2.4i, Fig. 2.4k). For surface fuel loads, the magnitude and direction of the treatment intensity effect varied among treatments. Burn-only treatments showed the strongest positive correlation between treatment intensity and fuel loads for many surface fuel variables (Fig. 2.4a-g), but more intense burn treatments showed the greatest reduction of litter loads (Fig. 2.4f). Thin-only treatments showed the smallest variability and magnitude of treatment intensity (not including un-treated control) (Fig. 2.4).

Long-term values of nearly all response variables were positively correlated with their pre-treatment value (Fig. 2.3, Fig. 2.5). Pre-treatment value (a continuous variable) usually had smaller effect size than treatment type (a categorical variable), but narrower confidence intervals (Fig. 2.3). The greatest reductions in fuel loads, basal area, and density were for plots with the highest pre-treatment values for these variables; treatments generally shifted these relationships so that reductions were greater from the pre-treatment to the long-term (Fig. 2.5). Stand structure and fuel profiles were less affected by topographic variables than by treatment type, treatment intensity, and pre-treatment value (Fig. 2.3).

Question 2: Modelled fire behavior and severity

Overall, modelled surface flame length increased and potential for crown fire (as measured by modelled torching and crowning indices) decreased in treated stands, though long-term and pre-treatment confidence intervals generally overlapped. Potential for crown fire decreased most strongly in thin-plus-burn (94% increase in torching index, 91% increase in crowning index) and burn-only (160% increase in torching index, 6% increase in crowning index) treatments (Table 2.2, Fig. 2.4m-p, Fig. 2.5m. In thin-only treatments, modelled surface flame lengths increased by 17% and crowning index increased by 26%, while torching index decreased by 12%. Modelled fire-caused tree mortality increased modestly in thin-only treatments (Table 2.2, Fig. 2.6). In the null scenario, treatments showed either a decrease in or smaller increase in modelled tree mortality, compared with models in other weather scenarios (Fig. 2.6).

Pretreatment conditions and treatment intensity both affected long-term treatment outcomes. All predicted long-term fire intensity and severity metrics were positively correlated with their predicted pre-treatment values (Fig. 2.5m-p, Fig. 2.7). Across treatment types, treatment intensity increased crowning index and canopy base height, whereas treatment intensity decreased litter, basal area, density, and canopy bulk density—albeit with wide confidence intervals of effects (Fig. 2.4f, 2.4h, 2.4i, 2.4k, 2.4l, and 2.4p). Surface flame lengths and total flame lengths were less affected by treatment intensity than other response variables (Fig. 2.4m-n).

Question 3: Target thresholds of predicted fire behavior and severity

Under 80th percentile weather conditions, modelled fire behavior met target thresholds for crowning index in most plots of all treatment types – including untreated controls, but thresholds were not met for surface flame length or basal area mortality (Table 2.3, Fig. 2.6). Thin-plus-burn treatment increased the number of plots meeting the torching index threshold (from 26% pre-treatment to 53% long-term) and the crowning index threshold (from 77% pre-treatment to 94% long-term) (Table 2.3). Burn-only treatments increased the number of plots meeting the torching index threshold (from 19% pre-treatment to 41% long-term) and modestly decreased the number of plots meeting the crowning index threshold (from 91% pre-treatment to 79% long-term) (Table 2.3). Thin-only treatments decreased the number of plots meeting the basal area mortality threshold (from 37% pre-treatment to 21% long-term) (Table 2.3). Pre-treatment values and weather had stronger effects than treatment for surface flame length and basal area mortality, while treatment, pre-treatment values, and weather affected torching index and crowning index (Fig. 2.6). Untreated units started with lower pre-treatment modelled basal area mortality values and higher torching indices than treated units (Fig. 2.6). Stand structure after moderate wildfire was simulated in long-term treated stands shifted live-tree diameter distributions to the right (i.e., toward larger-diameter trees) (Fig. 2.1, far right column) compared to stand structure after moderate wildfire was simulated in pre-treatment stands (Fig. 2.1, middle right column). These stand structure shifts were strongest for thin-plus-burn and thin-only treatments and weaker for burn-only and control stands.

2.5 Discussion

This study presents several insights about long-term treatment dynamics that are important for managing frequent-fire dry forests. Fifteen years after treatment basal area, density, and potential for crown fire were reduced relative to pre-treatment and un-treated controls. However, modelled surface flame length and wildfire-induced tree mortality were higher in the long-term than pre-treatment. Accounting for pre-treatment conditions and treatment intensity, two drivers that vary at a fine-scale, can help clarify long-term effects of treatments and can illustrate where treatments of a given type may have the greatest longevity. Threshold analyses and evaluating stand-structure outcomes of simulated wildfire can provide context about management objectives that may not be apparent from statistical comparisons of treatment and control values.

On average, treatments reduce long-term crown fire potential but not surface fire potential or modelled fire severity

Overall, treatment type can drive important differences in long-term stand structure and fire potential, as thin-plus-burn (the most intense treatment type) exhibited the strongest effects. In thin-only treatments, the low torching index and canopy base height we found are likely due to ladder fuel recovering quickly as advanced regeneration of shade-tolerant trees grow in response to treatment (Fig. 2.1) (Hood et al. 2020). While this suggests greater potential for surface fire to transition to crown fire, the high crowning indices suggests that fuel in the upper canopy is well spaced and less likely to support active crown fire. Conversely, in burn-only treatments, relatively low crowning indices suggest that canopy fuel is less affected by prescribed burning (Agee and Lolley 2006) and maintains greater potential for supporting active crown fire in the long-term than other treatments. However, long-term increases in torching indices and canopy base heights, and decreases in density, suggest that prescribed burning reduced understory vegetation and smaller tree saplings (Agee and Lehmkuhl 2009), decreasing potential for surface fire to transition to crown fire. As expected, the thin-plus-burn treatment demonstrated benefits of both thin-only treatments (reducing canopy fuel) and burn-only treatments (reducing ladder fuel). As such, thin-plus-burn treatments exhibited the greatest long-term reductions of overall fuel profiles, as well as the most consistent response among plots within any treatment type.

In contrast to their effects on crown fire potential, none of the treatments resulted in long-term reductions in surface fire potential. Modest increases in modelled surface flame lengths across all treatments may relate to observed changes in surface fuel and to reduced wind friction within stand of the thin-plus-burn treatment (Rebain et al. 2010), but the relative contributions of these observed changes to our FVS-FFE fire modelling results are unknown. Long-term increases in surface fuel may be partially due to factors external to treatments, as some increases in woody surface fuel and concurrent decreases in tree density (indicating tree mortality) were observed in all treatments including untreated control. Tree mortality contributes pulses of surface fuel as dead canopy fuel falls to the ground (Reed et al. 2023), and could be due to drought, succession, competition, and/or other local-scale disturbances across all stands (Kolb et al. 2016, Andrus et al. 2021). However, relatively large increases in surface fuel in thin-only units, and some sustained reductions in litter for burn-only and thin-plus-burn units, suggest that some short-term treatment effects on surface fuel (Schwilk et al. 2009) persisted for ~15 years (Busse and Gerrard 2020).

Ponderosa pine and Douglas-fir trees that are >50 cm in diameter are more likely to survive wildfires in interior dry frequent-fire forests (Peterson and Ryan 1986, Harrod et al. 1999, Swezy and Agee 2011), and low abundance of such trees in stands where treatments are applied constrains the potential for treatments to increase resilience to wildfire. However, both treated and untreated units are likely to become more resilient to wildfire over time as individual trees grow, barring a stand-replacing disturbance. For example, our study shows long-term increases in quadratic mean diameter, and slight long-term decreases in modelled basal area mortality under the null weather scenario. Multiple decades are likely required to grow substantial populations of large, highly fire-resistant trees. Wildfire resistance may develop more rapidly in treated units due to greater growth releases in remaining trees (Tepley et al. 2020). Continued reductions of surface fuels may be especially critical to buy time for large, fire-resistant trees to develop in stands are currently dominated by medium-diameter (e.g., 30-50 cm dbh) trees.

Accounting for fine-scale drivers can improve detection of treatment effects

The legacy of pre-treatment conditions is a common theme in restoration ecology (Thompson et al. 2018), and our work supports the assertion that pre-treatment conditions are important to consider in dry forest restoration (Jain et al. 2012, Zald et al. 2024). However, we generally detected larger effect sizes for treatment type than for pre-treatment conditions, suggesting that treatments can offset some of the constraints imposed by pre-treatment conditions. Future studies could sample and/or analyze within one treatment type, to remove the categorical variable of treatment type so that the ecological significance of pre-treatment values may be more directly compared with other continuous variables such as treatment intensity.

Although a treatment intensity-longevity tradeoff has been proposed (Jain et al. 2012), our findings do not support this tradeoff 15 years after treatment. Persistent effects of treatment intensity on stand structure, canopy fuel, and potential crown fire behavior likely relate to sparse long-term tree regeneration in our study area (Rossman et al. 2020). A treatment intensity-longevity tradeoff may be more likely in areas with rapid tree regeneration and/or crown responses to treatment, where treatments effects on stand structure and canopy fuel will diminish more rapidly (Jain et al. 2012, Ex et al. 2019, Zald et al. 2024). Future studies could benefit from consideration of the effect of treatment intensity across a wider productivity gradient, and use field data to more directly measure treatment intensity when data are available immediately following treatment.

For woody surface fuel, different effects of treatment intensity among treatment types likely reflects variable timing of tree mortality and subsequent fuel deposition. Short-term, activity fuel loads are greater in thin-only treatments than burn-only or thin-plus-burn treatments (Schwilk et al. 2009), which may reduce the ability of thin-only treatments to moderate wildfire severity immediately following treatment unless accompanied by surface fuel management (e.g., Stephens et al. 2009, Prichard and Kennedy 2012). In burn-only and thin-plus-burn treatments, however, trees killed by burning will also eventually contribute pulses of surface fuel (Battaglia et al. 2008, van Mantgem et al. 2016). In burn-only treatments, the pattern of greater surface fuel in more intensely treated plots was stronger in larger fuel classes (Fig. 2.4a-d). Larger fuel classes are expected to have more lagged responses to treatment and disturbance as their lower surface area to volume ratios drive lower decay rates (Harmon et al. 2020). It is plausible that when we made our long-term re-measurements, burn-killed trees had dropped most of their fine woody fuel (1-100 hour), and that these burn-induced inputs of fine woody fuel were at least partially decomposed. The burn-only treatments in our study were predominately low intensity (Agee and Lehmkuhl 2009), so it is possible that high deposition of woody surface fuel was localized to small areas of higher severity burn. In thin-only treatments, the negative association of treatment intensity with most woody surface fuel components could be caused by the decomposition of activity fuels, in combination with more intense thinning treatments having lower residual crown biomass and thus reduced ongoing contributions of woody surface fuel (Johnston et al. 2021).

The importance of fine-scale predictor variables is further supported by our GLMMs often predicting larger treatment-associated reductions in long-term wildfire potential than indicated by treatment-level summaries. The units sampled during our long-term re-measurement do not span the same productivity gradient for all treatments, so differences between GLMM predictions and summary level results may reflect GLMMs controlling for some of the variance in pre-treatment conditions and productivity. Specifically, the sampled control unit is at a lower elevation and therefore in a less productive area of the study area than the two control units that burned in the 2012 wildfire. Therefore, more productive areas were more likely to be represented in other treatments in the long-term sample period. This productivity difference between treated stands and un-treated control stands may reduce estimates of long-term effects in treated stands relative to untreated stands, especially if more productive stands respond more quickly to treatment (Jain et al. 2012).

Broadening assessments of long-term treatment efficacy and future research directions

Threshold analyses can add ecological and management context to studies of fuel treatment outcomes, but have obvious limitations which necessitate they are used in conjunction with other approaches. Managers may plan for different weather scenarios across varying contexts, and different thresholds of acceptability for potential fire behavior and/or differrent metrics of fire behavior altogether may be warranted in different ecological and societal contexts (Stephens et al. 2020, North et al. 2021). The thresholds we used reflect FFS goals of restoring low severity fire regimes in treated stands (McIver and Weatherspoon 2010), but managers could specify different threshold targets when goals are to mitigate potential for severe wildfire across broad landscapes with limited resources. For example, Ager et al. (2014) used a 2.4 m surface flame length threshold to characterize stands where severe wildfire effects are likely. In addition, stand structure after modelled wildfire in our long-term treatment units is large tree dominated and may be compatible with principles of fire resistance (Agee and Skinner 2005), although our treatments did not meet the target objectives of tree basal area survival set forth in the FFS guidelines. Despite the clear sensitivity of threshold analysis to the selection of thresholds and threshold metrics, threshold analysis may provide context about management goals that statistical comparisons of treatment and control values cannot provide alone.

Ongoing improvements in fire modelling methods can further inform threshold analyses of fuel treatment effectiveness. FVS-FFE and similar Rothermel-based fire behavior models can under-predict some aspects of fire behavior, due to poor representation of surface-to-crown fire transitions, spotting, and spatial heterogeneity (Parisien et al. 2019). In addition, FOFEM does not account for crown fire or delayed tree mortality (Lutes 2020), and thus actual fire effects may be more severe than our modelled outputs. Therefore, models may not represent the relative effects of treatment accurately where those treatments substantially alter canopy fuel loads. FVS-FFE and FOFEM are useful because they are widely used and well-documented tools (Rebain et al. 2010, Lutes 2020) with strengths and shortcomings that are well-known within the fire science and management communities. Ongoing improvement to widely-used fire modelling tools such as physics-based fire models (e.g., Hoffman et al. 2016, Parsons et al. 2017, Ritter et al. 2022, 2023) may enable more precise expectations of fire behavior and effects, and thus more precise threshold analyses.

2.6 Conclusion

Understanding long-term fuel treatment effects is crucial for scheduling effective, efficient, and context-dependent treatment maintenance (Kolden 2019, North et al. 2021), which can align treatment application with restoration goals (Laughlin et al. 2023). Our findings suggest that treatment-related reductions in basal area and potential for crown fire can persist for at least 15 years, especially where treatment intensity is greater. Maintenance treatments after this period can address potential for high surface flame lengths and resultant tree mortality in subsequent wildfire, though wildfire under moderate weather conditions may result in stand structure that meets restoration target objects. Including fine-scale drivers in analyses can yield insights about long-term treatment efficacy not apparent when aggregating plots within stands or within treatment types. Additionally, threshold analyses of long-term treatment effectiveness provided context about the ecological and management outcomes of treatments. Future studies more specifically designed to explore processes at fine spatial and temporal scales will likely improve insights on fuel treatment longevity and efficient treatment maintenance planning.

2.7 Tables

Table 2.1: Variables used in the generalized linear mixed models. All variables are fixed effects unless noted otherwise.

Variable	**Justification and model structure**	**Collection methods**
Pre-treatment value	Pre-treatment conditions may constrain possible long-term treatment effects (Jain et al. 2012).	The pre-treatment value of the response variable being tested in each model. For example, the model predicting long-term basal area includes the pre-treatment basal area value.
Topographic wetness index (TWI)	Topography is related to site productivity in moisture-limited dry forests (Tai et al. 2020), and topographic wetness index primarily reflects catchment position (Qin et al. 2011).	Calculated using the 'rsaga.wetness.index()' function in the RSAGA package (Brenning et al. 2018), using the methods of (Qin et al. (2011), and using SAGA GIS (Böhner and McCloy 2006) version 6.3.0. Based on a 10-m digital elevation model (University of Washington Earth and Space Science 2010).
Heat load index (HLI)	Topography is an indirect indicator of site productivity in moisture-limited dry forests (Tai et al. 2020), heat load index primarily reflects slope aspect and angle (McCune and Keon 2002).	Calculated using the 'hli' function in the SpatialEco package (Evans et al. 2021), using the methods of (McCune and Keon 2002). Based on a 10-m digital elevation model (University of Washington Earth and Space Science 2010).
Relativized differenced normalized burn ratio (RdNBR)	Used as an indicator of change in vegetation and fuel profiles (treatment intensity) since short-term post-treatment data is no longer available. Strong basis in physics (Knipling 1970), strong relationship with basal area loss in wildfires (Harvey et al. 2019), and used to track silvicultural treatments (Knight et al. 2022). Nested within treatment type to account for the likelihood that a given RdNBR value may indicate different types and amounts of fuel removed when used to measure different treatment types.	RdNBR without offsets calculated from Landsat 7 imagery with 30 m resolution, using Google Earth Engine and Python code modified from (Parks et al. 2021) to gather composite imagery from the growing season. The 2001 growing season was used as the base year for each treatment unit to reduce potential interannual bias, and the growing season after treatment used as the post-treatment reference. For example, units burned in 2006 had RdNBR calculated by comparing the growing seasons of 2001 and 2007.
Treatment type	Intent of the original study design. Used as a stand-alone categorical fixed effect, and as a factor to nest treatment intensity as measured by RdNBR. Control was used as reference for model output.	Treatment type applied (control, burn-only, thin-only, or thin plus plus).
Replicate unit (random effect)	Used as a random intercept to account for pseudoreplication that may occur because of plots being clustered within experimental units (Zuur et al. 2009).	Experimental unit.

Table 2.2: Response variables summaries by treatment type. The 'Pre-treatment values' section shows mean values ± 95% confidence intervals, while the 'Long-term change' section shows percent change of the treatment-level averages from the pre-treatment to the long-term period.

		Pre-treatment values				Long-term change			
Variable	**Units**	**Control**	**Burn**	**Thin**	**Thin + burn**	**Control**	**Burn**	**Thin**	**Thin + burn**
1-hour fuel	Mg/ha	0.5 ± 0.2	0.6 ± 0.2	0.4 ± 0.1	0.8 ± 0.3	+17%	+103%	+153%	+5%
10-hour fuel	Mg/ha	2.0 ± 0.7	2.8 ± 0.7	1.8 ± 0.6	2.3 ± 0.5	+148%	+134%	+352%	+105%
100-hour fuel	Mg/ha	2.2 ± 1.2	5.0 ± 1.5	5.5 ± 1.5	3.8 ± 1.0	+53%	+11%	+86%	+40%
1000-hour fuel sound	Mg/ha	4 ± 3	12 ± 5	13 ± 5	12 ± 4	+134%	+31%	+37%	+59%
1000-hour fuel rotten	Mg/ha	3 ± 3	8 ± 4	15 ± 7	8 ± 3	-62%	-32%	-25%	+10%
Litter	Mg/ha	26 ± 4	27 ± 3	26 ± 3	24 ± 2	+13%	-6%	+1%	-14%
Duff	Mg/ha	14 ± 5	22 ± 4	16 ± 3	11 ± 2	-17%	-29%	+41%	+3%
Canopy base height	meters	3.5 ± 1.0	2.4 ± 0.5	4.1 ± 0.7	3.1 ± 0.6	-2%	+98%	+3%	+98%
Canopy bulk density	kg/m^3	0.05 ± 0.01	0.06 ± 0.01	0.05 ± 0.01	0.07 ± 0.01	+10%	+10%	-3%	-55%
Basal area	m^2/ha	24 ± 5	24 ± 4	26 ± 4	25.2 ± 3.9	+27%	+14%	+5%	-40%
Density	trees/ha	529 ± 151	810 ± 191	527 ± 139	653 ± 167	-38%	-56%	-1%	-64%
Quadratic mean diameter	cm	27 ± 3	23 ± 2	28 ± 2	27 ± 2	+46%	+55%	+52%	+53%
Surface flame	meters	1.7 ± 0.1	1.9 ± 0.2	1.8 ± 0.2	1.9 ± 0.2	+7%	+5%	+17%	+12%
Total flame	meters	2.5 ± 0.7	3.9 ± 0.9	3.2 ± 0.9	5.3 ± 1.5	+9%	-14%	+50%	-40%
Torching index	km/hr	22 ± 12	13 ± 5	27 ± 8	17 ± 5	-15%	+160%	-12%	+94%
Crowning index	km/hr	65 ± 10	59 ± 7	64 ± 9	59 ± 9	-1%	+6%	+26%	+91%
Basal area mortality	percent	38 ± 10	47 ± 8	38 ± 7	48 ± 7	+1%	+3%	+23%	+0%
Density mortality	percent	51 ± 10	62 ± 7	50 ± 8	60 ± 7	+10%	-8%	+15%	-3%

Table 2.3: Percentage of plots meeting proposed thresholds of fire behavior and effects, by specific metric and by number of metrics.

	Control		Burn-only		Thin-only		Thin + burn	
Metric	Pre-treatment	Long-term	Pre-treatment	Long-term	Pre-treatment	Long-term	Pre-treatment	Long-term
Surface flame	8%	4%	9%	5%	10%	2%	9%	1%
Basal area mortality	21%	25%	28%	26%	37%	21%	23%	24%
Torching index	25%	25%	19%	41%	40%	40%	26%	53%
Crowning index	96%	88%	91%	79%	94%	87%	77%	94%
0 of 4 metrics ‘acceptable’	4%	8%	9%	12%	4%	13%	19%	3%
1 of 4 metrics ‘acceptable’	58%	58%	59%	47%	46%	42%	49%	43%
2 of 4 metrics ‘acceptable’	21%	21%	14%	22%	19%	27%	14%	33%
3 of 4 metrics ‘acceptable’	17%	8%	16%	16%	27%	15%	17%	21%
4 of 4 metrics ‘acceptable’	0%	4%	3%	3%	4%	2%	1%	0%

2.8 Figures

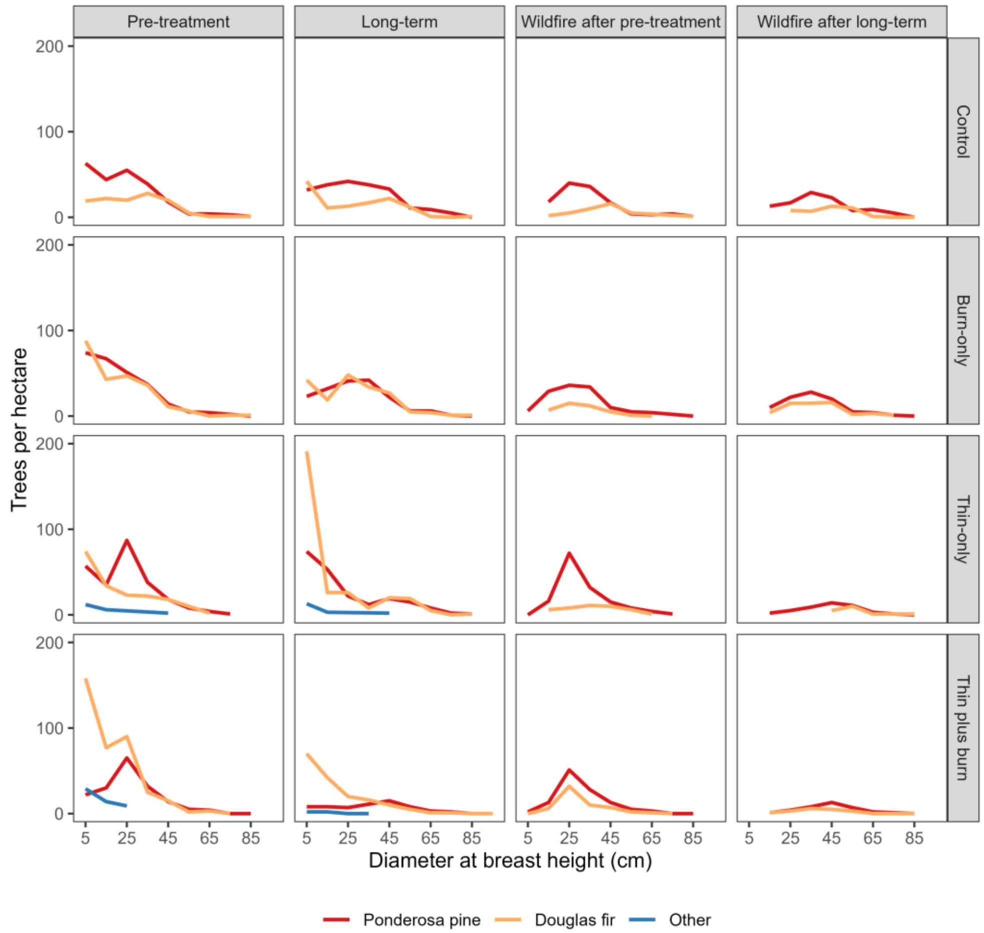

Figure 2.1: Tree diameter distributions by period (column) and treatment type (row). Densities (trees per hectare) are aggregated in 10 cm diameter classes (0-10 cm, 10-20 cm, etc.), and drawn at the midpoints of the classes. 'Wildfire after pre-treatment' and 'Wildfire after long-term' conditions represent FOFEM-modelled tree survival following an FVS-FFE-modelled wildfire burning immediately after the pre-treatment sample period and the long-term sample period, respectively, in the 'moderate' fire weather condition.

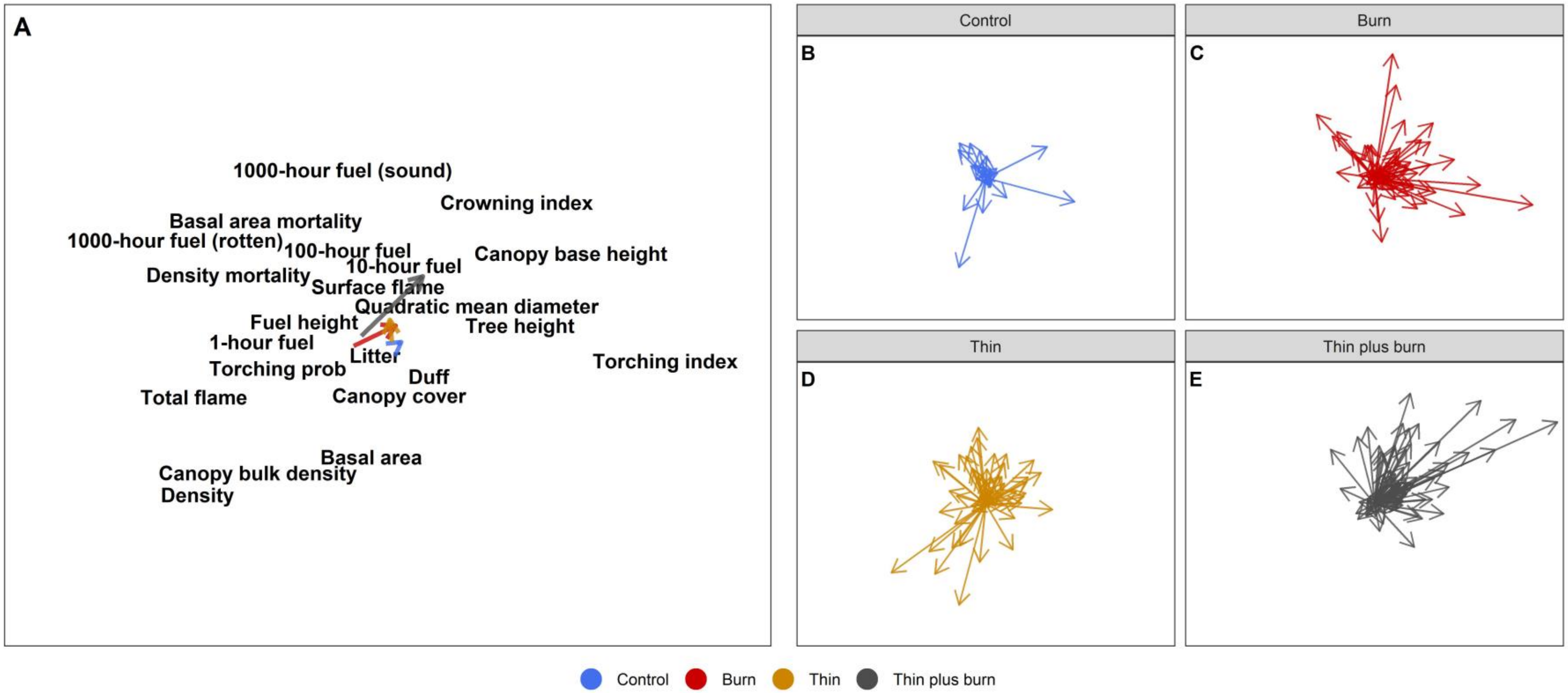

Figure 2.2: Arrows representing change in location within NMDS ordination space from pre-treatment to long-term at the treatment level (A) and the plot level (B-E). Text locations in plot A represent weighted average scores of the response variables used in the ordination. In the plot-level ordinations (B-E), each plot was translated so that its pre-treatment location is shown at the centroid; this enables direct comparisons of the direction and magnitude of change. Separate pre-treatment and long-term ordinations with absolute scores of plots are shown in Fig. 2.A.4.

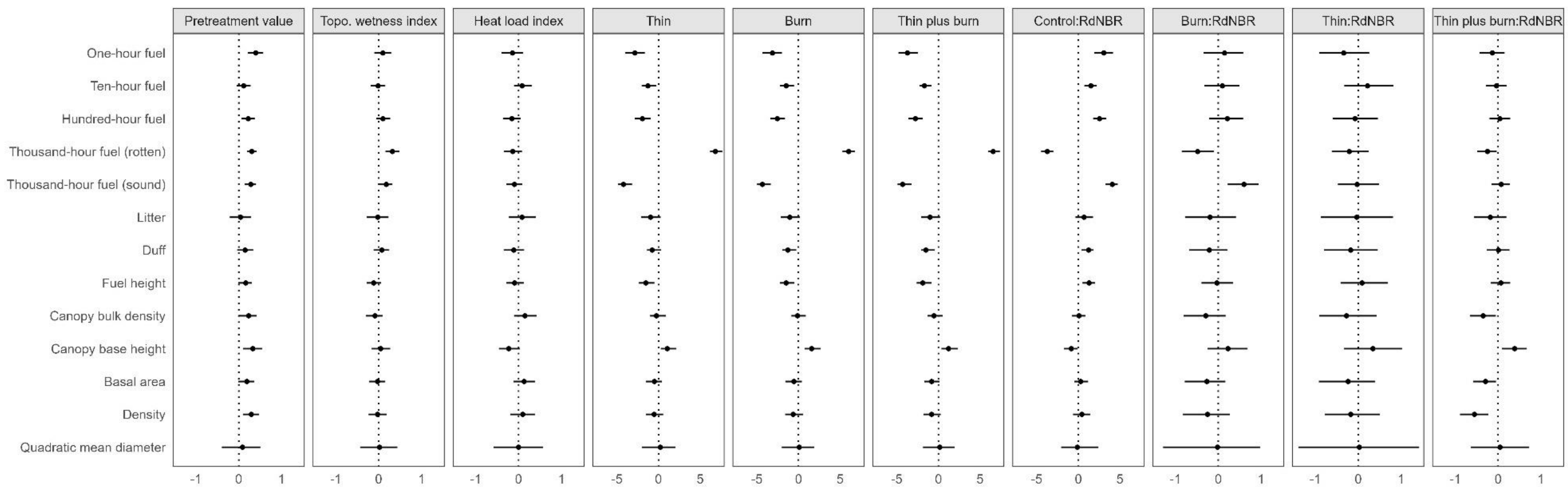

Figure 2.3: GLMM coefficient estimates with 95% confidence intervals, for field-measured response variables (y-axis) and faceted predictor variables. The x-axis represents coefficient estimates in terms of standard deviations. Confidence intervals fully right of 0 (dotted vertical line) denote significant positive correlations and intervals fully left of 0 denote significant negative correlations. Note different x-axis scales for continuous and categorical variables.

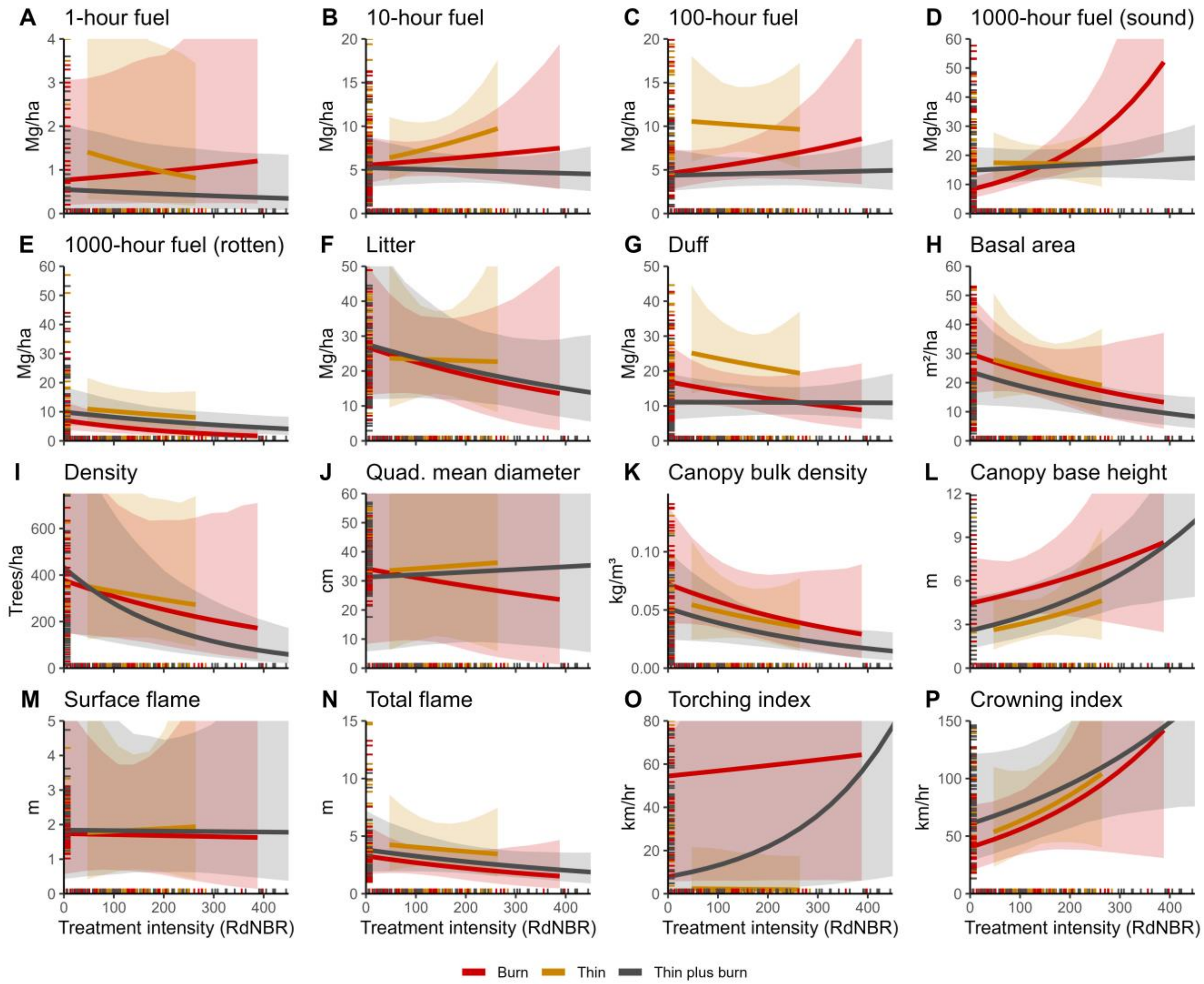

Figure 2.4: Marginal effect plots of treatment intensity and treatment type on long-term response variables, with bootstrapped 95% confidence intervals. All covariates not shown were held at average values. Rug plots show plot-level treatment intensity (RdNBR) values, colored by treatment category. Un-treated controls not shown due to low domain of RdNBR values on the x axes and large ranges on the y axes.

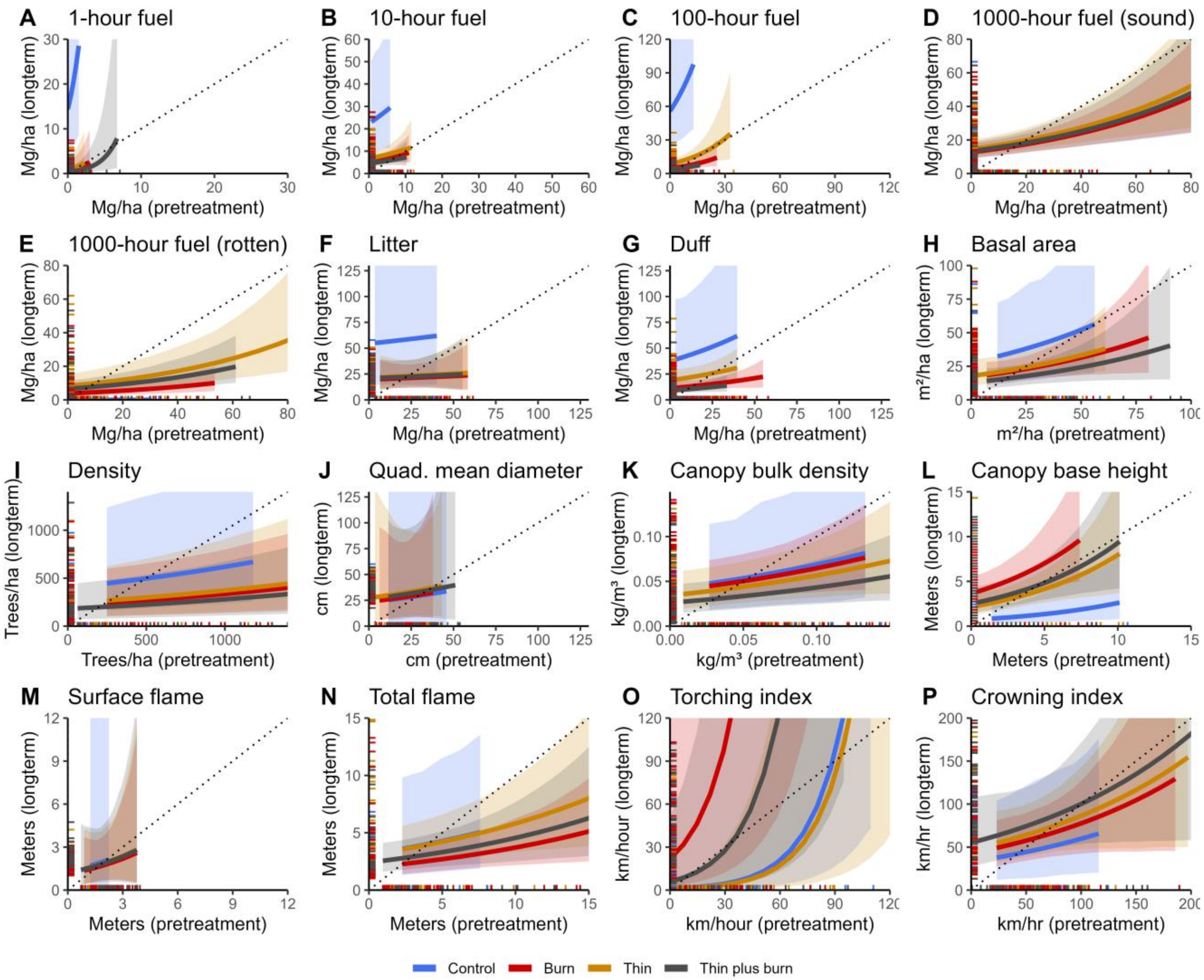

Figure 2.5: Marginal effect plots of pre-treatment value and treatment type on long-term response variables, with bootstrapped 95% confidence intervals. All covariates not shown were held at average values. Rug plots show plot level pre-treatment values (x-axis) and long-term values (y-axis) for the relevant variable, colored by treatment category. Dotted lines represents 1:1 relationship between pre-treatment and long-term values.

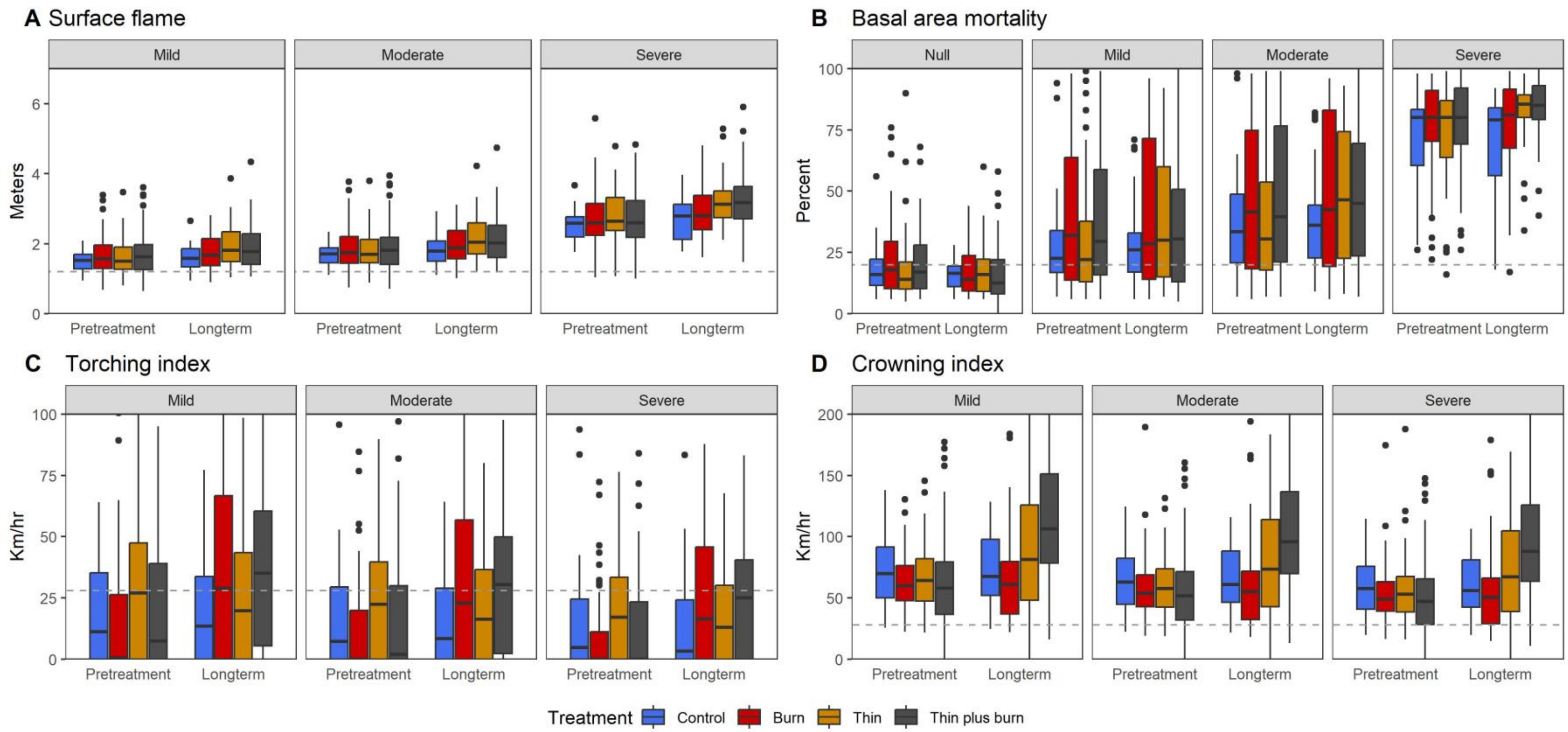

Figure 2.6: Fire modelling results compared with thresholds (dotted lines) proposed in literature. In each boxplot, the center line represents the median response within a treatment type; a treatment is considered acceptable if the median response is below the dotted line for surface flame (A) and basal area mortality (B), or above the dotted line for torching index (C) and crowning index (D). Surface flame length threshold reflects likely low severity fire effects (Ryan and Noste 1985, Alexander and Cruz 2019), basal area mortality threshold is from Fire and Fire Surrogates study goals (McIver and Weatherspoon 2010), torching and crowning index thresholds reflect 80th percentile wind gusts during the fire season near our study area.

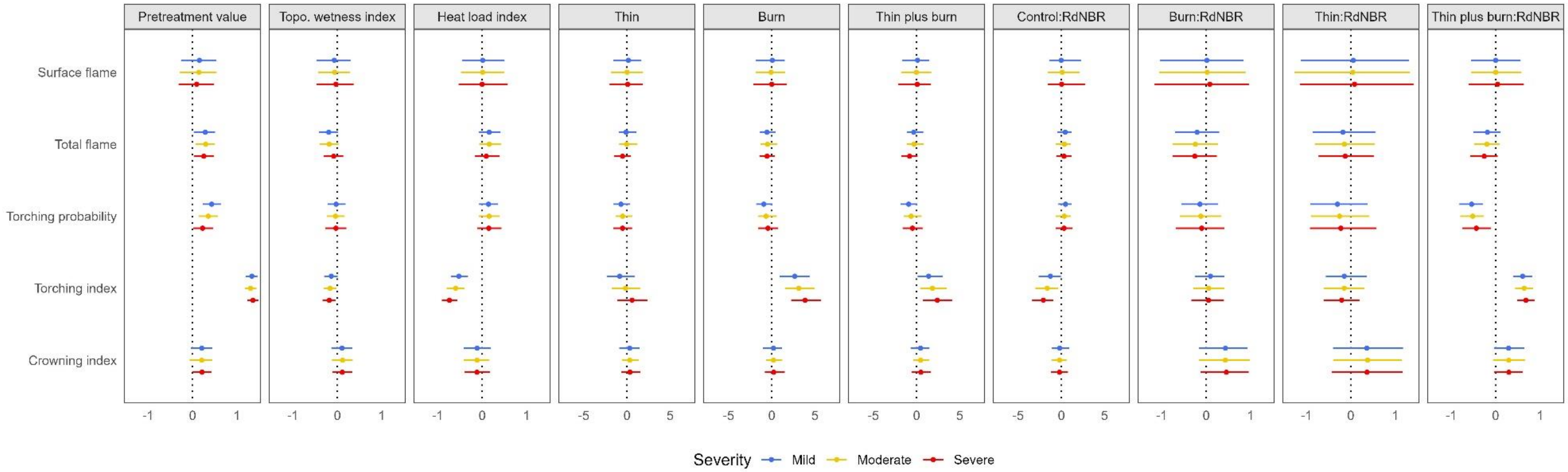

Figure 2.7: GLMM coefficient estimates with 95% confidence intervals, for modelled response variables (y-axis) and faceted predictor variables under multiple fire weather scenarios (colors). The x-axis represents coefficient estimates in terms of standard deviations. Confidence intervals fully right of 0 (dotted vertical line) denote significant positive correlations and intervals fully left of 0 denote significant negative correlations. Note different x-axis scales for continuous and categorical variables.

2.9 Appendix 2.1: Supplementary Tables and Figures

Table 2.A.1: Fuel moisture and fire weather parameters used in FVS-FFE wildfire modelling.

Metric	Weather Scenario	Value
One-hour Fuel Moisture (%)	Mild	4.5
	Moderate	3.5
	Severe	2.5
Ten-hour Fuel Moisture (%)	Mild	5.0
	Moderate	4.0
	Severe	3.0
Hundred-hour Fuel Moisture (%)	Mild	8.0
	Moderate	7.0
	Severe	5.0
Thousand-hour Fuel Moisture (%)	Mild	10.0
	Moderate	8.5
	Severe	7.0
Duff Moisture (%)	Mild	107.5
	Moderate	73.0
	Severe	32.0
Live Woody Fuel Moisture (%)	Mild	75.0
	Moderate	65.0
	Severe	59.5
Live Herbaceous Fuel Moisture (%)	Mild	62.0
	Moderate	50.5
	Severe	35.5
Windspeed (km/h)	Mild	3.7
	Moderate	4.7
	Severe	14.6
Temperature (°C)	Mild	20.6
	Moderate	24.2
	Severe	34.4

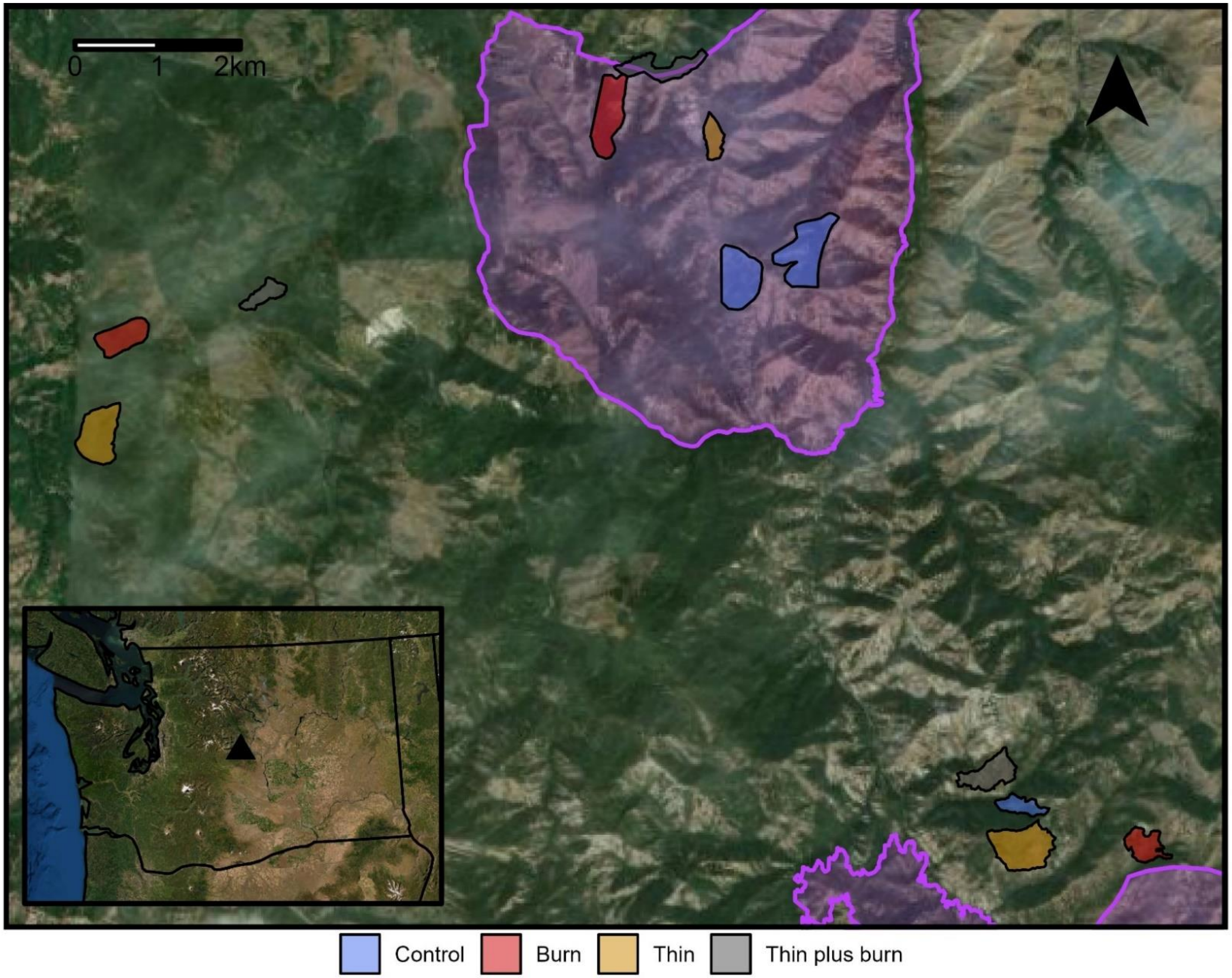

Figure 2.A.1: Northeastern Cascades FFS site. The purple polygons outline areas affected in 2012 wildfires; plots within these perimeters were excluded from analysis.

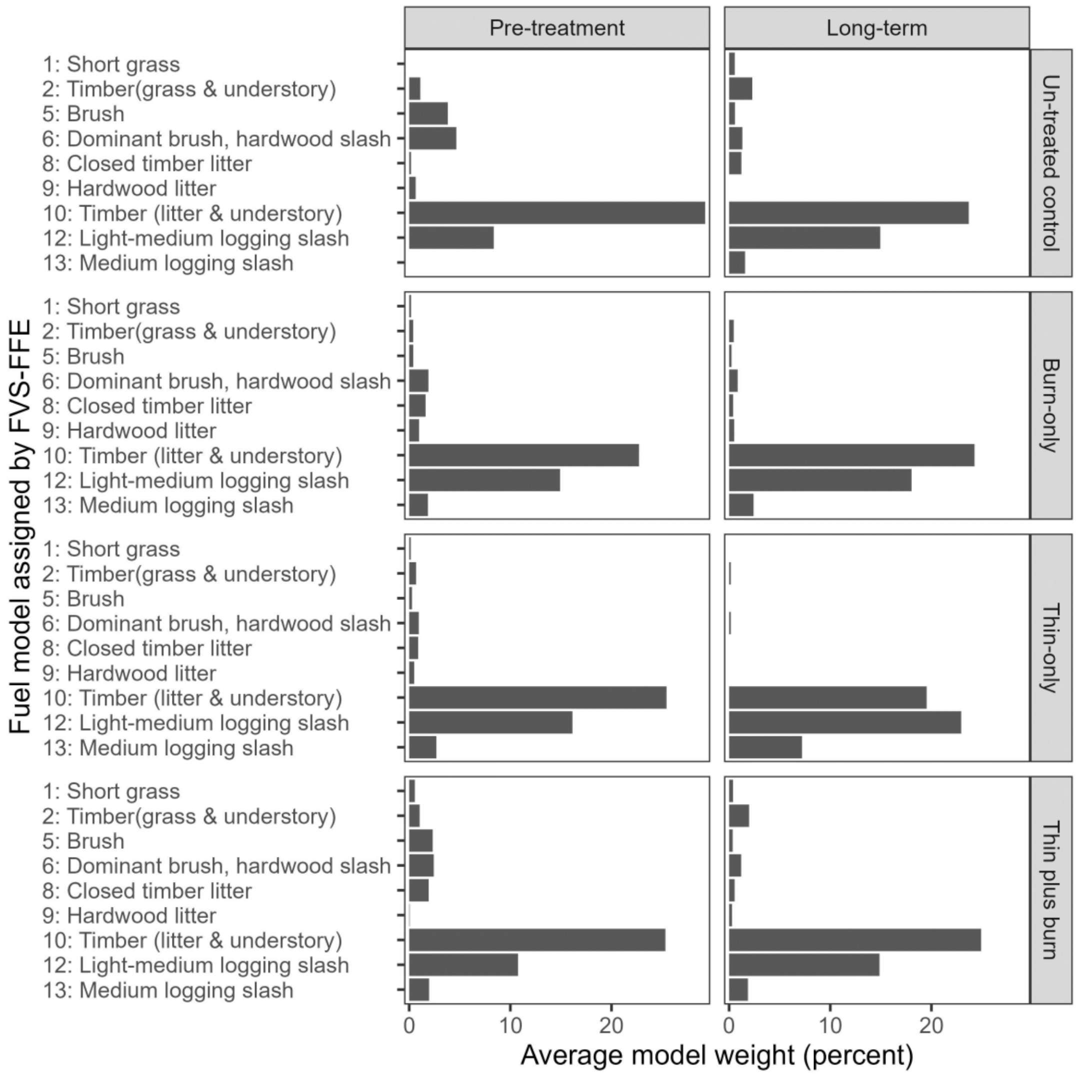

Figure 2.A.2: FVS-FFE fuel model (Rebain et al. 2010) weights averaged by combination of treatment types and sample period. FVS-FFE models were run at the plot level. Up to four fuel models were assigned to each plot and weighted on a continuous scale.

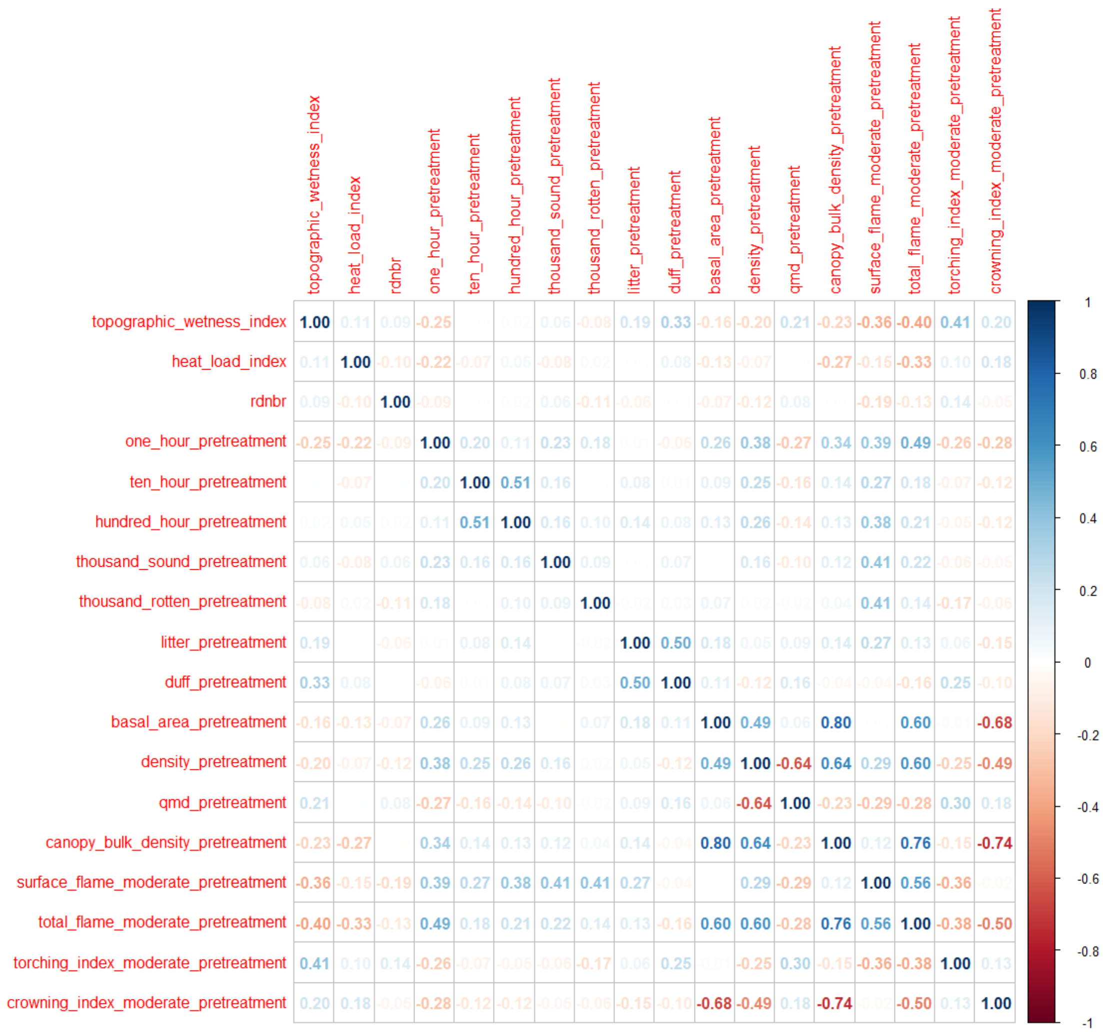

Figure 2.A.3: Correlation matrix of predictor variables used in GLMMs. The pre-treatment state of each response variable was only used in the model predicting the long-term outcome of that response variable. Therefore, covariance between pre-treatment values of different response variables does not affect GLMM performance.

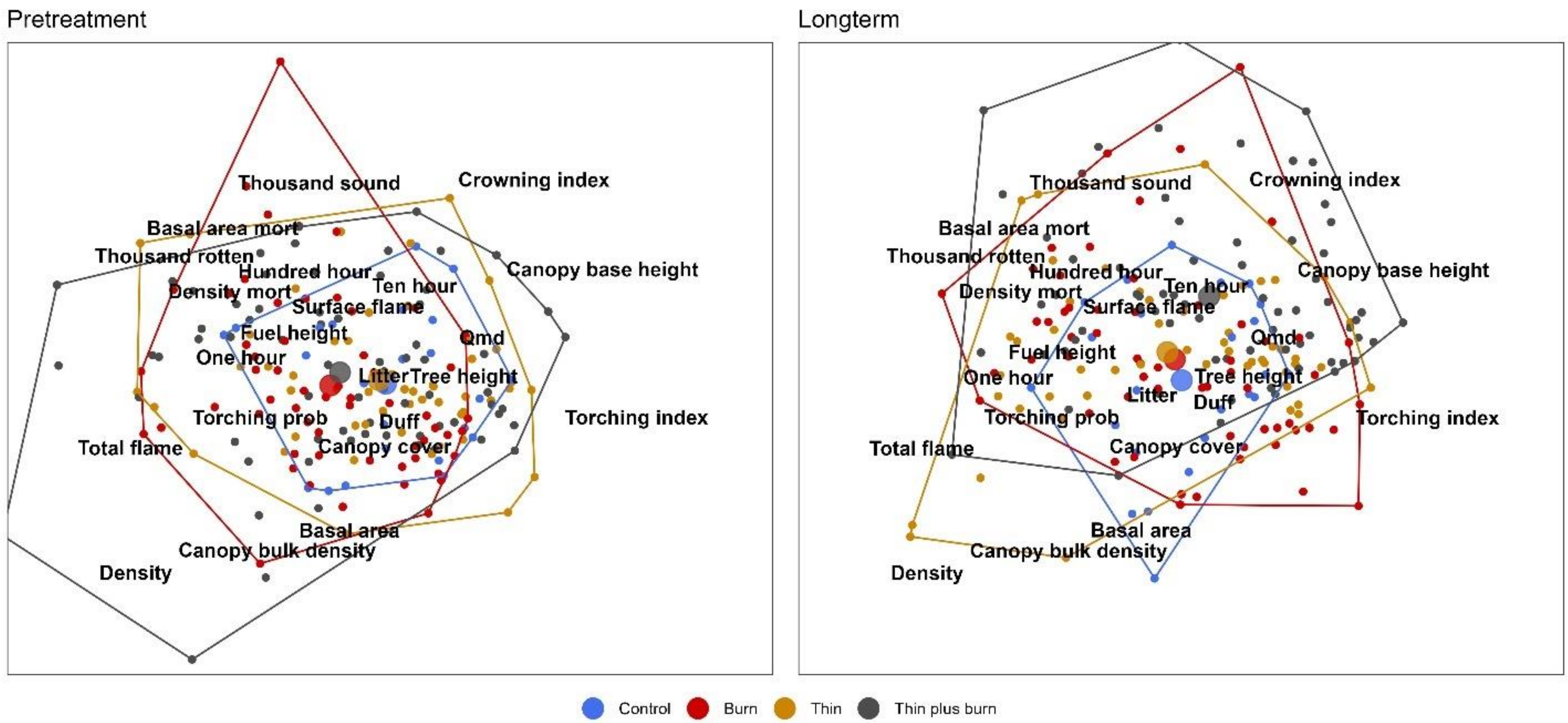

Figure 2.A.4: NMDS ordinations of fuel profile and stand structure in the pre-treatment and long-term periods. Sample periods are drawn separately but were part of a single ordination. Small points represent plot scores, large points represent treatment centroids, text indicates the weighted average score of each response variable, colors indicate treatment types, and lines demarcate convex hulls encompassing all of the responses for each treatment type.

2.10 Appendix 2.2: Bark Correction

In our long-term surveys, we initially counted bark flakes in the woody surface fuel surveys of 1-, 10-, and 100-hour fuel, and this was later found to be inconsistent with the protocols of the pre-treatment surveys. Therefore, we conducted a follow-up calibration survey in two units (Sand02 and Crow06) in 2021. In this survey, we completed 35 Brown's transects in which we tallied counts of both twigs and bark pieces by size class of fuel. Due to differences in twig morphology and bark flaking that we observed between ponderosa pine and other tree species, we used the calibration data to develop a linear model that predicted the proportion of Brown's transect counts that were twigs based on the proportion of basal area which was ponderosa pine. We used the resulting equation to adjust raw transect counts downward based on the expected proportion of counts that were twigs vs. bark. In the calibration data, one hour fuel was most sensitive to proportion of ponderosa pine, likely due to the high number of small bark flakes originating from ponderosa pine. In the crow 6 unit, which consisted of 92.6 percent ponderosa pine basal area, the proportion of transect count that were twigs was 9% for one hour fuels, 85% for 10 hour fuels, and 82% for hundred hour fuels. In the sand02 unit, which consisted of 13.1% ponderosa pine basal area, proportion of transect counts that were twigs was 94% for one hour fuels, 90% for 10 hour fuels, and 85% for hundred hour fuels.

2.11 References

Abatzoglou, J. T., and A. P. Williams. 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proceedings of the National Academy of Sciences of the United States of America 113:11770–11775.

Agee, J. K., and J. F. Lehmkuhl. 2009. Dry forests of the Northeastern Cascades Fire and Fire Surrogate project site, Mission Creek, Okanogan-Wenatchee National Forest. Page Res. Pap. PNW-RP-577. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 158 p. Portland, OR.

Agee, J. K., and M. R. Lolley. 2006. Thinning and Prescribed Fire Effects on Fuels and Potential Fire Behavior in an Eastern Cascades Forest, Washington, USA. Fire Ecology 2:3–19.

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Ager, A. A., M. A. Day, C. W. McHugh, K. Short, J. Gilbertson-Day, M. A. Finney, and D. E. Calkin. 2014. Wildfire exposure and fuel management on western US national forests. Journal of Environmental Management 145:54–70.

Alexander, M. E., and M. G. Cruz. 2019. Fireline Intensity. Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires:1–8.

Andrus, R. A., R. K. Chai, B. J. Harvey, K. C. Rodman, and T. T. Veblen. 2021. Increasing rates of subalpine tree mortality linked to warmer and drier summers. Journal of Ecology 109:2203–2218.

Bates, D., M. Maechler, B. Bolker, S. Walker, R. H. B. Christensen, H. Singmann, B. Dai, F. Scheipl, G. Grothendieck, P. Green, and J. Fox. 2019. Package “lme4.” https://cran.r-project.org/web/packages/lme4/index.html.

Battaglia, M. A., F. W. Smith, and W. D. Shepperd. 2008. Can prescribed fire be used to maintain fuel treatment effectiveness over time in Black Hills ponderosa pine forests? Forest Ecology and Management 256:2029–2038.

Böhner, J., and K. R. McCloy. 2006. SAGA - analysis and modelling applications. Collection Göttinger geographische Abhandlungen 115:1–130.

Bolker, B. M., M. E. Brooks, C. J. Clark, S. W. Geange, J. R. Poulsen, M. H. H. Stevens, and J. S. S. White. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology & Evolution 24:127–135.

Bradshaw, L., and E. McCormick. 2000. FireFamily Plus user’s guide, Version 2.0. Gen. Tech. Rep. RMRS-GTR-67. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 67.

Brenning, A., D. Bangs, M. Becker, P. Schratz, and F. Polakowski. 2018. Package “RSAGA”. https://github.com/r-spatial/RSAGA.

Brown, J. K. 1971. A Planar Intersect Method for Sampling Fuel Volume and Surface Area. Forest Science 17:96–102.

Busse, M., and R. Gerrard. 2020. Thinning and Burning Effects on Long-Term Litter Accumulation and Function in Young Ponderosa Pine Forests. Forest Science 66:761–769.

Cansler, C. A., V. R. Kane, P. F. Hessburg, J. T. Kane, S. M. A. Jeronimo, J. A. Lutz, N. A. Povak, D. J. Churchill, and A. J. Larson. 2022. Previous wildfires and management treatments moderate subsequent fire severity. Forest Ecology and Management 504:119764.

Chiono, L. A., K. L. O’Hara, M. J. De Lasaux, G. A. Nader, and S. L. Stephens. 2012. Development of Vegetation and Surface Fuels Following Fire Hazard Reduction Treatment. Forests 3:700–722.

Crotteau, J. S., C. R. Keyes, S. M. Hood, D. L. R. Affleck, and A. Sala. 2018. Fuel dynamics after a bark beetle outbreak impacts experimental fuel treatments. Fire Ecology 14:13.

Das, A. J., N. L. Stephenson, and K. P. Davis. 2016. Why do trees die? Characterizing the drivers of background tree mortality. Ecology 97:2616–2627.

Dudney, J., R. A. York, C. L. Tubbesing, A. T. Roughton, D. Foster, S. L. Stephens, and J. J. Battles. 2021. Overstory removal and biological legacies influence long-term forest management outcomes on introduced species and native shrubs. Forest Ecology and Management 491:119149.

Evans, J. S. , M. A. , Murphy, and K. Ram. 2021. Package “spatialEco” https://github.com/jeffreyevans/spatialEco.

Ex, S. A., J. P. Ziegler, W. T. Tinkham, and C. M. Hoffman. 2019. Long-Term Impacts of Fuel Treatment Placement with Respect to Forest Cover Type on Potential Fire Behavior across a Mountainous Landscape. Forests 2019, Vol. 10, Page 438 10:438.

Hagmann, R. K., P. F. Hessburg, S. J. Prichard, N. A. Povak, P. M. Brown, P. Z. Fulé, R. E. Keane, E. E. Knapp, J. M. Lydersen, K. L. Metlen, M. J. Reilly, A. J. S. Meador, S. L. Stephens, J. T. Stevens, A. H. Taylor, L. L. Yocom, M. A. Battaglia, D. J. Churchill, L. D. Daniels, D. A. Falk, P. Henson, J. D. Johnston, M. A. Krawchuk, C. R. Levine, G. W. Meigs, A. G. Merschel, M. P. North, H. D. Safford, T. W. Swetnam, and A. E. M. Waltz. 2021. Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. Ecological Applications 0:e02431.

Hall, S. A., C. Burke, and N. T. Hobbs. 2006. Litter and dead wood dynamics in ponderosa pine forests along a 160-year chronosequence. Ecological Applications 16:2344–2355.

Hanan, E. J., M. C. Kennedy, J. Ren, M. C. Johnson, and A. M. S. Smith. 2022. Missing Climate Feedbacks in Fire Models: Limitations and Uncertainties in Fuel Loadings and the Role of Decomposition in Fine Fuel Accumulation. Journal of Advances in Modeling Earth Systems 14:e2021MS002818.

Haque, K., A. K. Azad, Y. Hossain, T. Ahmed, M. Uddin, M. Hossain. 2021. Wildfire in Australia during 2019-2020, Its Impact on Health, Biodiversity and Environment with Some Proposals for Risk Management: A Review. Journal of Environmental Protection 12:391–414.

Harmon, M. E., B. G. Fasth, M. Yatskov, D. Kastendick, J. Rock, and C. W. Woodall. 2020. Release of coarse woody detritus-related carbon: A synthesis across forest biomes. Carbon Balance and Management 15:1.

Harris, R. M. B., T. A. Remenyi, G. J. Williamson, N. L. Bindoff, and D. M. J. S. Bowman. 2016. Climate–vegetation–fire interactions and feedbacks: trivial detail or major barrier to projecting the future of the Earth system? Wiley Interdisciplinary Reviews: Climate Change 7:910–931.

Harrod, R. J., D. W. Peterson, N. A. Povak, and E. K. Dodson. 2009. Thinning and prescribed fire effects on overstory tree and snag structure in dry coniferous forests of the interior Pacific Northwest. Forest Ecology and Management 258:712–721.

Harvey, B. J., R. A. Andrus, and S. C. Anderson. 2019. Incorporating biophysical gradients and uncertainty into burn severity maps in a temperate fire-prone forested region. Ecosphere 10:e02600.

Hessburg, P. F., and J. K. Agee. 2003. An environmental narrative of Inland Northwest United States forests, 1800–2000. Forest Ecology and Management 178:23–59.

Hessburg, P. F., D. J. Churchill, A. J. Larson, R. D. Haugo, C. Miller, T. A. Spies, M. P. North, N. A. Povak, R. T. Belote, P. H. Singleton, W. L. Gaines, R. E. Keane, G. H. Aplet, S. L. Stephens, P. Morgan, P. A. Bisson, B. E. Rieman, R. B. Salter, and G. H. Reeves. 2015. Restoring fire-prone Inland Pacific landscapes: seven core principles. Landscape Ecology 30:1805–1835.

Hessburg, P. F., S. J. Prichard, R. K. Hagmann, N. A. Povak, and F. K. Lake. 2021. Wildfire and climate change adaptation of western North American forests: a case for intentional management. Ecological Applications:e02432.

Hood, S. M., S. Baker, and A. Sala. 2016. Fortifying the forest: thinning and burning increase resistance to a bark beetle outbreak and promote forest resilience. Ecological Applications 26:1984–2000.

Hood, S. M., C. R. Keyes, K. J. Bowen, D. C. Lutes, and C. Seielstad. 2020. Fuel Treatment Longevity in Ponderosa Pine-Dominated Forest 24 Years After Cutting and Prescribed Burning. Frontiers in Forests and Global Change 3:78.

Hood, S. M., J. M. Varner, P. Van Mantgem, and C. A. Cansler. 2018. Fire and tree death: understanding and improving modeling of fire-induced tree mortality. Environmental Research Letters 13:113004.

Jain, Theresa B., Mike A. Battaglia, Han-Sup. Han, Russell T. Graham, Christopher R. Keyes, Jeremy S. Fried, and Jonathan E. Sandquist. 2012. A comprehensive guide to fuel management practices for dry mixed conifer forests in the northwestern United States Gen Tech Rep RMRS-GTR-292, 331. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Johnston, J. D., J. H. Olszewski, B. A. Miller, M. R. Schmidt, M. J. Vernon, and L. M. Ellsworth. 2021. Mechanical thinning without prescribed fire moderates wildfire behavior in an Eastern Oregon, USA ponderosa pine forest. Forest Ecology and Management 501:119674.

Kalies, E. L., and L. L. Yocom Kent. 2016. Tamm review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. Forest Ecology and Management 375:84–95.

Keifer, M., J. W. van Wagtendonk, and M. Buhler. 2006. Long-term surface fuel accumulation in burned and unburned mixed-conifer forests of the Central and Southern Sierra Nevada, CA (USA). Fire Ecology 2:53–72.

Kennedy, M. C., M. C. Johnson, and S. C. Harrison. 2021. Model Predictions of Postwildfire Woody Fuel Succession and Fire Behavior Are Sensitive to Fuel Dynamics Parameters. Forest Science 67:30–42.

Knight, C. A., R. E. Tompkins, J. A. Wang, R. York, M. L. Goulden, and J. J. Battles. 2022. Accurate tracking of forest activity key to multi-jurisdictional management goals: A case study in California. Journal of Environmental Management 302:114083.

Knipling, E. B. 1970. Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. Remote Sensing of Environment 1:155–159.

Kolb, T. E., C. J. Fettig, M. P. Ayres, B. J. Bentz, J. A. Hicke, R. Mathiasen, J. E. Stewart, and A. S. Weed. 2016. Observed and anticipated impacts of drought on forest insects and diseases in the United States. Forest Ecology and Management 380:321–334.

Kolden, C. A. 2019. We’re Not Doing Enough Prescribed Fire in the Western United States to Mitigate Wildfire Risk. Fire 2:30.

Low, K. E., B. M. Collins, A. Bernal, J. E. Sanders, D. Pastor, P. Manley, A. M. White, and S. L. Stephens. 2021. Longer-term impacts of fuel reduction treatments on forest structure, fuels, and drought resistance in the Lake Tahoe Basin. Forest Ecology and Management 479:118609.

Lutes, D. C. 2020. FOFEM 6.7 User Guide. Missoula, MT.

van Mantgem, P. J., L. B. Lalemand, M. B. Keifer, and J. M. Kane. 2016. Duration of fuels reduction following prescribed fire in coniferous forests of U.S. national parks in California and the Colorado Plateau. Forest Ecology and Management 379:265–272.

McCune, B., and D. Keon. 2002. Equations for potential annual direct incident radiation and heat load. Journal of Vegetation Science 13:603–606.

McCune, Bruce., and J. B. Grace. 2002. Analysis of ecological communities. Mjm Software Design, Gleneden Beach, Oregon.

McIver, J. D., and C. P. Weatherspoon. 2010. On conducting a multisite, multidisciplinary forestry research project: Lessons from the national fire and fire surrogate study. Forest Science 56:4–17.

Moreira, F., D. Ascoli, H. Safford, M. A. Adams, J. M. Moreno, J. M. C. Pereira, F. X. Catry, J. Armesto, W. Bond, M. E. González, T. Curt, N. Koutsias, L. McCaw, O. Price, J. G. Pausas, E. Rigolot, S. Stephens, C. Tavsanoglu, V. R. Vallejo, B. W. Van Wilgen, G. Xanthopoulos, and P. M. Fernandes. 2020 Wildfire management in Mediterranean-type regions: paradigm change needed. Environmental Research Letters 15:011001.

Morici, K. E., and J. D. Bailey. 2021. Long-Term Effects of Fuel Reduction Treatments on Surface Fuel Loading in the Blue Mountains of Oregon. Forests 12:1306.

North, M. P., R. A. York, B. M. Collins, M. D. Hurteau, G. M. Jones, E. E. Knapp, L. Kobziar, H. McCann, M. D. Meyer, S. L. Stephens, R. E. Tompkins, and C. L. Tubbesing. 2021. Pyrosilviculture Needed for Landscape Resilience of Dry Western United States Forests. Journal of Forestry 119:520–544.

Oksanen, J., G. Simpson, F. G. Blanchet, R. Kindt, P. Legendre, P. R. , Minchin, R. B. , O'Hara, P. Solymos, M. H. H. , Stevens, E. Szoecs, H. Wagner, M. Barbour, M. Bedward, B. Bolker, D. Borcard, M. Friendly, B. Furneaux, G. Hannigan, M. O. , Hill, L. Lahti, D. McGlinn, M.-H. Ouellette, E. R. Cunha, T. Smith, A. Stier, C. J. F. , Ter Braak, and J. Weedon. 2022, October 11. Package "Vegan." Comprehensive R Archive Network (CRAN). https://CRAN.R-project.org/package=vegan.

Parisien, M. A., D. A. Dawe, C. Miller, C. A. Stockdale, and O. B. Armitage. 2019. Applications of simulation-based burn probability modelling: A review. 2020. 28:913-916.

Parks, S. A., L. M. Holsinger, M. A. Voss, R. A. Loehman, and N. P. Robinson. 2021. Correction: Parks et al. Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. Remote Sensing 13:1–7.

Prichard, S. J., and M. C. Kennedy. 2012. Fuel treatment effects on tree mortality following wildfire in dry mixed conifer forests, Washington State, USA. International Journal of Wildland Fire 21:1004.

Prichard, S. J., D. L. Peterson, and K. Jacobson. 2010. Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. Canadian Journal of Forest Research 40:1615–1626.

Prichard, S. J., N. A. Povak, M. C. Kennedy, and D. W. Peterson. 2020. Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. Ecological Applications. eap.2104.

Qin, C. Z., A. X. Zhu, T. Pei, B. L. Li, T. Scholten, T. Behrens, and C. H. Zhou. 2011. An approach to computing topographic wetness index based on maximum downslope gradient. Precision Agriculture 12:32–43.

Rebain, S. A. , E. D. , Reinhardt, N. L. , Crookston, S. J., Beukema, W. A., Kurz, J. A., Greenough, D. C. E., Robinson, and D. C. Lutes. 2010. The Fire and Fuels Extension to the Forest Vegetation Simulator: Updated Model Documentation. Fort Collins, Colorado.

Reed, C. C., S. M. Hood, D. R. Cluck, and S. L. Smith. 2023. Fuels change quickly after California drought and bark beetle outbreaks with implications for potential fire behavior and emissions. Fire Ecology 2023 19:1 19:1–19.

Reinhardt, E., and N. L. Crookston. 2003. The Fire and Fuels Extension to the Forest Vegetation Simulator. Gen. Tech. Rep. RMRS-GTR-116. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 209 p. 116.

Reinhardt, E. D., R. E. Keane, and J. K. Brown. 1997. First Order Fire Effects Model: FOFEM 4.0, user’s guide. Gen. Tech. Rep. INT-GTR-344. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station. 65 p. 344.

Reinhardt, E. D., R. E. Keane, D. E. Calkin, and J. D. Cohen. 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. Forest Ecology and Management 256:1997–2006.

Rossman, A. K., J. D. Bakker, D. W. Peterson, and C. B. Halpern. 2020. Long-term effects of fuels treatments, overstory structure, and wildfire on tree regeneration in dry forests of Central Washington. Forests 11:888.

Rossman, A. K., C. B. Halpern, R. J. Harrod, L. S. Urgenson, D. W. Peterson, and J. D. Bakker. 2018. Benefits of thinning and burning for understory diversity vary with spatial scale and time since treatment. Forest Ecology and Management 419–420:58–78.

Ryan, K. C., and N. V. Noste. 1985. Evaluating Prescribed Fires. Pages 230–238 in J. E. Lotan, editor. Symposium and Workshop on Wildland Fire. USDA Forest Service Intermountain Forest and Range Experiment Station.

Schoennagel, T., J. K. Balch, H. Brenkert-Smith, P. E. Dennison, B. J. Harvey, M. A. Krawchuk, N. Mietkiewicz, P. Morgan, M. A. Moritz, R. Rasker, M. G. Turner, and C. Whitlock. 2017. Adapt to more wildfire in western North American forests as climate changes. Proceedings of the National Academy of Sciences 114(18):4582–4590.

Schwilk, D. W., J. E. Keeley, E. E. Knapp, J. McIver, J. D. Bailey, C. J. Fettig, C. E. Fiedler, R. J. Harrod, J. J. Moghaddas, K. W. Outcalt, C. N. Skinner, S. L. Stephens, T. A. Waldrop, D. A. Yaussy, and A. Youngblood. 2009. The national Fire and Fire Surrogate study: effects of fuel reduction methods on forest vegetation structure and fuels. Ecological Applications 19:285–304.

Stephens, S. L., M. A. Battaglia, D. J. Churchill, B. M. Collins, M. Coppoletta, C. M. Hoffman, J. M. Lydersen, M. P. North, R. A. Parsons, S. M. Ritter, and J. T. Stevens. 2020. Forest Restoration and Fuels Reduction: Convergent or Divergent? BioScience 71:85–101.

Stephens, S. L., B. M. Collins, and G. Roller. 2012a. Fuel treatment longevity in a Sierra Nevada mixed conifer forest. Forest Ecology and Management 285:204–212.

Stephens, S. L., J. D. McIver, R. E. J. Boerner, C. J. Fettig, J. B. Fontaine, B. R. Hartsough, P. L. Kennedy, and D. W. Schwilk. 2012b. The Effects of Forest Fuel-Reduction Treatments in the United States. BioScience 62:549–560.

Stephens, S. L., J. J. Moghaddas, C. Edminster, C. E. Fiedler, S. Haase, M. Harrington, J. E. Keeley, E. E. Knapp, J. D. McIver, K. Metlen, C. N. Skinner, and A. Youngblood. 2009. Fire treatment effects on vegetation structure, fuels, and potential fire severity in western U.S. forests. Ecological Applications 19:305–320.

Tai, X., W. R. L. Anderegg, P. D. Blanken, S. P. Burns, L. Christensen, and P. D. Brooks. 2020. Hillslope Hydrology Influences the Spatial and Temporal Patterns of Remotely Sensed Ecosystem Productivity. Water Resources Research 56:e2020WR027630.

Tepley, A. J., S. M. Hood, C. R. Keyes, and A. Sala. 2020. Forest restoration treatments in a ponderosa pine forest enhance physiological activity and growth under climatic stress. Ecological Applications 30:e02188.

Thompson, R. M., A. J. King, R. M. Kingsford, R. Mac Nally, and N. L. R. Poff. 2018. Legacies, lags and long-term trends: Effective flow restoration in a changed and changing world. Freshwater Biology 63:986–995.

Tinkham, W. T., C. M. Hoffman, S. A. Ex, M. A. Battaglia, and J. D. Saralecos. 2016. Ponderosa pine forest restoration treatment longevity: Implications of regeneration on fire hazard. Forests 7:137.

University of Washington Earth and Space Science. 2010. 10-meter Data. http://gis.ess.washington.edu/data/raster/tenmeter/.

Urza, A. K., B. B. Hanberry, and T. B. Jain. 2023. Landscape-scale fuel treatment effectiveness: lessons learned from wildland fire case studies in forests of the western United States and Great Lakes region. Fire Ecology 19:1–12.

Zuur, A. F., E. N. Ieno, N. J. Walker, A. A. Saveliev, and G. M. Smith. 2009. Mixed effects models and extensions in ecology with R. First edition. Springer Publishing. New York, NY.

Chapter 3: Fuel profile and stand structural components show variable trajectories following thin-plus-burn treatment

Don C. Radcliffe[1*], Karen E. Kopper[2,3], Kathleen L. Patronik[2], Jon D. Bakker[1], Brian J. Harvey[1]

[1]University of Washington, School of Environmental and Forest Sciences, Seattle, WA, USA
[2]National Park Service, North Cascades National Park, Marblemount, WA, USA
[3]National Park Service, Interior Region 1, North Atlantic- Appalachian
*Corresponding author: dradclif@uw.edu

3.1 Abstract

Fuel treatments ('treatments') such as thinning and/or prescribed burning are commonly applied in dry and historically frequent-fire forests of interior western North America ('dry forests'), to reduce potential for severe wildfire and restore characteristically open stand structure. However, trajectories of fuel profiles and stand structure after treatment are not well understood, leading to potential for mis-interpretation of long-term treatment monitoring and inefficiencies in treatment maintenance planning. In this study, we analyzed post-treatment trajectories from a long-term monitoring dataset of 19 plots on National Park Service lands in Washington State, USA. Samples were collected before thin-plus-burn treatment and at consistent intervals for fifteen years following treatment. For a suite of fuel and stand structure variables, we asked 1) what are the shapes of post-treatment trajectories, and how do they vary among individual fuel profile and stand structural components?, 2) how does among-plot heterogeneity (i.e., coefficient of variation) change with over since treatment?, and 3) how does treatment intensity affect responses to treatment over time? Surface fuel showed non-linear, convex patterns of change following treatment. Surface fuel trajectories were characterized by a period of accumulation often resulting in peak fuel loading above pre-treatment values, followed by subsequent

reduction over time. Surface fuel particle size affected timing of trajectories, with larger classes showing slower accumulation and slower subsequent reduction. Treatment-driven reductions in basal area were largely sustained throughout the duration of the study, and tree densities declined into the long-term. Treatment increased the among-plot coefficient of variation for basal area and tree density throughout the study duration. More intense treatments showed greater reductions in many fuel components, but treatment intensity was also positively associated with faster fuel accumulation rates and greater long-term tree density. Together these results suggest that evaluations of long-term treatment effectiveness are likely sensitive to the timing of surveys and assumptions about surface fuel trajectories. These insights may inform treatment maintenance scheduling and contextualize long-term treatment studies with fewer sample periods.

3.2 Introduction

In dry and historically frequent-fire forests of interior western North America ('dry forests'), fuel and restoration treatments ('treatments') such as thinning and/or prescribed burning are commonly used to address fuel accumulation resulting from fire suppression and exclusion of Indigenous fire (Stephens et al. 2020, Prichard et al. 2021). Treatments are shown to have substantial benefits for restoring dry forest structure and reducing potential for severe wildfire in the years immediately following implementation (Schwilk et al. 2009, Stephens et al. 2012b, Prichard et al. 2020, Cansler et al. 2022b). Additionally, long-term studies (e.g., >10 years following treatment) suggest that combination treatments such as thinning followed by prescribed burning (thin-plus-burn) often provide sustained reductions in canopy fuel and tree basal area for at least two decades, while less intense treatment types have more limited long-term benefits (Battaglia et al. 2008, van Mantgem et al. 2016, Hood et al. 2020, Morici and Bailey 2021, Radcliffe et al. 2024, Brodie et al. 2024). Although these studies have established general expectations for long-term responses among common treatment types, drivers of observed variation in long-term effects within a given treatment type have received less study (Radcliffe et al. 2024). Knowledge gaps about long-term treatment effects include uncertainty about how trajectories of fuel profiles and stand structure change continuously with time following treatment, patterns of fine-scale (e.g., plot-level or <1ha) heterogeneity with time following treatment, and the effects of treatment intensity on long-term responses to treatment.

Detailed understanding of the shape and magnitude of fuel trajectories would be helpful for scheduling treatment maintenance and planning wildland firefighting operations (Jain et al. 2012). Fine woody surface fuel is an important driver of surface fire intensity (Brown 1974), and may be especially dynamic over time. Following cultural burning or prescribed burning, pulses of fine woody surface fuel are expected from any branches and trees killed from burning (Reinhardt et al. 2008). However, the timing of surface fuel pulses and subsequent decomposition patterns remain a key uncertainty (Kennedy et al. 2021, Hanan et al. 2022). The timing of surface fuel dynamics is likely related to the fuel size class, because of variations in decomposition rates as a function of surface area to volume ratio (Keane 2015). For example, smaller fuel classes (e.g., 1-hour) are likely to fall from the canopy sooner after treatment and decompose more rapidly relative to larger classes (e.g., 1000-hour) (Keane et al. 2016). Therefore, evaluations of long-term treatment effectiveness (e.g., Crotteau et al. 2018, Hood et al. 2020, Morici and Bailey 2021, Radcliffe et al. 2024) are likely to be highly sensitive to the timing of sampling and assumptions about post-treatment fuel trajectories.

Multiple-scale heterogeneity of fuel profiles and stand structure is characteristic of dry forests with frequent fire regimes (Harrod et al. 1999, Chamberlain et al. 2023), and heterogeneity can increase dry forest resilience to wildfire by disrupting continuity of fuel (Larson and Churchill 2012, Koontz et al. 2020). Multiple pathways of heterogeneity following treatment are plausible, and may vary depending on details of treatment implementation and environmental context (Radcliffe et al. 2024). Heterogeneity could increase with time since treatment, if fine-scale variations in post-treatment canopy gap structure and degree of mineral soil exposure facilitates variations in responses of vegetation and fuel that become more accentuated with time after treatment (Keane 2015, Dudney et al. 2021). Alternatively, heterogeneity could decline with time since treatment if fine-scale differences in treatment implementation are mitigated by vegetation growth and fuel responses over time (Jain et al. 2012). Additionally, the spatial patterns produced by treatments likely affect trajectories of heterogeneity over time since treatment (Churchill et al. 2013). Many traditional forestry practices emphasized spatial uniformity to optimize tree growth and timber value, resulting in homogenized forest structure (Franklin et al. 2018, Fahey et al. 2018) and reduced resilience to disturbance (Holling and Meffe 1996). In recent decades, more treatments are designed to increase fine-scale spatial heterogeneity of forest structure (Churchill et al. 2013, Dickinson and Cadry 2017), inspired in part by reconstructions of historic stand structure (Larson and Churchill 2012).

Observed variation in long-term responses may be partially driven by differences in treatment implementation. For example, treatment intensity, which can be defined as the amount of fuel removed during treatment, may have substantial long-term impacts on responses of stand structure and canopy fuel (Radcliffe et al. 2024), and shrubs (Dudney et al. 2021). By this definition, greater treatment intensity will be associated with lower short-term fuel loads, given a level of pre-treatment fuel loading. Long-term impacts of increased treatment intensity are less clear, however, and more intense treatment could result in larger pulses of woody surface fuel and greater understory vegetation growth in the long-term (Jain et al. 2012). This potential for a tradeoff between treatment intensity and treatment longevity is likely contingent on site productivity, as greater pre-treatment canopy biomass, greater capacity for post-treatment vegetation growth, and greater decomposition rates are expected on more productive sites (Jain et al. 2012, Ex et al. 2019).

To address these knowledge gaps, in long-term treatment effects, we leveraged a dataset with repeated measurements on permanent plots following thin-plus-burn treatments from the National Park Service Fire Effects Monitoring Program in Washington, State, USA. We used these data to address the following study questions:

1) What are the post-treatment trajectories of fuel profile and stand structure?
2) How does treatment affect heterogeneity of fuel profiles and stand structure over time?
3) How does treatment intensity affect fuel profiles and stand structure, and how do the effects of treatment intensity change with time since treatment?

3.3 Methods

Study areas

We used data from the National Park Service Fire Effects Monitoring program in Washington State (USA). These data were collected on two distinct administrative units: the

North Cascades National Recreation Area ('North Cascades'), and Lake Roosevelt National Recreation Area ('Lake Roosevelt').

The North Cascades Fire Effects Monitoring plots are located in the Stehekin Valley, just up-slope from Lake Chelan in north-central Washington State. The area is a mixed conifer forest dominated by mesic Douglas-fir (*Pseudotsuga menziesii*), with occasional ponderosa pine (*Pinus ponderosa*) (Kopper 2022). Mixed severity fire has impacted the landscape both pre- and post-European colonization, establishing a complex mosaic of burn severity with variable-sized and aged forest (Kopper 2022). In the 20th century, fire suppression and exclusion of Indigenous fire have led to higher fuel loading and a higher density of shade tolerant trees (e.g., Douglas-fir).

The Lake Roosevelt Fire Effects Monitoring plots are located along the shore of Lake Roosevelt in eastern Washington State, in dry ponderosa pine forests commonly found throughout the mid to lower elevations of the Columbia Basin (Wright and Agee 2004). Historically, forest structure and fuel profiles were shaped by frequent low severity fires. Due to fire suppression and exclusion of Indigenous fire, relatively shade tolerant species like Douglas-fir have become more common in recent decades (Wright and Agee 2004).

Treatment selection and implementation

Treatment units are managed to meet goals of the North Cascades Fire Management Plan. Management decisions are based on public safety, risk of severe wildfire, and restoration of precolonial forest structure. Treatment units are monitored annually using the Fire Management Handbook created by the National Park Service in 1996 and updated in 2003 (National Park Service 2003). Fire Effects Monitoring plots were placed within the unit using restricted random sampling and are field verified before permanent establishment (National Park Service 2003).

Within Washington State, the first plots were established in 1996, and the NPS progressively established more plots throughout time. Plots were consistently measured before treatment, and 1-, 2-, 5-, 10-, 15- years following treatment. This sampling timeline reset following each new treatment entry.

From a broader pool of available Fire Effects Monitoring data, we focused on plots that were monitored for the full 15 years following treatment, without an additional maintenance treatment conducted during that 15 year period. Our focus narrowed the scope to thin-plus-burn treatments (thinning followed by a prescribed burn, with a range of zero to three years between the two treatments). This resulted in a sample of 19 plots from four stands. These 19 plots included three plots in one stand from Lake Roosevelt and 16 plots in three stands from North Cascades. Eight plots received a prescribed burn treatment five to six years before the thin-plus-burn treatment (all in North Cascades), and 11 plots received only a thin-plus-burn treatment. Visual checks did not indicate substantial differences in post-treatment trajectories among plots receiving a prescribed burn before thin-plus-burn treatment and plots receiving only thin-plus-burn treatment. Given the limited sample size and likely variable fine-scale histories previous to treatments which are inherent to dry forests (Hessburg et al. 2015), all 19 plots were lumped for analyses and termed ‘thin-plus-burn’ treatments throughout this paper.

Field methods

Each plot was 50m x 20m, with the orientation randomly selected at time of installation. At each plot, measurements included tree (overstory/poles/seedlings) and fuel surveys. For all overstory (> 15cm dbh) and pole-sized trees (2.5cm < dbh > 15cm) within the plot, measurements included species, diameter at breast height (dbh), and status (live or dead). Surface fuel variables were measured using four planar intercept transects (Brown 1971) per plot. At

Lake Roosevelt, the transect length was 30.5m and at North Cascades the transect length was 15.2m. The transects were placed at 10m, 20m, 30m, and 40m along the centerline spanning the major axis of the rectangular plot. Each transect ran along an azimuth that was randomly chosen when the plot were first installed. For each transect all downed woody debris that fully intersected the transect were measured: 1- and 10-hour fuels are counted for the first 1.83m along the transect length, and 100-hour fuel are counted for the first 3.66 m along the transect length. 1000-hour fuels were counted along the entire length of transect and the diameter and decay class of each log is recorded. Litter and duff depth were recorded at nine points along each transect and spaced every 1.52 m.

Analytical methods

Response variables included biomass of woody surface fuel (1-hour [Mg/ha], 10-hour [Mg/ha], 100-hour [Mg/ha], 1000-hour sound [Mg/ha], 1000-hour rotten [Mg/ha]), biomass of other surface fuel (litter [Mg/ha], duff [Mg/ha]), and stand structure (basal area [m^2/ha], tree density [trees/ha]).

To assess the post-treatment trajectories of fuel profile and stand structure (Q1), we used summary graphs. Summary statistics were plotted for each timestep, with 95% confidence intervals around mean values within time periods, and plot-level trajectories throughout the study period. To quantitively determine whether observed trends of each response variable were linear or non-linear through time, we modelled how fuel loads were affected by time as a continuous predictor variable. For each response variable, we modeled responses over time on a plot level, excluding the pre-treatment period. We used generalized linear mixed models with a fixed effect(s) of time since treatment, a random effect of plot, and a gamma distribution of errors with a log link. One 'linear' model used only years since treatment as a fixed effect, while a 'non-linear' (quadratic) model used years since treatment and years since treatment squared as two fixed effects. Both models were run with the function glmer() function from the R package 'lme4' (Bates et al. 2024). We then conducted model selection using Akaike's Information Criterion (AIC), to quantify whether the linear or quadratic model was a better fit (Akaike 1973, Burnham and Anderson 2002). The AIC score was then used to determine which model better characterized the data, using a parameter deviance value of 2 (Burnham and Anderson 2002).

To assess how treatment affected heterogeneity of fuel profiles and stand structure over time (Q2), we used coefficient of variation and non-metric multidimensional scaling (NMDS) ordination. Coefficient of variation is the standard deviation divided by the mean, and controls for inherent positive correlation between the standard deviation and the mean (Brown 1998). For each response variable, we used the among-plot coefficient of variation for each time since treatment step (pre-treatment, and 1, 2, 5, 10, and 15 years following treatment. This among-plot coefficient of variation is calculated using all 19 plots, and we did not produce estimates of uncertainty. We also assessed heterogeneity in multivariate space, using NMDS ordination. We scored plot-visits based on all response variables, first relativizing each response variable by its maximum (all variables were scaled continuously from 0 to 1, with a 0 value given to the plot with the lowest value of a response variable and a 1 value given to the plot with the highest value of a response variable, and other values corresponding to their distance in between). We then ran a single ordination using data from all plot visits (19 plots over 6 time step for a total of 114 plot-visits). To choose a final solution, we used the lowest number of NMDS axes containing a stress lower than 0.2 (McCune and Grace 2002). The final NMDS had 2 axes and a stress of 0.18. After running the NMDS, we plotted centroids and convex hulls in NMDS space for each post-treatment timestep. To provide context for NMDS space, we plotted 'species scores' of response variables, from the function ‘wascores()’ in R package ‘vegan’ (Oksanen et al. 2023). General trends in multivariate heterogeneity were assessed using the domain and range of the convex hulls along the x and y axes; we considered this an exploratory analyses and did not use statistical significance testing.

To assess the effect of treatment intensity on treatment outcomes (Q3), we ran separate generalized linear models for responses 2, 5, 10, and 15 years after treatment. We used separate models for each time step for two reasons: to keep models parsimonious given limited sample size and nonlinear effects of time since treatment (Zuur et al. 2009), and to explore whether and how relationships between predictor variables and responses change with time since treatment. We expected the relationship between treatment intensity and fuel profile responses to change with time since treatment (Jain et al. 2012), and capturing this interaction effect between treatment intensity and time in a model including all timesteps would require model structures likely to overfit our data (Zuur et al. 2010). We quantified treatment intensity on the plot-level as the absolute change from the pre-treatment measurement to the 1-year post-treatment measurement, specific to the response variable being tested in each model. Using this method, both positive and negative treatment intensity are possible. We originally intended to quantify treatment intensity as the proportional change from pre-treatment to 1-year post-treatment, but this resulted in some large negative values for different woody surface fuel classes, in cases where the pre-treatment value of a plot was near zero and then treatment caused short-term increases. We originally intended to test the effect of both treatment intensity and pre-treatment condition on responses at different timesteps (Radcliffe et al. 2024). However, we found that pre-treatment condition and treatment intensity were highly correlated for many response variables (>0.65 for 5 of 9 response variables). We chose to test treatment intensity only, as this reflects management action. For each tested combination of response variable and timestep, we ran two models: one model of treatment intensity effects on absolute values of the response ('absolute effects model'), and one model of treatment intensity effects on relative change of the response variable ('relative change model'), calculated as percent change from the 1-year post-treatment value to the value at the time period being measured. Both metrics of treatment intensity were centered and scaled by standard deviation prior to modelling, for direct comparison of effect sizes among response variables. The absolute effects model used a gamma error distribution and a log link, while the relative effects model used a normal error distribution and an identity link. Rotten 1000-hour fuel was not included in treatment intensity analyses, because of model convergence failures likely related to high variance.

3.4 Results

Question 1: Trends in fuel loads and stand structure through time

Within broad categories of surface fuel and stand structure, different response variables show similar shapes of responses, with timing of trajectory patterns related to the size of fuel class (Fig. 3.1). Woody surface fuel classes showed distinct convex trajectories over time, with periods of post-treatment increases followed by periods of post-treatment decreases (Fig. 3.1a-d). The timing of peak fuel accumulation was related to the size of the fuel class. For example, 1-hour fuel peaked 2 years after treatment (Fig. 3.1a) while 10- and 100-hour fuel peaked 5-10 years after treatment (Fig. 3.1b-c). The 1000-hour fuel loads in aggregate increased throughout the duration of the study, as 1000-hour sound fuel peaked 5 years after treatment (Fig. 3.1d), after which time 1000-hour rotten fuel showed significant accumulation increasing through at least the 15-year study period (Fig. 3.1e). Large variation in individual plot trajectories was present among all surface fuel classes (Fig 3.1f-g). Stand structural variables showed more sustained effects of treatment, with more limited average change in time since treatment relative to the size of the average treatment effect (Fig. 3.1h-i). Model selection based on AIC score suggested that all response variables except for basal area showed non-linear trends of change over time (Fig. 3.2).

Question 2: Trends in among-plot heterogeneity through time

Heterogeneity in stand structure was increased by treatment and effects persisted through the study period, as indicated by among-plot coefficient of variation for several measures (Fig. 3.3). For stand structure, treatment-driven increases in coefficient of variation were more sustained (Fig. 3.3h-i), although the coefficient of variation for density began to trend downward from 10-15 years after treatment (Fig. 3.3i). For surface fuel, coefficient of variation trends were inconsistent within and among response variables (Fig 3.3a-g). In multivariate space, the convex hull for pre-treatment did not overlap with any of the post-treatment convex hulls, indicating sustained treatment effects overall (Fig. 3.4).

Question 3: Effects of treatment intensity over time

Treatment intensity was commonly negatively associated with long-term absolute values of fuel (Fig. 3.5) but positively associated with rate of fuel increase relative to immediate post-treatment values (Fig. 3.6). The patterns of treatment intensity model coefficient estimates among models of different time period were inconsistent among surface fuel variables (Fig. 3.5 and Fig. 3.6). Patterns of coefficient estimates were more consistent over time for stand structural variables, with basal area and density both showing relatively more positive associations with treatment intensity 15 years after treatment than other time steps (Fig. 3.5).

3.5 Discussion

This study helps address critical knowledge gaps in understanding of long-term treatment effects, by exploring post-treatment trajectories of fuel profiles and stand structure with a permanent plot dataset sampled at frequent post-treatment intervals. Surface fuel loads showed non-linear, convex responses to treatment, likely driven by deposition of canopy fuel killed by treatment (Keane 2015). For woody surface fuel, the breadth of the overall trajectory and the timing of peak fuel loads was related to the size of fuel class, consistent with the expected trend of slower decomposition for larger fuel classes (Harmon et al. 2020). The persistent negative effect of treatment on tree density and basal area, and positive effect on stand structural heterogeneity, suggest that treatments have some sustained benefit for increasing forest resilience to wildfire over at least 15 years (Larson and Churchill 2012). We saw evidence that greater treatment intensity related to reduced surface fuel loads and more open stand structure into the long-term. However, greater post-treatment accumulation rates in more intensely treated plots suggested compensatory responses that partially mitigated the long-term benefits of more intense treatment. Treatment intensity in our study may be confounded with pre-treatment value, and therefore, site productivity (McLeod and Running 2011, Zhang et al. 2011), so our treatment intensity results should be interpreted cautiously.

Question 1: Trajectories over time

Convex trajectories of surface fuel through time, with variable timing of peak accumulation, have important management and research implications. For any given size class of woody surface fuel, elevation of average fuel loads above the average pre-treatment fuel loads may be common for at least some post-treatment time interval. While thin-only treatments are widely reported to increase short-term surface fuel accumulation through deposition of activity fuel (Agee and Skinner 2005, Schwilk et al. 2009, Prichard et al. 2021), surface fuel depositions from prescribed burning have received less attention to date. Lower attention to activity fuel from prescribed burn may be related to delayed surface fuel deposition following fire (Battaglia et al. 2008, Reinhardt et al. 2008, Keane 2015) in combination with scarcity of data 5-10 years following burn-only and thin-plus burn treatment, which our data suggest is a period of high surface fuel loading. If the surface fuel trajectories that our data suggest are widely applicable to dry forests, elevation of woody surface fuel should be expected within the first 10 years after a thin-plus-burn treatment. However, some of the potential for intense surface fire may be mitigated by the variation in the timing of peak fuel loads among size classes of woody surface fuel, reduced post-treatment loads of litter and duff, and the wide among-plot variation in woody surface fuel responses. Using fire models to explore implications of variable surface fuel trajectories on potential surface fire intensity and potential tree mortality is a promising opportunity for future research.

Our data adds to the building evidence that thin-plus-burn treatments provide sustained benefits of more open forest conditions and reduced potential for crown fire for at least 15-20 years following implementation (Hood et al. 2020, Radcliffe et al. 2024, Brodie et al. 2024). Overall trends towards slightly decreasing tree density and slightly increasing basal area over time suggest that stand structural conditions may continue to be substantially more open than pre-treatment conditions for more than our 15-year study period. Decreasing tree density over time could be driven by delayed mortality following prescribed burning (Swezy and Agee 2011, Hood et al. 2018), decreasing moisture availability due to climate change (Allen et al. 2010, Young et al. 2017), and/or competition among residual trees in clumps (Larson and Churchill 2012).

Sustained reductions in basal area and tree density could result in reduced rates of woody surface fuel deposition over time, and establish a lower equilibrium for surface fuel loading (Keane 2015). However, our summary data of fine fuel classes with more rapid patterns of response to treatment (1-hour fuel and litter) unsurprisingly suggest that true 'equilibrium' states of fuel loading are unlikely. After periods of sustained reduction relative to pre-treatment fuel loads, these fuel classes show accumulations from 10-15 years following treatment. Given observed patterns of tree density and basal area do not show increases over the study period, long-term inputs of fine fuels may include vegetation not captured in our tree data (Keane 2015). These may include herbaceous plants (Rossman et al. 2018), shrubs (Dudney et al. 2021) and/or saplings (Rossman et al. 2020) with a dbh of less than 2.5 cm, which could be explored in future work.

Our work suggests several additional avenues for future studies of fuel profile trajectories following treatment. Further study is needed to determine if factors like site productivity affect the timing of post-treatment trajectories for surface fuel. Additionally, future studies exploring fuel profile trajectories following less intense treatment types like burn-only and/or thin-only treatments are likely to find different trajectories (Johnston et al. 2021). Given the highly dynamic nature of surface fuel suggested by our data, future studies may benefit from sampling surface fuel at an even higher frequency than used in this study (e.g., surveys every one or two years, especially for fine woody surface fuel) (Keane et al. 2016, Johnston et al. 2021).

Question 2: Trends of among-plot heterogeneity over time

The persistent effect of treatment on heterogeneity of density and basal area suggests that thin-plus-burn treatment reduced continuity of fuel over the long-term. Stand structural metrics such as basal area are strongly related to potential for crown-fire (Radcliffe et al. 2024), and spatial variation in stand structure is related to spatial variation in fuel deposition and fuel moisture dynamics (Larson and Churchill 2012). Our assessment includes only the among-plot scale of heterogeneity for relatively large plots, although several spatial scales of heterogeneity are important to consider in dry forest restoration (Hessburg et al. 2015).

Inconsistent trends in surface fuel heterogeneity on permanent plots over time may reflect high spatiotemporal variability inherent to surface fuel (Keane 2015, Keane et al. 2016, Vakili et al. 2016). Inconsistencies may also be reflective of the among-plot scale incorporating multiple fuel transects being broader than the spatial scale of variation for many of the finer woody surface fuel components (Keane et al. 2012). Similar to other studies investigating heterogeneity of surface fuel, our data showed that heterogeniety was greater for larger classes of fuel (Keane et al. 2012, Vakili et al. 2016).

Question 3: Treatment intensity effects

Fuel profiles may exhibit a compensatory response to greater treatment intensity over time, perhaps mitigating but not eliminating the effects of more intense treatment over the long-term. Therefore, our findings do not strongly support a treatment intensity-longevity tradeoff (Jain et al. 2012) 15 years after treatment. These results should be interpreted with caution, however, because of the positive associations between pre-treatment condition and treatment intensity for many response variables. For example, 2-year post-treatment duff and tree density both showed positive associations with treatment intensity, defined as the change from pre-treatment to 1-year post-treatment value. This outcome could result from plots with very high pre-treatment values having the capacity for greater duff and tree density removals and also greater residual duff and tree density values. Furthermore, dry forest productivity and biomass is highly related to moisture dynamics (McLeod and Running 2011, Zhang et al. 2011), and although our data did not span a wide environmental gradient in a balanced manner, there could be confounding effects of fine-scale site productivity and pre-treatment values.

3.6 Conclusions

We used a small but intensively sampled dataset to study trajectories of fuel profiles and stand structural after treatment, helping address critical knowledge gaps in understanding of long-term treatment effects arising from low sampling frequency in many published studies. We found dynamic, non-linear and variable trajectories of surface fuel in the 15 years following treatment, with the timing and magnitude of peak surface fuel accumulation associated with the size of the fuel class. These patterns may indicate that evaluations of treatment effectiveness are sensitive to the exact timing of surveys and assumptions about surface fuel trajectories. In contrast, treatment maintained sustained decreases of basal area and tree density, and sustained increases in heterogeneity of basal area and density, supporting the long-term effectiveness of thin-plus-burn treatments in increasing some aspects of dry forest resilience to wildfire. Greater treatment intensity was associated with lower absolute values for many fuel profile components for the duration of our study. However, these reductions may be partially mitigated by compensatory responses to treatment intensity, whereby greater short-term removal resulted in greater post-treatment accumulation rates. These results on treatment intensity could be confounded with pre-treatment value, and therefore, site productivity, which would also result in greater rates of biomass accumulation following treatment. Further study will be needed to determine if our results, which are drawn from a small number of plots, are broadly applicable in dry and historically frequent-fire forests. Our findings can be used to help contextualize the current understanding of long-term treatment effects, and to demonstrate the value of increasing funding for long-term post-treatment monitoring with high sampling frequency.

3.7 Figures

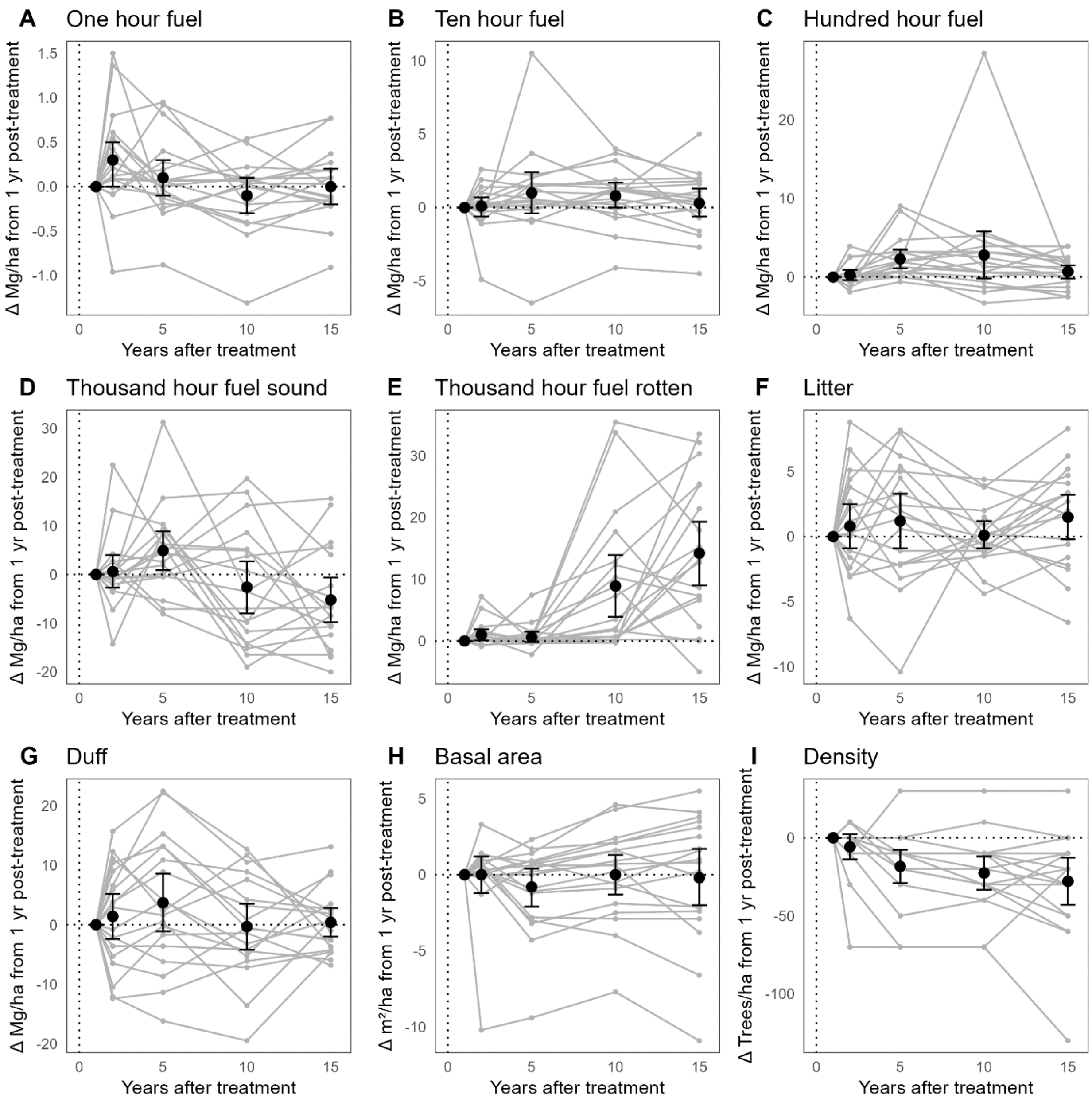

Figure 3.1: Fuel profiles and stand structure trajectories over time relative to immediate post-treatment outcomes (horizontal dotted lines). Black dots represent means within time periods, black vertical bars represent 95% confidence intervals around those means. Gray lines and points represent plot level trajectories, and while lines are shown to display these trajectories, they do not necessarily indicate linear change between the sample periods. Vertical dotted lines represent the time of burn implementation in the 'thin-plus-burn' sequence.

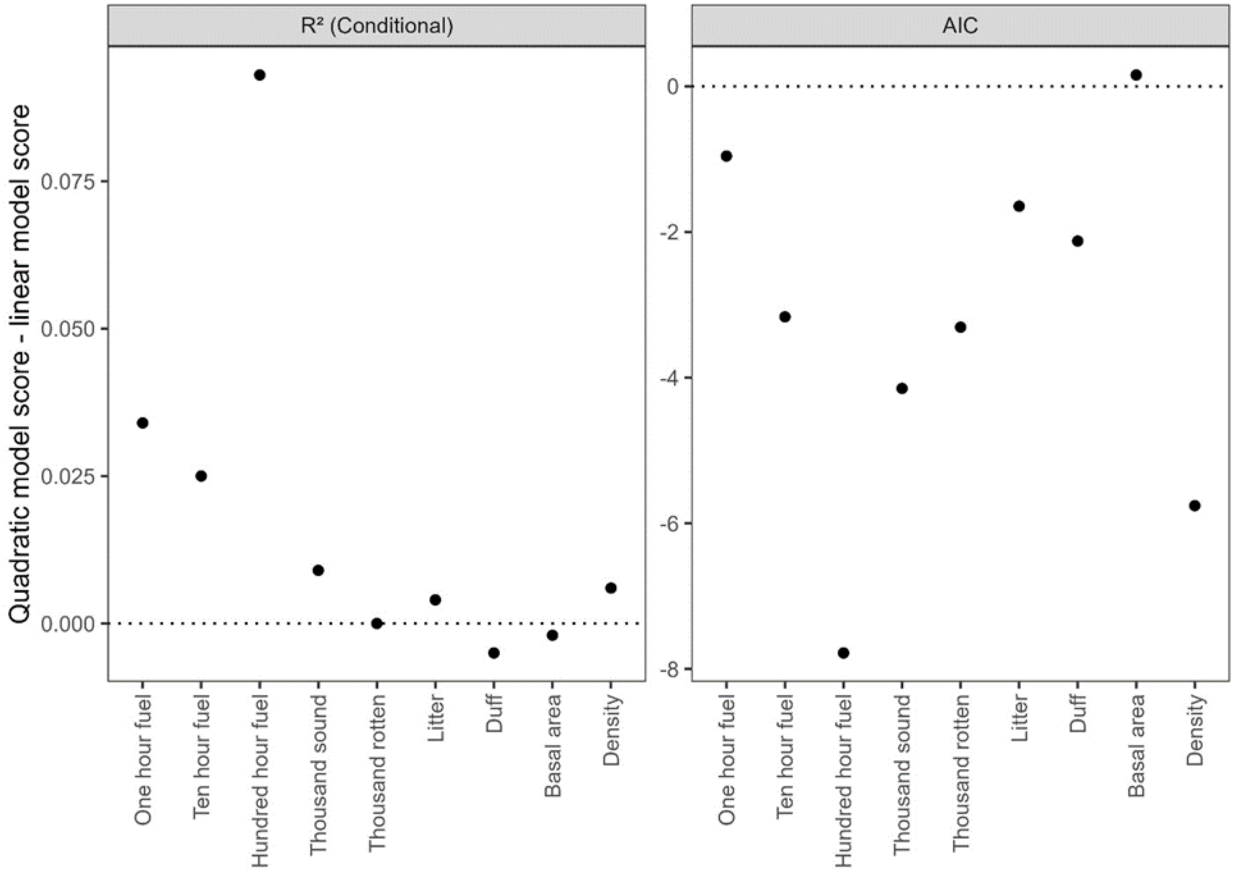

Figure 3.2: Differences in model fit (left) and AIC score (right) between linear and quadratic models of fuel profile and stand structure trajectories over time. Dotted horizontal lines indicate no difference between models. For model fit (left), points above the horizontal line represent a better model fit for the quadratic model, while for AIC (right), points below the horizontal line represent better AIC score for the quadratic model. AIC was used to determine pattern of effects because of the inherent bias towards better model fit with the extra quadratic parameter included in the non-linear model.

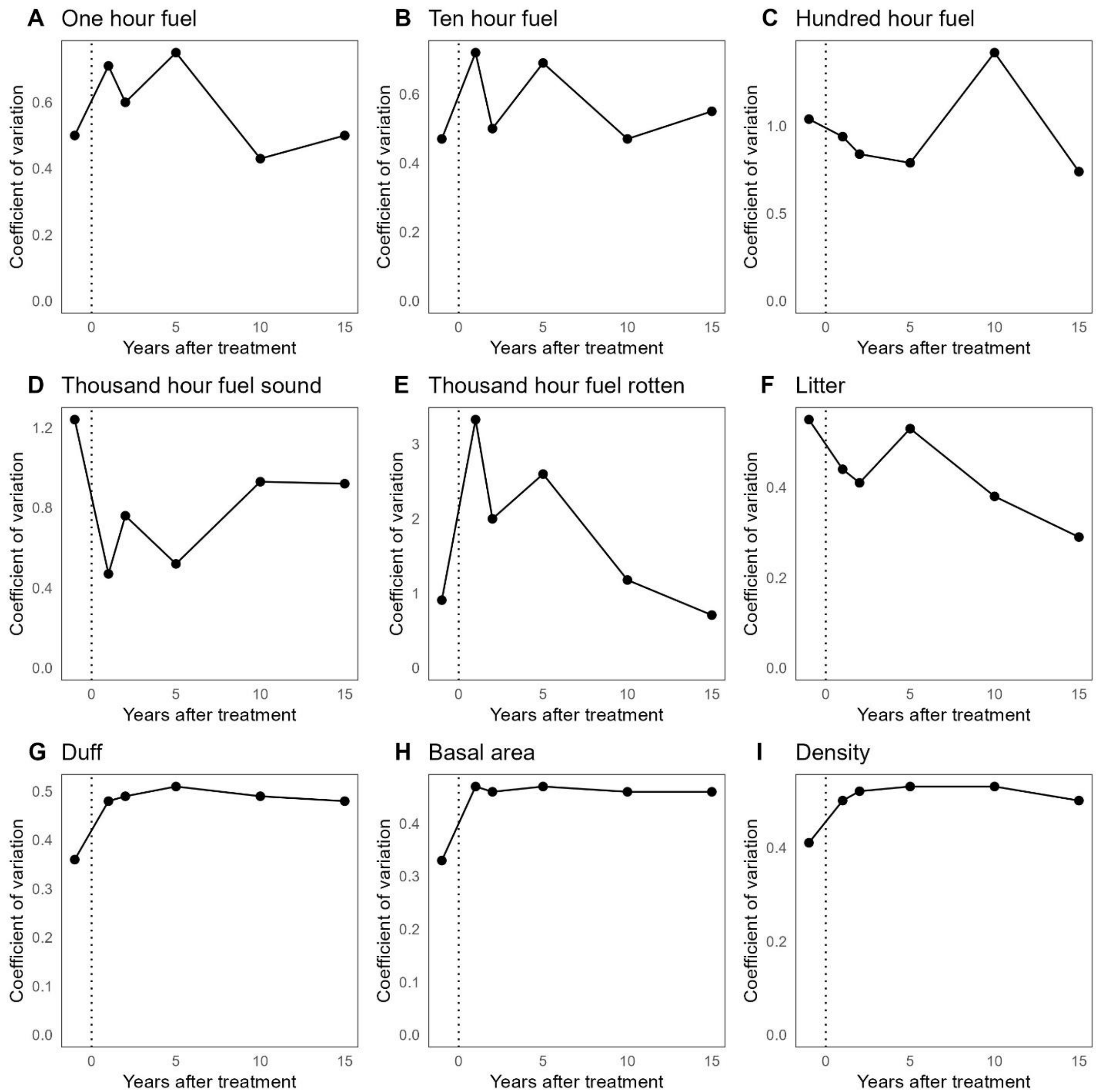

Figure 3.3: Heterogeneity of surface fuels and stand structure following treatment. Points show coefficient of variation among the 19 study plots, for the indicated time step. The dotted vertical lines show the year of treatment, and the dots to the left of the dotted vertical lines represent pre-treatment measurements, which were taken at a range of 1-8 years preceding the finishing of the treatment sequence (thin-plus-burn, or burn followed 5-6 years later by a thin-plus-burn) and represented here as -1.

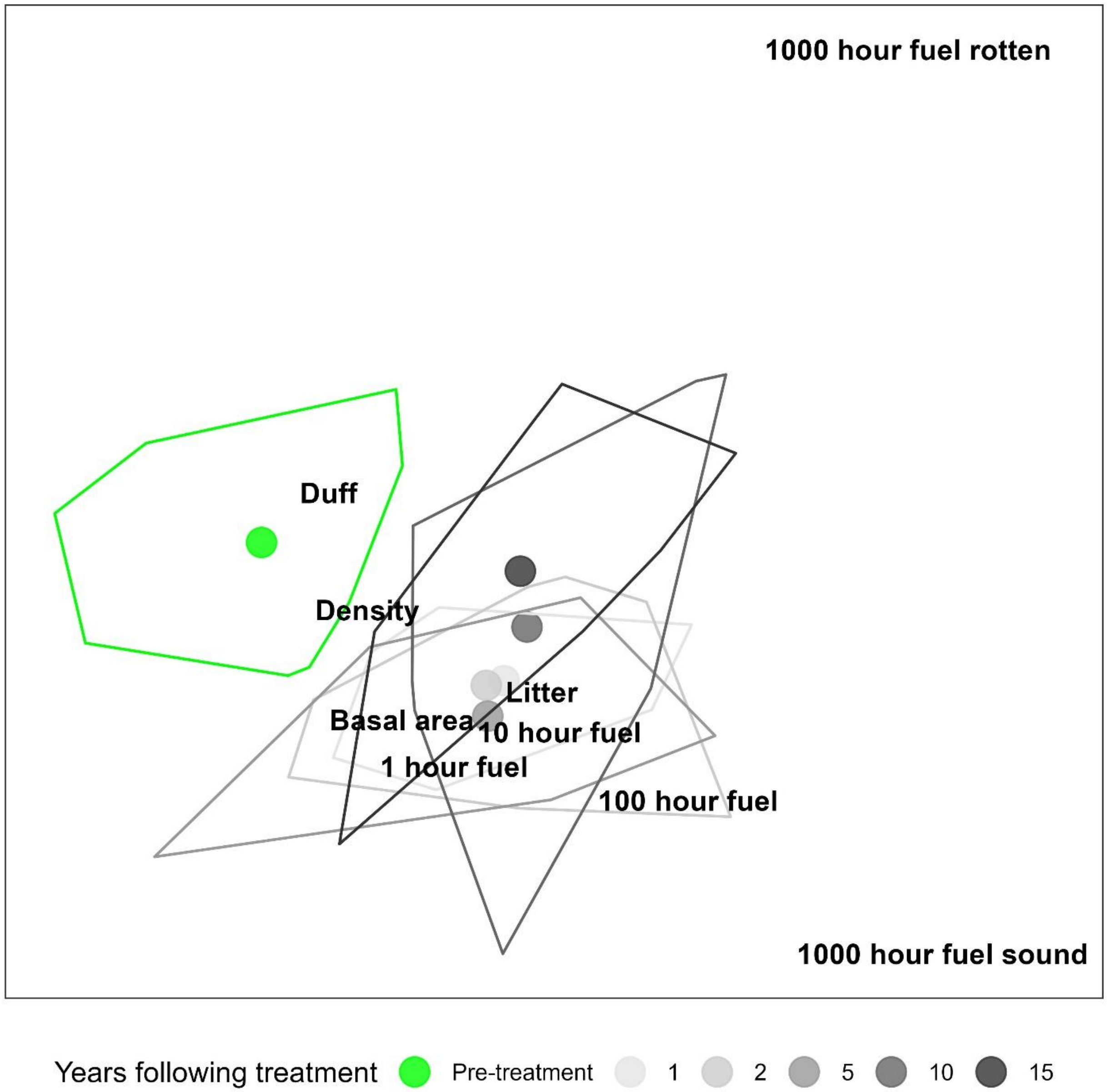

Figure 3.4: Visualization of NMDS scores for study plots, visually distinguished by time since treatment. Points represent centroids of a given time since treatment, and lines represent convex hulls of plot scores. Text indicates 'species scores' of response variables.

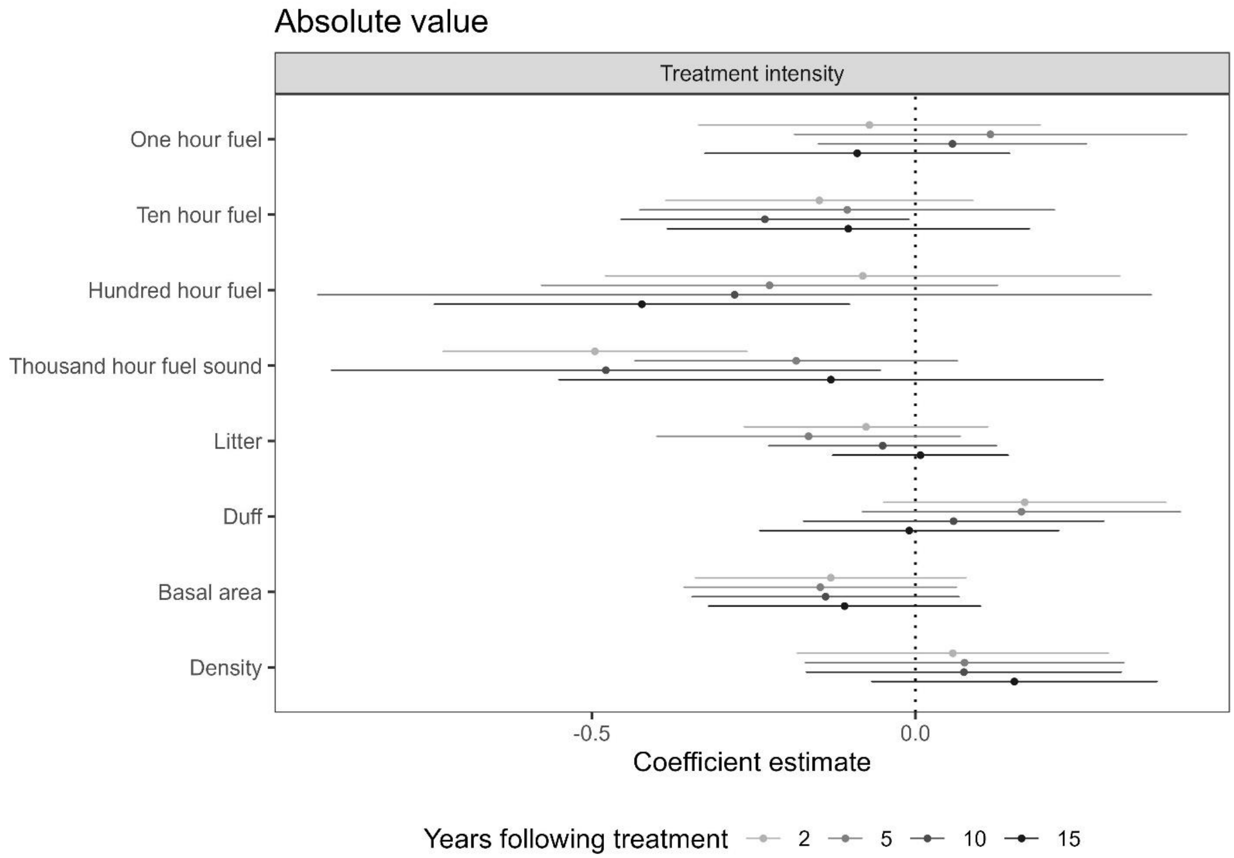

Figure 3.5: Effects of treatment intensity on the absolute value of surface fuel and stand structure, modelled at four different time-since-treatment intervals. Points represent coefficient estimates, horizontal lines represent 95% confidence interval, and dotted vertical line represents no association. A confidence interval that does not overlap with the dotted line provides evidence of a significant effect. Treatment intensity (i.e., the plot-level difference between pre-treatment values and 1-year post-treatment values) was measured as the percent change from pre-treatment to 1-year post-treatment values, was specific to each response variable measured and was centered and scaled by standard deviation prior to analysis for direct comparisons among response variables.

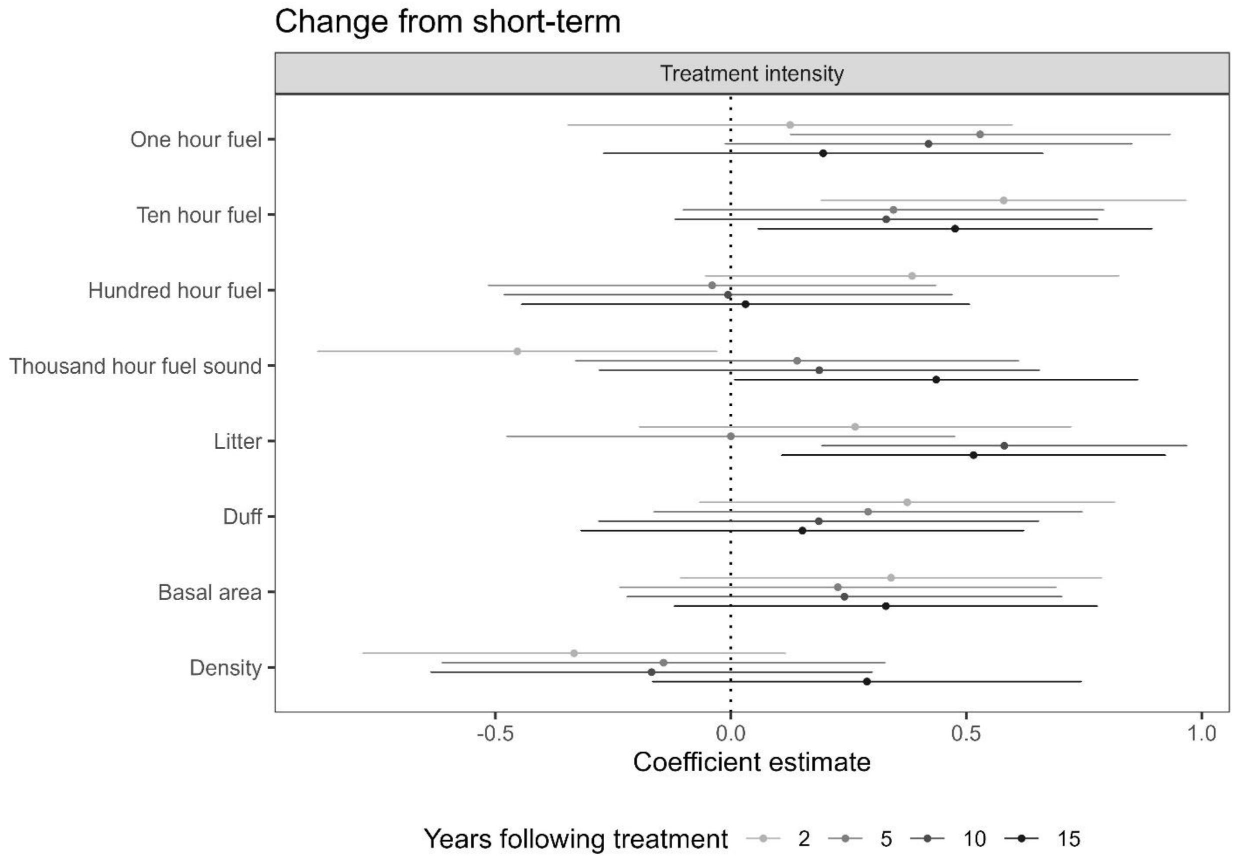

Figure 3.6: Effects of treatment intensity on the change in fuel and stand structure relative to their short-term post-treatment levels, modelled at four time-since-treatment intervals. Points represent model coefficient estimates, horizontal lines represent 95% confidence interval, and dotted vertical line represents no association. A confidence interval that does not overlap with the dotted line provides evidence of a significant effect. Relative change was centered and scaled by standard deviation prior to analysis. Treatment intensity (i.e., the plot-level difference between pre-treatment values and 1-year post-treatment values) was measured as the percent change from pre-treatment to 1-year post-treatment values, was specific to each response variable measured and was centered and scaled by standard deviation prior to analysis for direct comparisons among response variables.

3.8 Appendix 3.1: Supplementary Figures

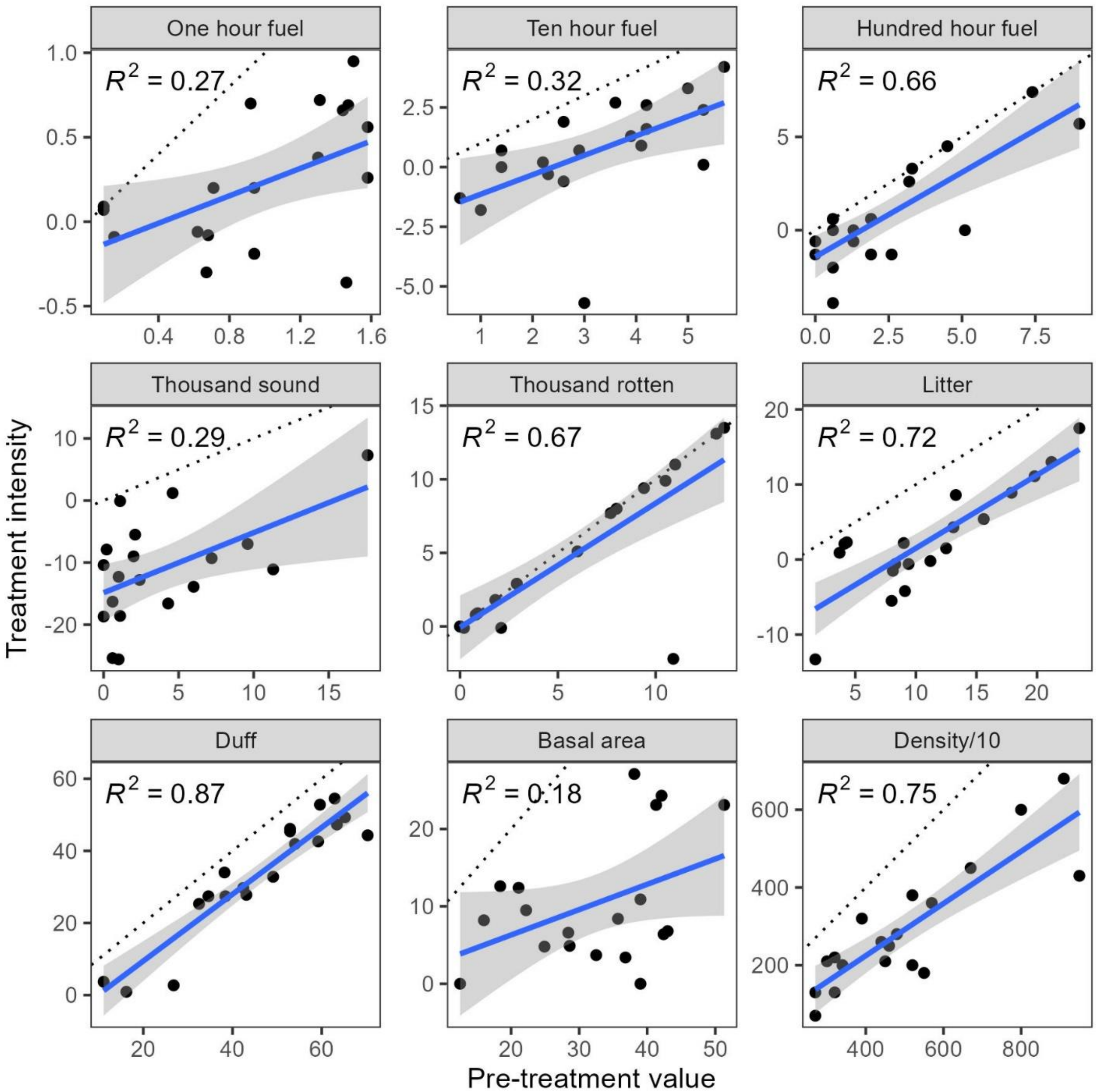

Figure 3.A.1: Correlations between treatment intensity and pre-treatment value. Treatment intensity was defined as the plot-level difference between pre-treatment values and 1-year post-treatment values, specific to each response variable measured. Treatment intensity and pre-treatment values were measured in the same units: Mg/ha for all surface fuel, m^2/ha for basal area, and trees/ha for tree density. Diagonal dotted line represents unison between pre-treatment value and treatment intensity (i.e., 100% removal of the indicated response variable in treatment).

3.9 References

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Akaike, H. 1973. Maximum likelihood identification of Gaussian autoregressive moving average models. Biometrika 60:255–265.

Allen, C. D., A. K. Macalady, H. Chenchouni, D. Bachelet, N. McDowell, M. Vennetier, T. Kitzberger, A. Rigling, D. D. Breshears, E. H. (Ted) Hogg, P. Gonzalez, R. Fensham, Z. Zhang, J. Castro, N. Demidova, J.-H. Lim, G. Allard, S. W. Running, A. Semerci, and N. Cobb. 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. Forest Ecology and Management 259:660–684.

Bates, D., M. Maechler, B. Bolker, S. Walker, R. H. B. Christensen, H. Singmann, B. Dai, F. Scheipl, G. Grothendieck, P. Green, J. Fox, A. Bauer, and P. Krivitsky. 2024. lme4: Linear Mixed Effects Models using "Eigen" and S4. https://cran.r-project.org/web/packages/lme4/lme4.pdf

Battaglia, M. A., F. W. Smith, and W. D. Shepperd. 2008. Can prescribed fire be used to maintain fuel treatment effectiveness over time in Black Hills ponderosa pine forests? Forest Ecology and Management 256:2029–2038.

Brodie, E. G., E. E. Knapp, W. R. Brooks, S. A. Drury, and M. W. Ritchie. 2024. Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. Fire Ecology 20:1–20.

Brown, C. E. 1998. Coefficient of Variation *in* Applied Multivariate Statistics in Geohydrology and Related Sciences. 155–157. 1st edition. Springer-Verlag Berlin Heidelburg. Berlin.

Brown, J. 1974. Handbook for inventorying downed woody material. Gen. Tech. Rep. INT-16. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 24 p.

Brown, J. K. 1971. A Planar Intersect Method for Sampling Fuel Volume and Surface Area. Forest Science 17:96–102.

Burnham, Kenneth P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. First edition. Springer New York, New York, NY.

Cansler, C. A., V. R. Kane, P. F. Hessburg, J. T. Kane, S. M. A. Jeronimo, J. A. Lutz, N. A. Povak, D. J. Churchill, and A. J. Larson. 2022. Previous wildfires and management treatments moderate subsequent fire severity. Forest Ecology and Management 504:119764.

Chamberlain, C. P., G. R. Cova, C. A. Cansler, M. P. North, M. D. Meyer, S. M. A. Jeronimo, and V. R. Kane. 2023. Consistently heterogeneous structures observed at multiple spatial scales across fire-intact reference sites. Forest Ecology and Management 550:121478.

Churchill, D. J., A. J. Larson, M. C. Dahlgreen, J. F. Franklin, P. F. Hessburg, and J. A. Lutz. 2013. Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring. Forest Ecology and Management 291:442–457.

Crotteau, J. S., C. R. Keyes, S. M. Hood, D. L. R. Affleck, and A. Sala. 2018. Fuel dynamics after a bark beetle outbreak impacts experimental fuel treatments. Fire Ecology 14:13.

Dickinson, Y. L., and J. D. Cadry. 2017. An evaluation of tree marking methods for implementing spatially heterogeneous restoration. Journal of Sustainable Forestry 36:47–64.

Dudney, J., R. A. York, C. L. Tubbesing, A. T. Roughton, D. Foster, S. L. Stephens, and J. J. Battles. 2021. Overstory removal and biological legacies influence long-term forest management outcomes on introduced species and native shrubs. Forest Ecology and Management 491:119149.

Ex, S. A., J. P. Ziegler, W. T. Tinkham, and C. M. Hoffman. 2019. Long-Term Impacts of Fuel Treatment Placement with Respect to Forest Cover Type on Potential Fire Behavior across a Mountainous Landscape. Forests 2019, Vol. 10, Page 438 10:438.

Fahey, R. T., B. C. Alveshere, J. I. Burton, A. W. D'Amato, Y. L. Dickinson, W. S. Keeton, C. C. Kern, A. J. Larson, B. J. Palik, K. J. Puettmann, M. R. Saunders, C. R. Webster, J. W. Atkins, C. M. Gough, and B. S. Hardiman. 2018. Shifting conceptions of complexity in forest management and silviculture. Forest Ecology and Management 421:59–71.

Franklin, J. F., N. K. Johnson, and D. L. Johnson. 2018. Ecological Forest Management. First edition. Waveland Press, Long Grove, IL.

Hanan, E. J., M. C. Kennedy, J. Ren, M. C. Johnson, and A. M. S. Smith. 2022. Missing Climate Feedbacks in Fire Models: Limitations and Uncertainties in Fuel Loadings and the Role of Decomposition in Fine Fuel Accumulation. Journal of Advances in Modeling Earth Systems 14:e2021MS002818.

Harmon, M. E., B. G. Fasth, M. Yatskov, D. Kastendick, J. Rock, and C. W. Woodall. 2020. Release of coarse woody detritus-related carbon: A synthesis across forest biomes. Carbon Balance and Management 15:1.

Harrod, R. J., B. H. McRae, and W. E. Hartl. 1999. Historical stand reconstruction in ponderosa pine forests to guide silvicultural prescriptions. Forest Ecology and Management 114:433–446.

Hessburg, P. F., D. J. Churchill, A. J. Larson, R. D. Haugo, C. Miller, T. A. Spies, M. P. North, N. A. Povak, R. T. Belote, P. H. Singleton, W. L. Gaines, R. E. Keane, G. H. Aplet, S. L. Stephens, P. Morgan, P. A. Bisson, B. E. Rieman, R. B. Salter, and G. H. Reeves. 2015. Restoring fire-prone Inland Pacific landscapes: seven core principles. Landscape Ecology 30:1805–1835.

Holling, C. S., and G. K. Meffe. 1996. Command and control and the pathology of natural resource management. Conservation Biology 10:328–337.

Hood, S. M., C. R. Keyes, K. J. Bowen, D. C. Lutes, and C. Seielstad. 2020. Fuel Treatment Longevity in Ponderosa Pine-Dominated Forest 24 Years After Cutting and Prescribed Burning. Frontiers in Forests and Global Change 3:78.

Hood, S. M., J. M. Varner, P. Van Mantgem, and C. A. Cansler. 2018. Fire and tree death: understanding and improving modeling of fire-induced tree mortality. Environmental Research Letters 13:113004.

Jain, Theresa B., Mike A. Battaglia, Han-Sup. Han, Russell T. Graham, Christopher R. Keyes, Jeremy S. Fried, and Jonathan E. Sandquist. 2012. A comprehensive guide to fuel management practices for dry mixed conifer forests in the northwestern United States Gen Tech Rep RMRS-GTR-292, 331. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Johnston, J. D., J. H. Olszewski, B. A. Miller, M. R. Schmidt, M. J. Vernon, and L. M. Ellsworth. 2021. Mechanical thinning without prescribed fire moderates wildfire behavior in an Eastern Oregon, USA ponderosa pine forest. Forest Ecology and Management 501:119674.

Keane, R. E. 2015. Wildland fuel fundamentals and applications. Wildland Fuel Fundamentals and Applications. Springer International Publishing. New York.

Keane, R. E., Y. Bergeron, and S. Gauthier. 2016. Spatiotemporal Variability of Wildland Fuels in US Northern Rocky Mountain Forests. Forests 7:129.

Keane, R. E., K. Gray, V. Bacciu, and S. Leirfallom. 2012. Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA. Landscape Ecology 27:1213–1234.

Kennedy, M. C., M. C. Johnson, and S. C. Harrison. 2021. Model Predictions of Postwildfire Woody Fuel Succession and Fire Behavior Are Sensitive to Fuel Dynamics Parameters. Forest Science 67:30–42.

Koontz, M. J., M. P. North, C. M. Werner, S. E. Fick, and A. M. Latimer. 2020. Local forest structure variability increases resilience to wildfire in dry western U.S. coniferous forests. Ecology Letters 23:483–494.

Kopper, K. E. 2022. Fire Regimes in National Parks of the Pacific Northwest: Implications for Climate Change. Dissertation. University of Washington. Seattle.

Larson, A. J., and D. Churchill. 2012. Tree spatial patterns in fire-frequent forests of western North America, including mechanisms of pattern formation and implications for designing fuel reduction and restoration treatments. Forest Ecology and Management 267:74–92.

Legendre, P., and L. Legendre. 2012. Numerical Ecology. Third edition. Elsevier. Oxford.

van Mantgem, P. J., L. B. Lalemand, M. B. Keifer, and J. M. Kane. 2016. Duration of fuels reduction following prescribed fire in coniferous forests of U.S. national parks in California and the Colorado Plateau. Forest Ecology and Management 379:265–272.

McCune, Bruce., and J. B. Grace. 2002. Analysis of ecological communities. Mjm Software Design, Gleneden Beach, Oregon.

McLeod, S. D., and S. W. Running. 2011. Comparing site quality indices and productivity in ponderosa pine stands of western Montana. Canadian Journal of Forest Research 18:346–352.

Morici, K. E., and J. D. Bailey. 2021. Long-Term Effects of Fuel Reduction Treatments on Surface Fuel Loading in the Blue Mountains of Oregon. Forests 12:1306.

Oksanen, J., G. Simpson, F. G. Blanchet, R. Kindt, P. Legendre, P. R. , Minchin, R. B. , O'Hara, P. Solymos, M. H. H. , Stevens, E. Szoecs, H. Wagner, M. Barbour, M. Bedward, B. Bolker, D. Borcard, M. Friendly, B. Furneaux, G. Hannigan, M. O. , Hill, L. Lahti, D. McGlinn, M.-H. Ouellette, E. R. Cunha, T. Smith, A. Stier, C. J. F. , Ter Braak, and J. Weedon. 2023, October 11. Package "Vegan." Comprehensive R Archive Network (CRAN). https://CRAN.R-project.org/package=vegan.

Prichard, S. J., P. F. Hessburg, R. K. Hagmann, N. A. Povak, S. Z. Dobrowski, M. D. Hurteau, V. R. Kane, R. E. Keane, L. N. Kobziar, C. A. Kolden, M. North, S. A. Parks, H. D. Safford, J. T. Stevens, L. L. Yocom, D. J. Churchill, R. W. Gray, D. W. Huffman, F. K. Lake, and P. Khatri-Chhetri. 2021. Adapting western North American forests to climate change and wildfires: 10 common questions. Ecological Applications 31:e02433.

Prichard, S. J., N. A. Povak, M. C. Kennedy, and D. W. Peterson. 2020. Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. Ecological Applications 30:e02104.

Radcliffe, D. C., J. D. Bakker, D. J. Churchill, E. C. Alvarado, D. W. Peterson, M. M. Laughlin, and B. J. Harvey. 2024. How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests? Forest Ecology and Management 553:121594.

Reinhardt, E. D., R. E. Keane, D. E. Calkin, and J. D. Cohen. 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. Forest Ecology and Management 256:1997–2006.

Rossman, A. K., C. B. Halpern, R. J. Harrod, L. S. Urgenson, D. W. Peterson, and J. D. Bakker. 2018. Benefits of thinning and burning for understory diversity vary with spatial scale and time since treatment. Forest Ecology and Management 419–420:58–78.

Rossman, A. K., J. D. Bakker, D. W. Peterson, and C. B. Halpern. 2020. Long-term effects of fuels treatments, overstory structure, and wildfire on tree regeneration in dry forests of Central Washington. Forests 11:888.

Schwilk, D. W., J. E. Keeley, E. E. Knapp, J. McIver, J. D. Bailey, C. J. Fettig, C. E. Fiedler, R. J. Harrod, J. J. Moghaddas, K. W. Outcalt, C. N. Skinner, S. L. Stephens, T. A. Waldrop, D. A. Yaussy, and A. Youngblood. 2009. The national Fire and Fire Surrogate study: effects of fuel reduction methods on forest vegetation structure and fuels. Ecological Applications 19:285–304.

National Park Service. 2003. Fire Monitoring Handbook. Boise (ID): Fire management Program Center, National Interagency Fire Center. 274p.

Stephens, S. L., M. A. Battaglia, D. J. Churchill, B. M. Collins, M. Coppoletta, C. M. Hoffman, J. M. Lydersen, M. P. North, R. A. Parsons, S. M. Ritter, and J. T. Stevens. 2020. Forest Restoration and Fuels Reduction: Convergent or Divergent? BioScience 71:85–101.

Stephens, S. L., J. D. McIver, R. E. J. Boerner, C. J. Fettig, J. B. Fontaine, B. R. Hartsough, P. L. Kennedy, and D. W. Schwilk. 2012. The Effects of Forest Fuel-Reduction Treatments in the United States. BioScience 62:549–560.

Swezy DM, Agee JK. 1991. Prescribed-fire effects on fine-root and tree mortality in old-growth ponderosa pine. Canadian Journal of Forest Research 21: 626–634.

Vakili, E., C. M. Hoffman, R. E. Keane, W. T. Tinkham, Y. Dickinson, E. Vakili, C. M. Hoffman, R. E. Keane, W. T. Tinkham, and Y. Dickinson. 2016. Spatial variability of surface fuels in treated and untreated ponderosa pine forests of the southern Rocky Mountains. International Journal of Wildland Fire 25:1156–1168.

Wright, C. S., and J. K. Agee. 2004. Fire and Vegetation History in the Eastern Cascade Mountains, Washington. Ecological Applications 14:443–459.

Young, D. J. N., J. T. Stevens, J. M. Earles, J. Moore, A. Ellis, A. L. Jirka, and A. M. Latimer. 2017. Long-term climate and competition explain forest mortality patterns under extreme drought. Ecology Letters 20:78–86.

Zhang, J., Oliver, W. W., & Busse, M. D. (2011). Growth and development of ponderosa pine on sites of contrasting productivities: Relative importance of stand density and shrub competition effects. Canadian Journal of Forest Research, 10:2426–2438.

Zuur, A. F., E. N. Ieno, and C. S. Elphick. 2010. A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution 1:3–14.

Zuur, A. F., E. N. Ieno, N. J. Walker, A. A. Saveliev, and G. M. Smith. 2009. Mixed effects models and extensions in ecology with R. First edition. New York, NY.

Chapter 4: Edge effects and landscape context of fuel treatments affect songbird occupancy in western dry forests

Don C. Radcliffe[1*], Sarah J. Converse[1,2,3], Stephen N. Matthews[4], Daniel C. Donato[5], Brian J. Harvey[1]

[1]School of Environmental and Natural Resources, University of Washington, Seattle, WA, USA
[2]School of Aquatic and Fisheries Sciences, University of Washington, Seattle, WA, USA
[3]Washington Cooperative Fish and Wildlife Research Unit, US Geological Survey, Seattle, WA, USA
[4]Washington State Department of Natural Resources, Olympia, Washington, USA
[5]School of Environment and Natural Resources, Ohio State University, Columbus, Ohio, USA

Corresponding author: dradclif@uw.edu

4.1 Abstract

Context Managing for biodiversity in dry, historically frequent-fire forests requires maintaining landscape mosaics of varying forest structures. Fuel treatments ('treatments') such as thinning and prescribed burning are widely applied to manage fuel, restore forest structure, and improve habitat for open-forest species. However, less is known about edge and landscape effects of treatments on biodiversity.

Objectives We posed two research questions regarding the effects of thin-plus-burn treatments on songbird communities. First, how do songbirds respond to proximity to edge of treatment? And second, how do songbirds respond to landscape-scale canopy cover, described at multiple spatial scales?

Methods We conducted songbird point-counts during the breeding season at transects straddling edges of treated and un-treated patches in interior dry forests of the US Pacific Northwest. For species measured in >5% of point visits, we used Bayesian occupancy models to test for edge and landscape effects.

Results Higher occupancy probability was observed in interior positions away from edges for 6 of 19 study species (5 positively associated with interior-un-treated areas, 1 positively associated with interior-treated areas). Landscape context of canopy cover had varied effects on songbird species, ranging from relatively consistent lack of effects across scales, consistent effects across scales, and changing magnitude and/or direction of effects across scales.

Conclusions Occupancy of breeding birds was related to spatial configuration and landscape context of fuel treatments in variable ways across species. Greater songbird diversity may be supported by management actions that provide interior habitats (both treated and un-treated) far from treatment edges, and that provide a range of landscape contexts of surrounding forest cover. These strategies are likely to be compatible with fuel management needs.

4.2 Introduction

Many forests that historically experienced frequent, low-intensity fire are characterized by spatial heterogeneity in forest structure (Larson and Churchill 2012, Koontz et al. 2020, Bragg et al. 2020, Chamberlain et al. 2023). However, fire suppression, exclusion of Indigenous fire, and other human land-use changes have led to homogenization of forest structure, as well as accumulation of fuels, in many fire forests around the world (Baker 1994, Wardell-Johnson and Horwitz 2000, Hessburg et al. 2005, Loepfe et al. 2010, Hanberry et al. 2012, Hagmann et al. 2021). Homogenization of forest structure can contribute to loss of alpha and beta biodiversity (Schulte et al. 2007, Lelli et al. 2019), and to uncharacteristically intense and severe wildfire behavior (Vega-García and Chuvieco 2006, Loepfe et al. 2010). In dry and historically frequent fire forests of interior western North America ('dry forests'), severe wildfires often erode forest resilience by killing large canopy trees of species adapted to survive fire and/or creating uncharacteristically large patches of stand-replacing fire (Coop et al. 2020, Prichard et al. 2021, Cova et al. 2023). Accordingly, dry forest managers have applied fuel treatments such as thinning and/or prescribed burning across millions of hectares of western North America (Stephens and Ruth 2005, Barnett et al. 2016), to disrupt continuity of fuel (Finney 2001, Agee and Skinner 2005), and restore forest structure (Moore et al. 1999, Churchill et al. 2013) at multiple spatial scales (Hessburg et al. 2015).

In addition to wildfire mitigation, biodiversity is a critical consideration in dry forest restoration planning, for ensuring that focus on the wildfire mitigation goal is balanced with other ecological needs (Lehmkuhl et al. 2007, Gaines et al. 2010, Stephens et al. 2014). On a local (e.g., patch) scale, fuel treatments create relatively open-forest conditions (Schwilk et al. 2009, Stephens et al. 2012b) and often serve as valuable habitat for species favoring more sparsely-vegetated ('open') forests, though they can also cause loss of habitat for species favoring more densely vegetated ('dense') forests (Converse et al. 2006, Gaines et al. 2007, Fontaine and Kennedy 2012, Saab et al. 2022).

Landscape effects of fuel treatment on biodiversity, such as spatial proximity to edges and landscape context, have received less research than stand-level effects (Latif et al. 2022). While the scale and magnitude of spatial effects of habitat alteration are organism-specific (Wiens 1989, Betts et al. 2014), spatial effects of treatments on overall biodiversity are likely to manifest at several spatial scales relative to forest patch structure. Within a patch of suitable habitat, proximity to discrete edges may affect habitat quality, with many habitat specialists negatively affected by edges at relevant scales (Laurance and Yensen 1991, Fischer and Lindenmayer 2007, Newell and Rodewald 2011, Pfeifer et al. 2017). On a patch-scale, the size and shape of a patch determine the amount of organism-specific edge and interior habitats, with larger and simpler shaped patches containing greater proportions of organism-specific interior habitat (Fletcher et al. 2007). At broader scales (larger than a forest patch), habitat variety is maximized in areas with intermediate amounts of closed (un-treated and un-disturbed) and open (treated or disturbed) forest (Connell 1978, Latif et al. 2020). Variability in canopy cover conditions may provide diverse habitats, thereby meeting the needs of species with different preferences (Latif et al. 2020), and support cross-habitat interactions such as habitat complementarity, supplementation, and spillover (Tewksbury et al. 1998, Tscharntke et al. 2012). However, canopy cover variation at scales that do not match organism-specific habitat needs may reduce habitat quality (Betts et al. 2014, Hadley and Betts 2016), highlighting the need for spatially-explicit studies to inform achievement of biodiversity goals during fuel treatment planning (Lehmkuhl et al. 2007).

Here, we explore edge and landscape effects of thin-plus-burn fuel treatments on dry forest songbirds. Thin-plus-burn treatments are frequently the most effective fuel reduction and forest structure restoration technique among studied treatment types (Schwilk et al. 2009, Brodie et al. 2024, Davis et al. 2024). Songbirds are relatively conspicuous and abundant indicators of biodiversity that can be sampled noninvasively (Wotton et al. 2020, Fraixedas et al. 2020). Furthermore, songbirds are highly mobile, so the landscape context surrounding a patch may be especially important to determining habitat quality (Betts et al. 2007, Latif et al. 2022). While songbirds are only one component of overall biodiversity, they can provide a valuable gauge of environmental quality and degradation (Rosenberg et al. 2019). We asked two study questions:

1) How do songbirds respond to proximity to the edge of a relatively open treated forest

patch and a relatively dense un-treated forest patch, both within and outside of the treatment?

2) How do songbirds respond to landscape context of forest canopy cover surrounding treated areas, at a range of spatial scales?

We hypothesized that:

1) More specialized songbird species would show an association with interior positions of their preferred habitat (dense-forest vs. open-forest), while generalists would show either preference of edge habitats or no significant habitat associations.
2) Canopy cover would have a range of magnitudes and directions of effects on songbird occupancy, ranging by species. Species preferring more dense-forest conditions would show a positive association with landscape canopy cover, and species preferring more open-forest conditions would show a negative association with landscape canopy cover, though some species may show associations with intermediate landscape canopy cover. The scale of strongest canopy cover effects would be variable by species.

4.3 Methods

Study area

The Malheur National Forest in the Blue Mountains of Oregon contains large areas of dry forests with historically frequent fires (Agee 1996, Heyerdahl et al. 2001), and many restoration and fuel treatments have been conducted in recent decades (Abrams 2019, Johnston et al. 2021). Dry forests of the Blue Mountains exist at intermediate elevations, and are dominated by ponderosa pine (*Pinus ponderosa*) and Douglas fir (*Psuedotsuga menziesii*), with western larch

(*Larix occidentalis*), lodgepole pine (*Pinus contorta*) and grand fir (*Abies grandis*) as common associates in some dry forest types (Agee 1996). At lower elevations, dry forests are often interspersed with western juniper (*Juniperus occidentalis*) woodlands and open sagebrush (*Artemisia* spp.) (Agee 1996). Vegetation communities and historical fire return intervals are heavily affected by topographic position, with more open-forest structure existing on ridgetops and south- and west- facing slopes due both to climate conditions and historical fire regimes (Agee 1996, Heyerdahl et al. 2001).

The climate of the Blue Mountains is characterized by cold winters and hot, dry summers, with low humidity and large daily temperature fluctuations. The nearest weather station in Seneca, Oregon recorded an annual average of 35 cm of precipitation in 1991-2020 (National Oceanic and Atmospheric Administration 2023), and regional precipitation occurs mostly during late fall and early spring (Agee 1996). The range of average daily low to average daily high temperature from 1991-2020 was -11 – 3 degrees Celsius in the winter, and 3 – 26 degrees Celsius in the summer (National Oceanic and Atmospheric Administration 2023).

Study area selection

Thirteen study sites were selected from forested patches containing substantial amounts of ponderosa pine in the canopy, where there was a qualitatively distinct edge between a relatively open thin-plus-burn treated patch and a more densely vegetated un-treated patch (Fig. 4.1). Study sites were located outside of any recent wildfires known from satellite records (Eidenshink et al. 2007) and Forest Service records (FACTS database). A lack of wildfire evidence was confirmed in the field. All treated patches within study sites had received their most recent management entry within 11 years of sampling according to Forest Service records, a timeframe in which thin-plus-burn treatments are effective in maintaining substantial reductions of tree basal area and density (Hood et al. 2020, Radcliffe et al. 2024). Gravel logging access roads (‘logging roads’) composed the boundary of more than half of our transects (7/13). This is representative of mechanical treatments such as thinning plus burning, of which logging roads and skid trails are a necessary and inherent feature (Mederski 2006, Woolsey et al. 2024). Roads forming treatment edges were either dead end roads with limited vehicle travel (4) or only accessible by foot during time of sampling (3). Un-treated areas within study sites were located on steeper slopes and more north-easterly aspects than treated areas, on average. During treatment planning, reserved patches of dense and late-successional forest are often located on steeper and more north-easterly slopes (Camp et al. 1997, Wilson and Baker 1998, Hessburg et al. 2015) because these locations have greater moisture to promote vegetation growth and greater fuel moisture during the wildfire season (Agee 1996, Rodman et al. 2023). Additionally, treatments are often concentrated on gentler slopes due to greater ease of machinery access and less concern about soil erosion (North et al. 2015, Woolsey et al. 2024).

Sampling design

Within each of the 13 study sites, we established a transect perpedicular to and straddling the edge between the treated and untreated area. We then established four point-count locations along this transect. Point-count stations were arranged in 13 transects of four point-count stations each. Each transect straddled a distinct edge of a treated thin-plus-burn patch and an un-treated patch (Fig. 4.2), with one ‘edge’ point-count station on either side of the boundary 50 m from the boundary, and one ‘interior’ point-count station on either side of the boundary 150 m from the boundary (Fig. 4.3). Given the fragmentation of patch structure in many treatment project areas, locations for sampling greater than 150 m from an edge in both the treated and untreated side of a transect were scarce. Therefore, we did not attempt to add interior points further than 150 m from the treatment boundary.

We sampled bird communities three times at each of the 52 point-count stations between May 10 and June 11, 2023, for a total of 156 point-count visits. We conducted all point-counts using a double dependent-observer design, in which a primary observer softly called out all observations to a secondary observer maintaining the datasheet, and the secondary observer added and noted any observations they made that the primary observer missed (Golding et al. 2017). We used ten-minute point-counts, and all surveys were completed between sunrise and 10:30 am (Ralph et al. 1995). We sampled birds within a 50-m radius of the point-count location, to allow for relatively fine-scale spatial analyses and to minimize potential for unmodeled variability in detection probability arising from differences in vegetation cover between treated and un-treated stands (Hutto 2016). Observers estimated distances using a laser rangefinder any time a bird was visually detected, both within a one-week training period and throughout the data collection period. Before sampling, the observers waited for five minutes after arrival at a point, to account for disturbance to the natural behavior of the birds (Ralph et al. 1995, Matsuoka et al. 2014). Further descriptions of full point count methods are in Appendix A.

Several methods were used for describing vegetation at the study site-level and at the larger landscape level. During the 5-minute waiting period between arrival at a point and the start of point counts, the following vegetation metrics were collected: vegetation coverage from 0 – 6 m above the ground, estimated ocularly over a 20 m-radius circle surrounding the point center; basal area around the point center measured with a timber cruising prism; and canopy cover around the point center measured with a densiometer, with these collections dispersed among the first and second visit to a point. Vegetation data within sites is reported in Table 4.1. Additionally, we used 2021 Gradient Nearest Neighbor (GNN) data on canopy cover of conifers ('canopy cover') from the Landscape Ecology, Modelling, Mapping and Analysis research group (Ohmann and Gregory 2011). GNN data are gathered using a combination of satellite indices and imputation from Forest Inventory and Analysis plots (Smith 2002). We gathered canopy cover data within eight radial distances from the point-count centers: 90m, 180m, 360m, 540m, 720m, 1080m, 1800m, and 2700m.

Analyses

To assess our hypotheses about the response of songbirds to edge and landscape effects of treatment being dependent on habitat preferences, we assigned each bird species in our analysis to one of three *a priori* habitat preference categories. These three categories were: 'dense-forest favoring', 'open-forest favoring', and 'generalist'. Assignment of preferences was based on studies addressing fuel treatment effects on bird communities in interior western North American forests (e.g., Fontaine and Kennedy 2012, Latif et al. 2020, 2022, Saab et al. 2022), and on the Birds of the World database from the Cornell Laboratory of Ornithology (Billerman et al. 2023).

We analyzed each species that was detected in more than five percent of point-count visits ('study species'). For each study species, we ran two distinct classes of model: a model to evaluate evidence of edge effects (question 1), and a series of models exploring evidence of canopy cover effects at different landscape scales (question 2). We employed Bayesian single species mixed-effects occupancy modelling using the R package 'ubms' (Kellner 2023), which uses the interface of R package 'unmarked' (Chandler et al. 2023) while conducted model fitting using Markov-Chain Monte Carlo procedures in 'RStan' (Guo et al. 2023). We used the same model structures for each species, to allow direct comparison of results among species (Zuur et al. 2009). We used minimally informative prior distributions for all models, from package 'ubms' defaults. In each analysis, we combined the observations of both the primary and secondary observer at each visit, resulting in encounter histories for each species across 13 study sites, four points per study site, and three visits per point. We removed any birds that were identified solely from visual cues, to minimize potential for bias in detection probability that may arise from differences in vegetation between treated and un-treated patches. We fit each model using Markov Chain Monte Carlo with three chains of 15,000 iterations each, with a burn-in of 5,000 iterations. We assessed model convergence with trace plots, residual distributions, and monitoring for warnings from 'RStan' (Guo et al. 2023). Results were reported as 'associations' if the 95% credible interval did not include zero.

In the edge-effects model, we included only position relative to edge as a categorical covariate on occupancy, with levels corresponding to point-count locations within transects: 'untreated interior,' 'untreated edge', 'treated edge', and 'treated interior.' We used a random intercept of transect on the occupancy portion of the model, to account for spatial clustering of the four points within a transect (Zuur et. al 2009). We included detection models to account for sources of variation in detection. For all detection models, we used Julian day, time since sunrise, and vegetation coverage at 0 – 6 m above the ground as detection covariates. These detection covariates were screened for correlation, and all correlations were <0.7. Thus, our edge-effects model was, for each study species:

$$y_{ijk}|z_i \sim Bernoulli(p_{ij} * z_i)$$

$$z_i \sim Bernoulli(\psi_i)$$

$$logit(\psi_i) = \beta_0 + \beta_1[PosEdg_i] + \beta_{2K}$$

$$logit(p_{ij}) = \alpha_0 + \alpha_1 * VegCov_i + \alpha_2 * MinSun_{ij} + \alpha_3 * JulDat_{ij}$$

where y_{ijk} is the observation (0 or 1) at point *i* on transect *k* on visit *j*; *p* is the detection probability at point *i* on visit *j*; *z* is the true occupancy state at point *i* (0 = unoccupied, 1 = occupied); ψ_i is the occupancy probability at point *i*; β_0 is the logit-scale intercept for occupancy probability; β_1 is the occupancy coefficient for the effect of position relative to edge, *PosEdg*, at point *i*; α_0 is the logit-scale intercept for detection probability; α_1 is the detection coefficient for vegetation cover at 0 – 6 m above the ground, $VegCov_i$, at site *i*; α_2 is the detection coefficient for minutes since sunrise, $MinSun_{ij}$, at visit *j* to site *i*; and α_3 is the detection coefficient for Julian Date, $JulDat_{ij}$ at visit *j* to site *i*. β_{2k} is the random intercept term at transect *k*.

In the landscape effects model, we included position relative to edge, canopy cover, and canopy cover squared as covariates on occupancy, with the quadratic term allowing for non-linear effects of canopy cover. We used eight separate measures of canopy cover, and thus ran the landscape effects model eight times for each species, to explore the scale of canopy cover effects. These measures summarized canopy cover at eight radial distances from the point-count center: 90m, 180m, 360m, 540m, 720m, 1080m, 1800m, and 2700m. We chose to evaluate all of these scales as little information was available to inform *a priori* expectations of the appropriate scale. Thus, our landscape effects model was like the model for edge effects, with the exception of the logit-linear model on occupancy probability:

$$logit(\psi_{ik}) = \beta_0 + \beta_1[PosEdg_i] + \beta_2 * CanCov_i + \beta_3 * CanCov_i{}^2 + \beta_{4k}$$

which also included coefficients β_2 and β_3 for canopy cover at a given scale, $CanCov_i$, and canopy cover squared, $CanCov_i{}^2$, at site *i*, respectively. β_{4k} is the random intercept term at transect *k*.

4.4 Results

We detected 39 songbird species, 19 of which were present in more than 5% of point-count visits ('study species'). Of the 19 study species, 8 species were classified *a priori* as 'dense-forest favoring', 8 species were classified *a priori* as 'open-forest favoring', and 3 were classified as 'generalist' (Table 4.2).

Question 1: Edge Effects

Point occupancy of six species was positively associated with interior positions of un-treated or treated patches, while no species were associated with edge positions (Fig. 4.4). These associations were consistent with *a priori* expectations; five of eight dense-forest favoring species showed an association with un-treated interior forest (Dark-eyed Junco, Mountain Chickadee, Red-breasted Nuthatch, Western Tanager, and Yellow-rumped Warbler), and one of eight open-forest favoring species (Chipping Sparrow) showed an association with treated interior forest (Fig. 4.4).

Covariates in the detection component of the edge effects models varied across species in the direction and strength of effect (Fig. 4.A.1). The effect of vegetation cover on detection probability was positive for one species (Hermit Thrush). The effect of minutes since sunrise on detection probability was negative for two species (Mountain Chickadee and Yellow-rumped Warbler). The effect of Julian date on detection probability was negative for two species (Mountain Chickadee and White-breasted Nuthatch) and positive for three species (Western Tanager, Dusky Flycatcher, and Red Crossbill).

Question 2: Canopy cover effects

Occupancy of four species was related to landscape-scale canopy cover at some scale (Townsend's Warbler, Chipping Sparrow, Red Crossbill, Dusky Flycatcher) (Fig. 4.5, Fig. 4.A.3). Townsend's Warbler and Red Crossbill showed landscape associations consistent with *a priori* hypothesis (Fig. 4.A.4. Table 4.2). Landscape canopy cover had a positive effect on Townsend's Warbler occupancy (Figure 4.A.4, Table 4.2). Landscape cover also had a positive effect on Dusky Flycatcher occupancy, which was counter to predictions given Dusky Flycatcher's *a priori* habitat preference of open-forest (Table 2). Chipping Sparrow occupancy was greatest at intermediate values of landscape canopy cover, while landscape canopy cover was predicted to have a negative effect on this species (Fig. 4.4, Fig 4.A.4). Red Crossbill occupancy was negatively association with landscape canopy cover (Fig. 4.4, Fig 4.A.4). Marginal effects plots suggested that relationships exist between canopy cover and occupancy for several species, with wide credible intervals around trendlines (Fig. 4.5). The relationship between canopy cover and occupancy varied by scale for many species, including consistent relationships across scales, consistent lack of relationships among scales, and varying relationships across scales (Fig. 4.6).

4.5 Discussion

Our work adds important spatial context to the literature about dry forest fuel treatment effects on songbird diversity. We found evidence of both edge and landscape-context effects of fuel treatments on occupancy of several songbird species. We show that some breeding songbirds may avoid edges of discrete forest structural classes that represent less extreme changes than many edge effects studies comparing forest/non-forest edges. Our exploratory landscape analyses reinforce the known importance of using organism-specific scales of landscape analysis (Wiens 1989), including within a community of related organisms (Betts et al. 2014).

For overall songbird diversity, our results support maintaining diverse canopy cover conditions and patch sizes, while also avoiding excessive fine-scale fragmentation of forest structural classes. We found differences in occupancy at relatively small scales relative to the treatment edge - 50m to 150m - and these effects may extend further into interior habitat. Retaining dense-forest patches can present tradeoffs with fuel management objectives (Agee and Skinner 2005). However, our other findings may be consistent with wildfire management needs, because forest structural diversity (Larson and Churchill 2012, Koontz et al. 2020) and fuel treatment size (Prichard and Kennedy 2014, Kennedy and Johnson 2014) are often associated with reduced wildfire severity.

Question 1: Edge Effects

Our work suggests preference for interior habitat away from edges of treatment, which suggests that edge effects are one mechanism by which fragmentation of forest structural classes could be detrimental to dry forest biodiversity (Fischer and Lindenmayer 2007). Fragmentation may be a conservation challenge in some dry forest contexts, especially at lower elevations where fragmentation can be caused by strong abiotic gradients related to topography (Ireland et al. 2012, Hessburg et al. 2015) and disparate anthropogenic land-uses among different ownerships (Busby et al. 2012, Paveglio et al. 2019). Forest management is also a frequent source of forest fragmentation in dry forests (Tinker et al. 1998, Hessburg et al. 2015) and many other contexts (Kupfer 2006, Arroyo-Rodríguez et al. 2017). As fuel treatments (and wildfires) occur over increasing areas of dry forests with time, relatively large patches of discrete structural classes may become more scarce. Managers may therefore look for opportunities to retain, protect, or create relatively large patches of dense-forest where feasible within wildfire severity mitigation needs.

Relatively large dense-forest patches may be challenging to retain in fire-prone dry forest ecosystems, but are likely of high conservation value. Dense-forest patches are often a conservation focus for rare species such as the northern spotted owl (Gaines et al. 2010, Spies et al. 2019), and our work suggests dense patches may be valuable even to more common and widespread organisms. Dense-forest patches are challenging from a wildfire management perspective, however, because they often contain high fuel loads (Hagmann et al. 2021). Therefore, dense-forest locations should be planned carefully in relation to assets of high value to humans and potentially sensitive ecological areas (Stephens et al. 2020). Wildfire risk to dense-forests may be reduced by choosing favorable topographic sites in low-lying and/or north- and east-facing aspects and disrupting spatial continuity of fuel in the surrounding area (Camp et al. 1997, Wilson and Baker 1998), and possibly by using less intensive surface fuel treatments within dense-forest patches, such as low intensity prescribed burning (Stephens et al. 2014, Chiono et al. 2017, Gallagher et al. 2019).

Large patches of mature and relatively open dry forest are also likely to be scarce in modern landscapes (Hessburg et al. 2015), and our work suggests that interior open-forest habitat is important for at least one common songbird species. Our relatively modest sample size precluded analyses of some relatively uncommon open-forest specialists. These include White-headed Woodpecker, Mountain Bluebird, and Pygmy Nuthatch (Billerman et al. 2023), which we detected in our study but in less than five percent of our visits. With our work suggesting negative edge effects for regionally common songbird species, it is plausible that edge effects may have different impacts on rarer and more specialized species.

Spatial scale is especially crucial to interpretation of forest structure effects in dry forests, and 'large patches of discrete forest structures' should not be mistaken for homogeneity within those patches. For dry forests, fine-scale (<1ha) structural heterogeneity is a characteristic feature (Hessburg et al. 2015), an important mechanism of resilience to contagious disturbances (Larson and Churchill 2012), and a facilitator of biodiversity (Dodson and Peterson 2010, White et al. 2013, Roberts et al. 2020). Summaries of forest structure at our point centers reflects this heterogeneity, with large standard errors around means of summary values, and our un-treated and treated stands show overlap in their ranges of canopy cover, vegetation cover, and tree basal area values. 'Dense-forest' does not necessarily mean 'closed-canopy', illustrated by our un-treated patches containing many fine-scale canopy openings and an average canopy cover of only 49%. However, treated patches can be made homogeneous at finer scales; historically, forest thinning often created uniform spatial distributions of residual trees (Churchill et al. 2013, Fahey et al. 2018). Refinement is ongoing for methods of creating heterogeneity within treatment units (Dickinson et al. 2016, Dickinson and Cadry 2017), and greater adoption of these methods in dry forests is likely to have positive impacts on biodiversity (Dodson and Peterson 2010, White et al. 2013).

The lack of positive associations with edge habitat was surprising and could relate to our focus on vocalizing songbirds, the limited seasonality of our study, or the relatively fine-scale over which we analyzed edge effects. Some generalist species may gravitate towards edge habitats because of the diversity of resources found there (Tscharntke et al. 2012), and in some cases fragmented and/or edge habitats can contain more biodiversity than less fragmented habitats (Terraube et al. 2016, Fahrig 2017), albeit with fewer specialist species (Fletcher et al. 2018). Raptors and owls are among the taxa noted to favor edge habitats (McCollin 1998), and our focus on songbirds could lead to underestimation of positive edge effects by excluding many predatory species and possibly by reflecting edge avoidance in prey species (Rodríguez et al. 2001). Furthermore, our surveys during breeding season may not represent edge effects during other seasons. Finally, the scale of analysis was relatively fine with the 'edge' zone we surveyed only extending from 0-100 meters from the edge. It is possible that generalists could be drawn to forest edges, but at scales greater than 100 m, as has been observed for brown-headed cowbirds in agricultural landscapes of eastern North America (Howell et al. 2007).

Regionally common shrub-associated songbirds such as house wren, Nashville warbler, orange-crowned warbler, and spotted towhee (Saab et al. 2022, Billerman et al. 2023) were conspicuously absent from our data, which could have influenced edge effect analyses. Ungulate browsing pressure is sufficient to threaten aquatic and riparian conservation objectives in some areas of the Malheur National Forst (Charnley et al. 2018, Kauffman et al. 2022), and signs of wild and domestic ungulates were abundant in many of our study transects. Studies from dry forests with higher shrub cover will likely differ in assemblages of common bird species, and therefore may show different results than our study. It is possible that treated patches with higher shrub cover will show weaker edge effects or greater scale of edge effects, because of increased cover from predation in treated patches with low canopy cover (Foggia et al. 2018).

Question 2: Landscape context of canopy cover

The importance of matching scale of analyses to the species and/or process of interest has been a central tenet of landscape ecological research since its inception (Turner et al. 2015b). However, information about the appropriate scale of inference is often scarce (Lowe et al. 2022), and in many cases a single scale is used to study 'landscape effects' for a community of organisms (Latif et al. 2020), which is an inherent limitation of our edge-effects models. Our landscape models suggest that within communities (e.g., songbirds) and among guilds (e.g., dense-forest preferring vs. open-forest preferring species), there is variability in the scale of landscape effects. Therefore, it may be crucial for researchers to search for and use species-specific scales of inference in community analyses of landscape processes (Wiens 1989, Betts et al. 2014).

Variability in the magnitude and scale of landscape context effects also suggest that a conservation strategy of maintaining diverse canopy cover conditions and patch size distributions is likely important to facilitating high biodiversity in dry forests. It is likely infeasible or impossible to mathematically optimize fuel treatment patch size distributions and spatial configurations for all songbird species, and much less so for biodiversity generally. Management for overall forest biodiversity may seek to increase forest conditions that are under-represented at a given point in time, and to increase options for ecosystem response to unexpected changes (Franklin et al. 2018). Where feasible, consistent monitoring of biodiversity responses to forest management can allow for adaptive management based on habitat needs at a given point in time (McCarthy and Possingham 2007, Williams 2011). Funding for post-treatment monitoring is limited, however, so management plans that are mindful of possible edge and landscape effects of treatment is likely vital for biodiversity conservation in dry forests (Agee 1998).

Canopy cover may be a particularly well-suited metric to study landscape-scale bird habitat in dry forests, which contain relatively simple tree compositions and complex forest structures (Larson and Churchill 2012). Dry forests often show heterogeneity in patch structure due to large gradients in abiotic conditions and disturbance history, which can prevent discrete patch structures from developing in some cases (Hessburg et al. 2015). This dry forest heterogeneity is likely to be a challenge for patch-based landscape analyses at broader spatial scales where specific ecological conditions cannot be chosen with sample site selection. Canopy cover does not directly represent treatment but it is heavily affected by dry forest thinning (Stephens et al. 2009). Furthermore, canopy cover can be an important indicator of bird habitat dry forests (Latif et al. 2022) and other forest ecosystems (Franklin et al. 2023). Canopy cover may be relatively less useful for bird species that are associated with specific plant species such as ponderosa pine or particular forest structures such large trees and/or snags (Lyons-Tinsley and Peterson 2012), though Latif et al. (2022) found canopy cover associations with occupancy of many ponderosa pine specialist birds. Our results do not necessarily support the use of canopy cover as an indicator of landscape-scale habitat suitability in more speciose forest types, where tree species composition may be of equal or greater importance than structural variables in determining bird habitat (Adams and Matthews 2019).

Limitations

The paired treatment-control design was useful for minimizing biases in broad-scale species assemblages among different treatments and ensuring a true test of a structurally distinct treated/un-treated edge. However, the paired design also limited areas available for sampling and the distance from edge that could be sampled with adequate replication. Therefore, our edge effects models cover a limited range of scales of edge.

More intensive demographic analyses could build on our work. Our approach using occupancy probability in a limited seasonal window is an imperfect indicator of habitat quality, as we cannot characterize demographic parameters such as mortality, fecundity, immigration and emigration, which would be necessary to determine whether habitats being used by our study species are serving as ‘source’ and/or ‘sink’ populations within broader metapopulations (Horne

1983, Opdam et al. 1995, Robertson and Hutto 2006, Morrison et al. 2008). Studies employing more intensive fieldwork such as nest survival surveys may consider applying exploratory landscape analyses such as ours, to investigate whether occupancy patterned explored in this paper are representative of demographic processes.

4.6 Conclusions

Edge effects and landscape context of habitat are known to affect most forest organisms, but have received relatively little study in the context of fuel treatments in dry forests. By showing interior habitat preference for the majority of studied songbird species that prefer denser forest conditions, our work suggests that maintaining some relatively large patches of dense-forest will be of conservation value in otherwise heavily treated and/or burned areas of forest. High wildfire hazard in dense-forests presents challenges to justifying and executing the maintenance of un-treated patches, which can be mitigated by disrupting continuity of fuel profiles around un-treated patches. Additionally, our exploratory analyses of landscape context suggest varied magnitudes, directions, and scales of effects by species, supporting conservation approaches in maintenance of canopy cover diversity. These findings may be of use to managers, stakeholders, and policy makers interested in multiple-value management of fire-prone ecosystems.

4.7 Figures

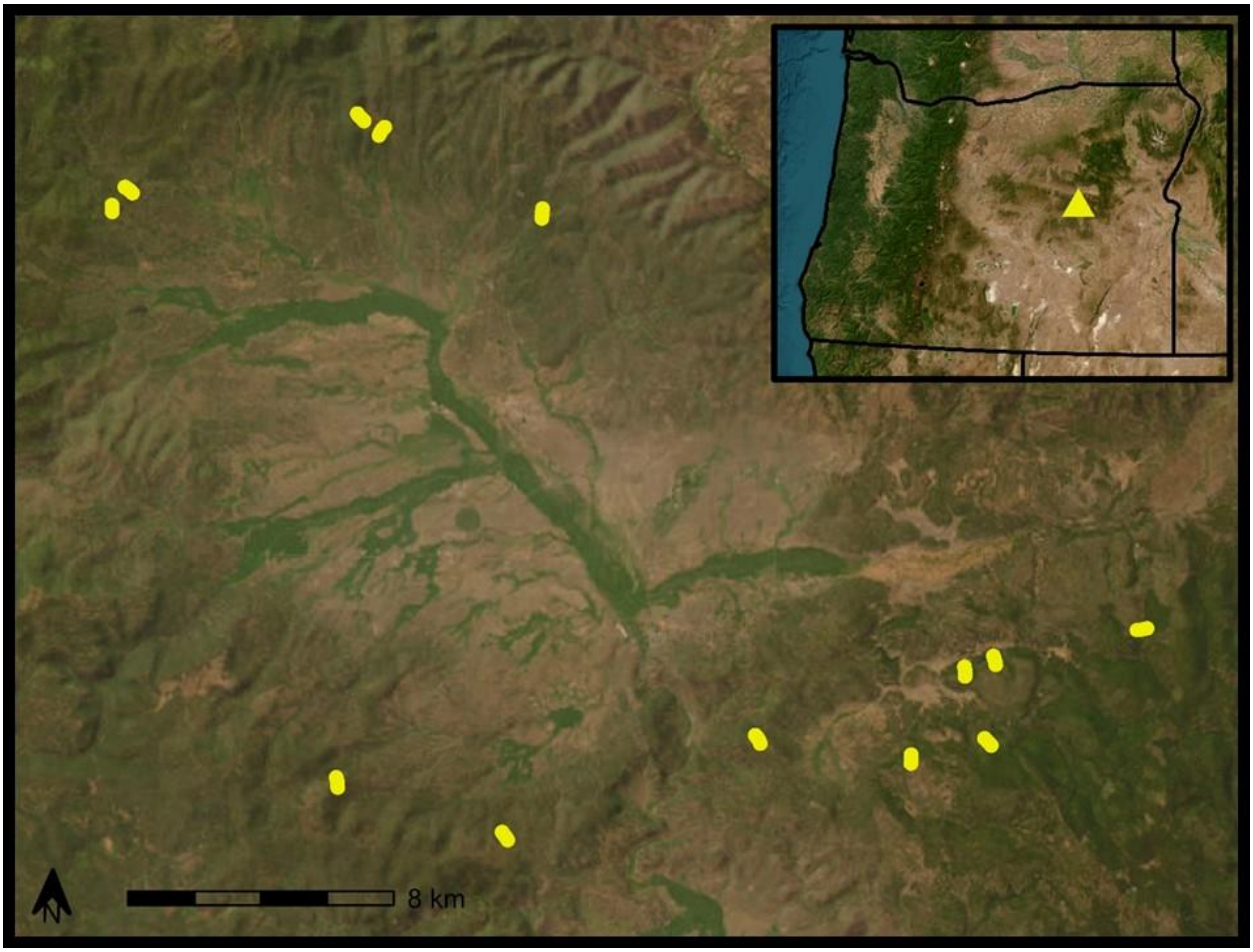

Figure 4.1: Map of study area surrounding the Bear Valley in eastern Oregon. Plots are shown in yellow circles and are grouped in 13 transects of 4 plots each.

Figure 4.2: Example of an edge between a treated forest patch (left) and an un-treated forest patch (right). Note differences in amount of understory vegetation, and that these dry forests rarely contain full canopy cover even when un-treated and un-disturbed. Photo by Don Radcliffe.

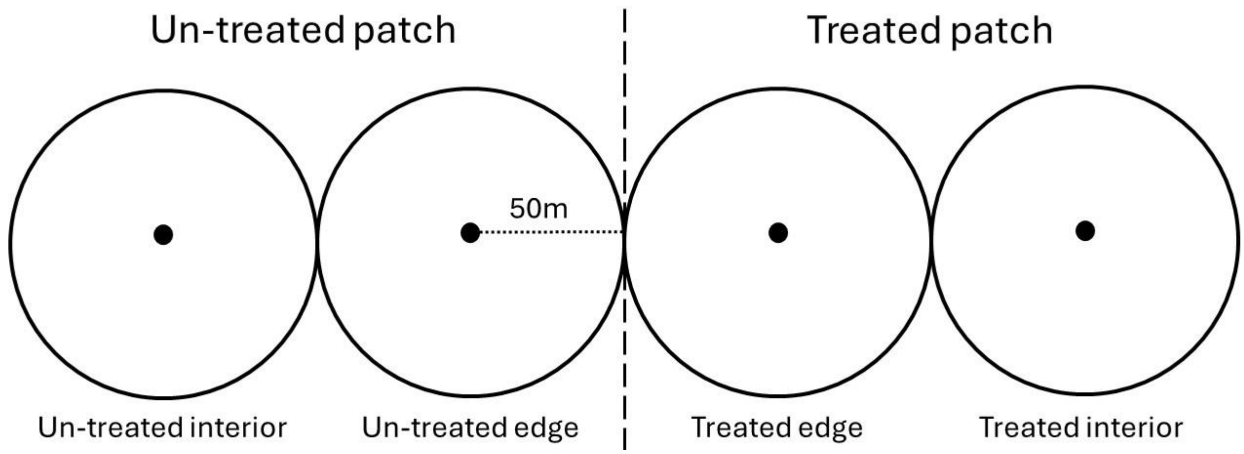

Figure 4.3: Aerial representation of spatial relationships of point-count stations within one transect. Dots represent centers of point-count stations. Circles represent boundaries of point-counts, a 50-meter radius around centers of the corresponding point-count centers (dotted line). The dashed line represents the treatment boundary. Labels underneath point-count stations represent the names of 'treatments' used in our models.

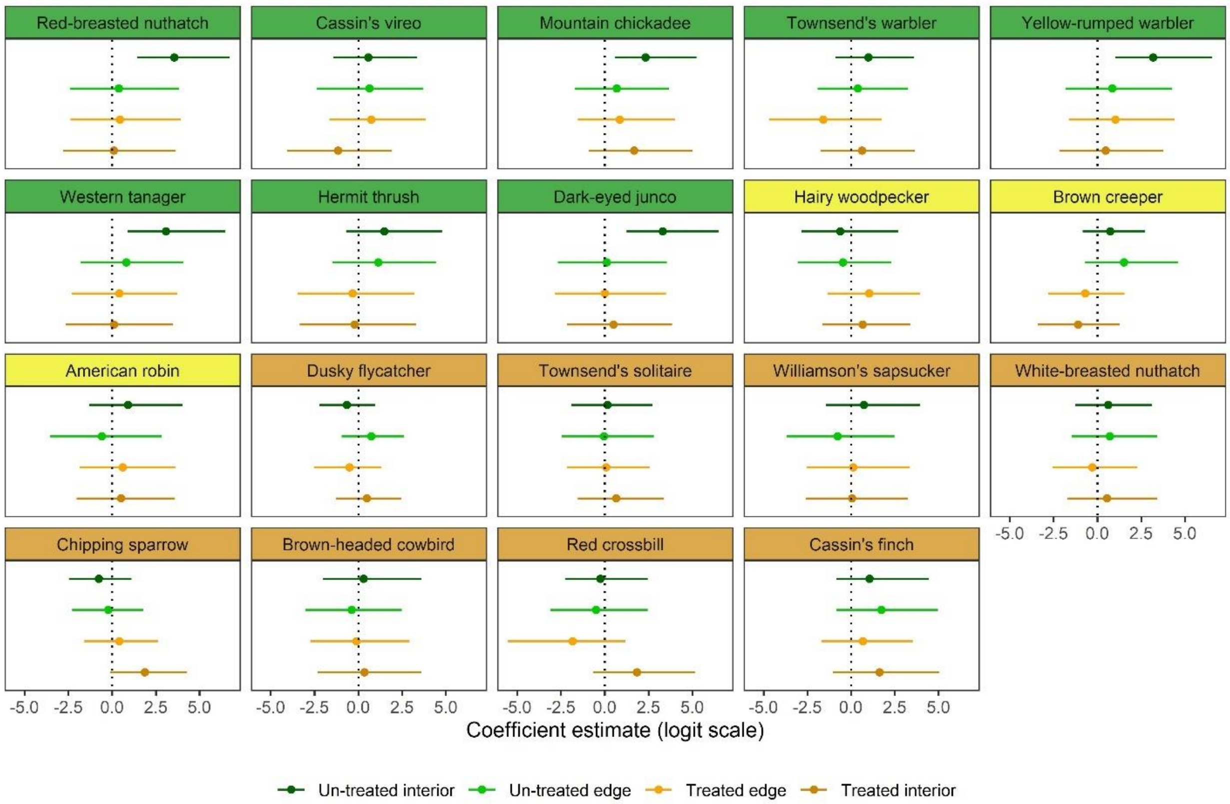

Figure 4.4: Occupancy coefficient estimates and 95% credible intervals from edge effects models, for all species found in >5% of point-count visits. Green panels indicate dense-forest favoring species, yellow panels indicate generalists, and orange panels indicate Open-forest favoring species, according to *a priori* habitat designation from Table 4.2. Species are further arranged by nesting and foraging guilds (Table 4.2).

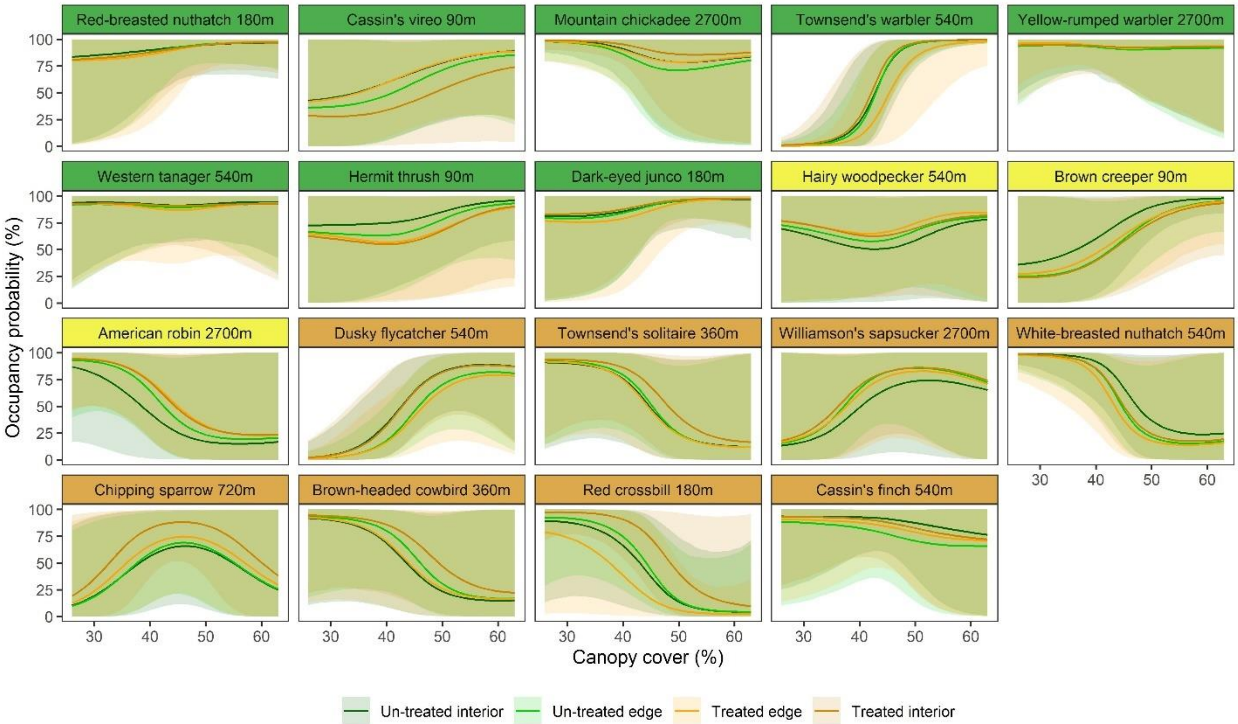

Figure 4.5: Marginal effects plots of canopy cover effects at selected scales, including linear and quadratic canopy cover terms, with 95% credible intervals. The number of meters in the facet labels represent the radius surrounding point-count center from which canopy cover data were collected prior to modelling, for the displayed graph. Species are arranged by foraging and nesting guilds (Table 4.2).

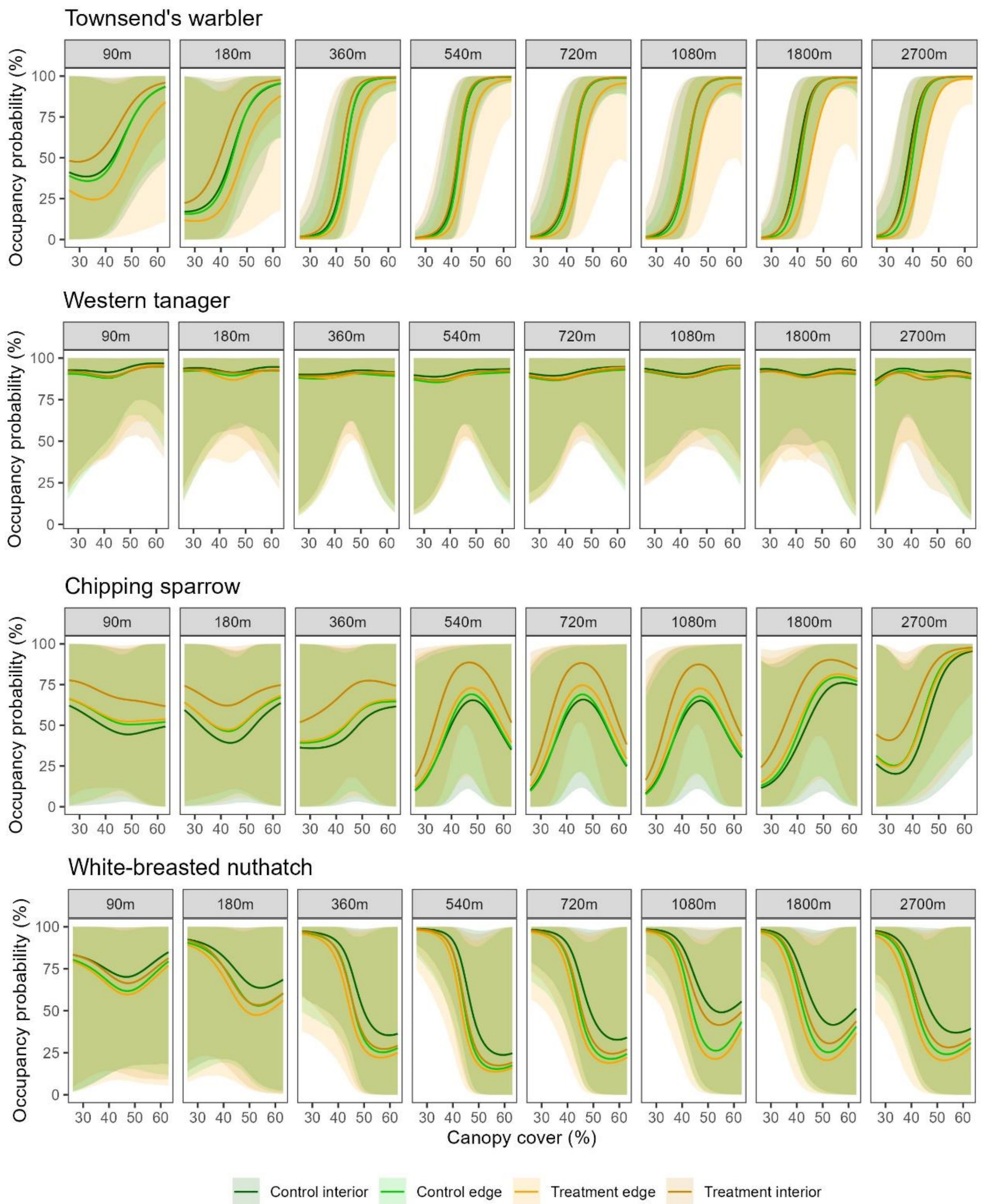

Figure 4.6: Examples of different relationships to scale in canopy cover analyses: relatively consistent effects of canopy cover across scales (Townsend's warbler), relatively consistent lack of effects of canopy cover across scales (Western tanager), changing relationships with canopy cover across scales (Chipping sparrow), and changing magnitude of effects of canopy cover across scales (White-breasted nuthatch). Plots are marginal effects plots of the effect of canopy cover on occupancy, including 95% credible intervals. Facet labels indicate the radius surrounding point-count center from which canopy cover data were collected before modelling.

4.8 Tables

Table 4.1: Summary statistics of forest structure in un-treated and treated patches

	Un-treated patches	**Treated patches**
Basal area (m^2/ha)	24 (1.2)	14 (0.8)
Vegetation cover 0-6m (%)	33 (3.8)	12 (1.2)
Field measured canopy cover (%)	75 (2.3)	47 (2.6)
GNN measured canopy cover (%)	50 (1.5)	42 (1.5)

Table 4.2: Study species present in 8 or more plot visits (>5%), arranged by *a priori* habitat preferences gathered from studies of fuel treatment effects on dry forest bird communities (e.g., Fontaine & Kennedy 2012, Latif et al. 2020, 2022, Saab et al. 2022), and foraging and nesting preferences from Birds of the World database (Billerman et al. 2023). 'Detections' column represents number of plot visits in which each species was detected

Species	Habitat expectation	Foraging guild	Nesting guild	Detections
Red-breasted nuthatch	Dense-forest favoring	Bark insectivore	Cavity	45
Cassin's vireo	Dense-forest favoring	Canopy foliage insectivore	Cavity	14
Mountain chickadee	Dense-forest favoring	Canopy foliage insectivore	Open cup	81
Townsend's warbler	Dense-forest favoring	Canopy foliage insectivore	Open cup	21
Yellow-rumped warbler	Dense-forest favoring	Canopy foliage insectivore	Open cup	69
Western tanager	Dense-forest favoring	Canopy foliage insectivore	Open cup	41
Hermit thrush	Dense-forest favoring	Omnivore	Open cup	12
Dark-eyed junco	Dense-forest favoring	Omnivore	Open cup	43
Hairy woodpecker	Generalist	Bark insectivore	Cavity	8
Brown creeper	Generalist	Bark insectivore	Cavity	30
American robin	Generalist	Shrub & ground insectivore	Open cup	13
Dusky flycatcher	Open-forest favoring	Aerial insectivore	Open cup	29
Townsend's solitaire	Open-forest favoring	Aerial insectivore	Open cup	19
Williamson's sapsucker	Open-forest favoring	Bark insectivore	Cavity	9
White-breasted nuthatch	Open-forest favoring	Bark insectivore	Cavity	25
Chipping sparrow	Open-forest favoring	Omnivore	Open cup	25
Brown-headed cowbird	Open-forest favoring	Omnivore	Open cup	10
Red crossbill	Open-forest favoring	Omnivore	Open cup	8
Cassin's finch	Open-forest favoring	Omnivore	Open cup	38

4.9 Appendix 4.1: Full Description of Field Methods

We conducted point-counts using a double dependent-observer design, in which a primary observer called out all observations to a secondary observer maintaining the datasheet, and the secondary observer added and noted any observations they made which the primary observer missed (Golding et al. 2017). Before sampling, the observers waited for five minutes after arrival at a point, to account for disturbance to the natural behavior of the birds (Ralph et al. 1995). We used relatively long ten-minute point-counts, because suitable sample transects were often located far from one another in rugged terrain (Golding et al. 2017). During sampling, individual birds were assigned to independently recorded time bands of 0-3, 3-5, and 5-10 minutes, and distance bands of 0-10, 10-25, 25-50, and 50+ meters according to first detection within a time band. Observers calibrated distances using a laser rangefinder any time a bird was visually located, both within a one-week training period and throughout the data collection period.

Observers recorded detection covariates during the five-minute waiting period. We recorded cloud cover on a scale of 0-3, and temperature with a thermometer. We recorded windspeed with an anemometer both immediately before and immediately after sampling. Woody vegetation coverage was estimated ocularly over a plot of 20m radius, in three vertical strata: 0-2m, 2-6m, and >6m, in intervals of 5%. We recorded canopy cover with four spherical densiometer measurements, one in each cardinal direction. Basal area of trees was recorded using the number of trees found in a cruising prism sweep (5m BA factor). Dominant tree species in the overstory and understory of the 50 m radius plot were recorded.

We recorded the GPS coordinates of each study transect, using a Garmin 64st. At each plot we took photos facing each cardinal direction from plot center.

4.10 Appendix 4.2: Supplementary Figures

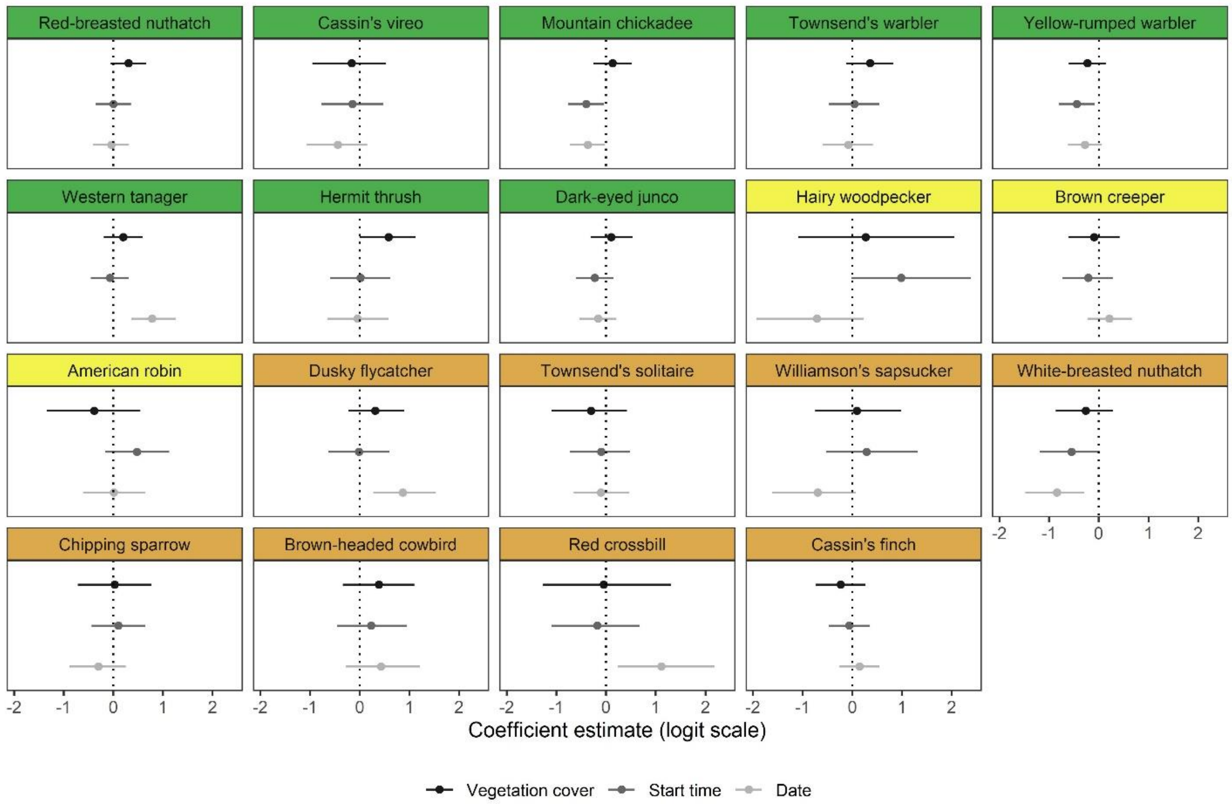

Figure 4.A.1: Detection coefficient estimates for edge effects models, with 95% credible intervals. Green panels indicate closed-canopy favoring species, yellow panels indicate generalists, and orange panels indicate open-canopy favoring species, according to *a priori* habitat designation from Table 4.1. Species are further arranged by nesting and foraging guilds (Table 4.1).

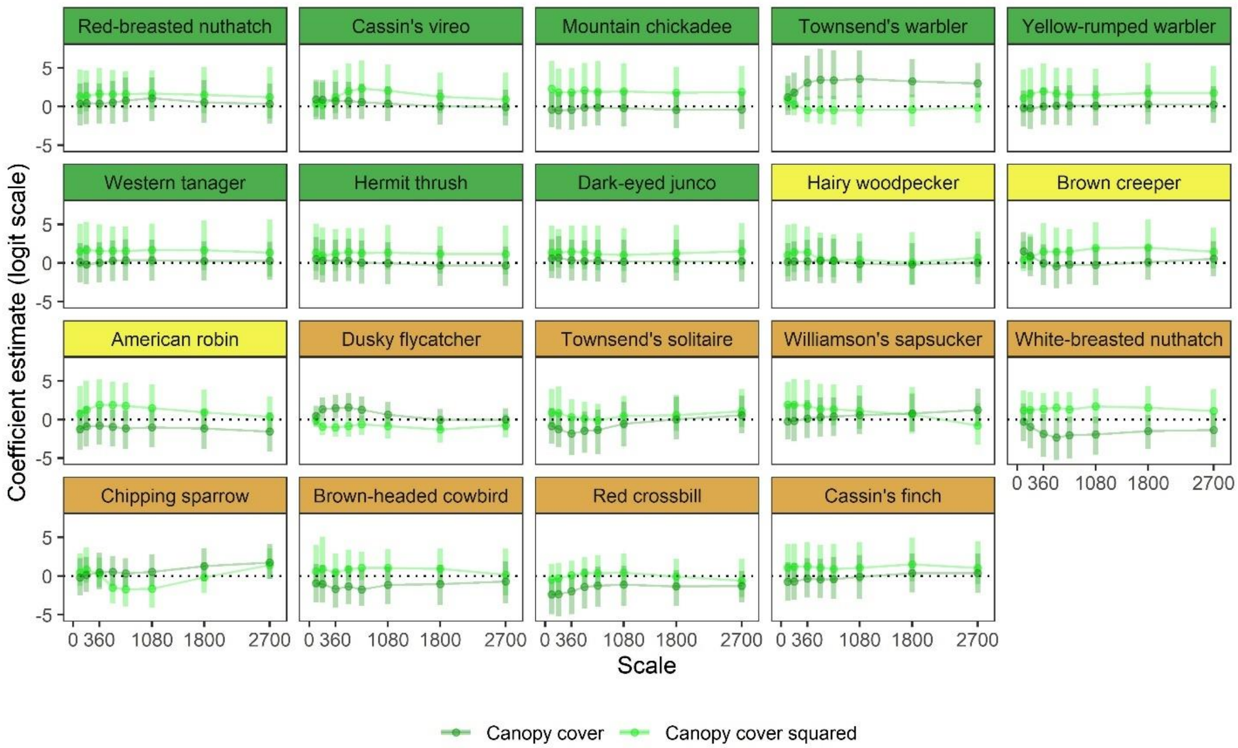

Figure 4.A.2: Variation in scale of landscape canopy cover effects on study species, in linear ('canopy cover') and quadratic ('canopy cover squared') space. Points are coefficient estimates from landscape models, and error bars are 95% credible intervals. Green panels indicate closed-canopy favoring species, yellow panels indicate generalists, and orange panels indicate open-canopy favoring species, according to *a priori* habitat designation from Table 4.2. Species are further arranged by nesting and foraging guilds (Table 4.2).

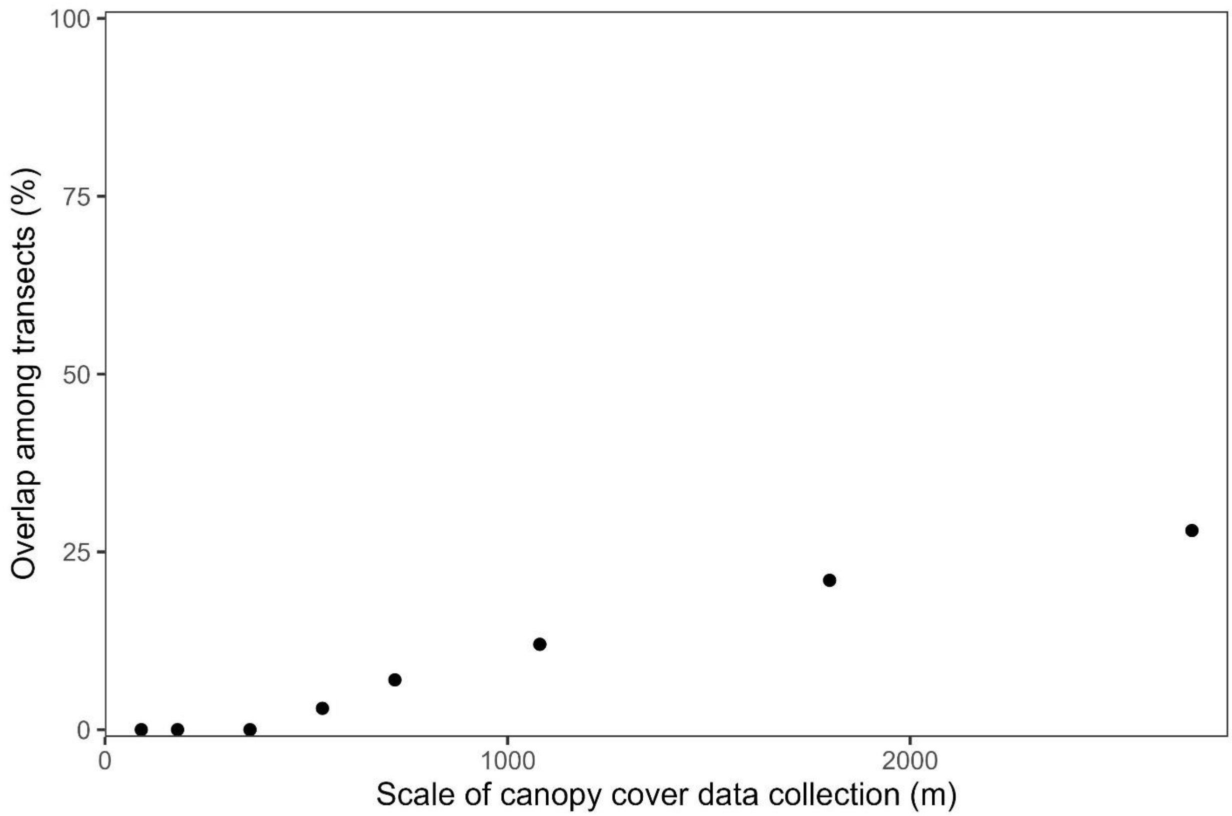

Figure 4.A.3: Proportion of the area of canopy cover data collection over which multiple transects overlapped, causing the same canopy cover data to contribute to landscape models for different transects.

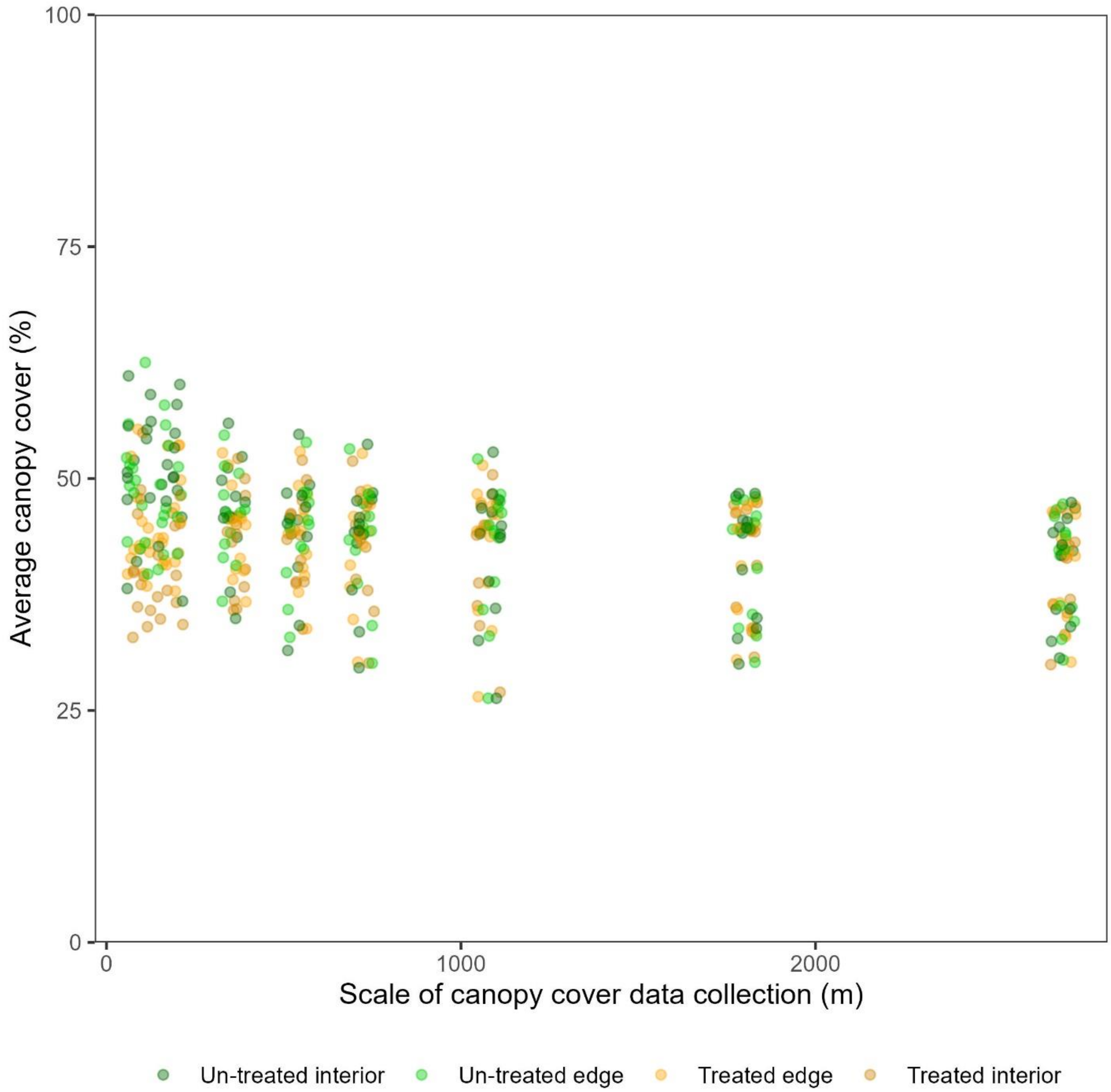

Figure 4.A.4: Average canopy cover by plot and scale of collection. Points represent unique combinations of plot and scale, and were jittered for visualization.

4.11 References

Abrams, J. 2019. The emergence of network governance in U.S. National Forest Administration: Causal factors and propositions for future research. Forest Policy and Economics 106:101977.

Adams, B. T., and S. N. Matthews. 2019. Diverse temperate forest bird assemblages demonstrate closer correspondence to plant species composition than vegetation structure. Ecography 42:1752–1764.

Agee, J. K. 1996. Fire in the Blue Mountains: A History, Ecology, and Research Agenda. Pages 119–145 in R. G. , Jaindl and T. M. Quigley, editors. Sustaining the land, people, and economy of the Blue Mountains. First edition. American Forests, Washington DC.

Agee, J. K. 1998. The landscape ecology of western forest fire regimes. Northwest Science 72:24–34.

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Arroyo-Rodríguez, V., F. P. L. Melo, M. Martínez-Ramos, F. Bongers, R. L. Chazdon, J. A. Meave, N. Norden, B. A. Santos, I. R. Leal, and M. Tabarelli. 2017. Multiple successional pathways in human-modified tropical landscapes: new insights from forest succession, forest fragmentation and landscape ecology research. Biological Reviews 92:326–340.

Baker, W. L. 1994. Restoration of Landscape Structure Altered by Fire Suppression. Conservation Biology 8:763–769.

Barnett, K., S. Parks, C. Miller, and H. Naughton. 2016. Beyond Fuel Treatment Effectiveness: Characterizing Interactions between Fire and Treatments in the US. Forests 7:237.

Betts, M. G., L. Fahrig, A. S. Hadley, K. E. Halstead, J. Bowman, W. D. Robinson, J. A. Wiens, and D. B. Lindenmayer. 2014. A species-centered approach for uncovering generalities in organism responses to habitat loss and fragmentation. Ecography 37:517–527.

Betts, M. G., G. J. Forbes, and A. W. Diamond. 2007. Thresholds in Songbird Occurrence in Relation to Landscape Structure. Conservation Biology 21:1046–1058.

Billerman, S. M., B. K. Keeney, P. G. Rodewald, and T. S. Schulenberg. 2023. Birds of the World. Cornell Lab of Ornithology. Ithica. https://birdsoftheworld.org/bow/home

Bragg, D. C., B. B. Hanberry, T. F. Hutchinson, S. B. Jack, and J. M. Kabrick. 2020. Silvicultural options for open forest management in eastern North America. Forest Ecology and Management 474:118383.

Brodie, E. G., E. E. Knapp, W. R. Brooks, S. A. Drury, and M. W. Ritchie. 2024. Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. Fire Ecology 20:1–20.

Busby, G. M., H. J. Albers, and C. A. Montgomery. 2012. Wildfire Risk Management in a Landscape with Fragmented Ownership and Spatial Interactions. Land Economics 88:496–517.

Camp, A., C. Oliver, P. Hessburg, and R. Everett. 1997. Predicting late-successional fire refugia pre-dating European settlement in the Wenatchee Mountains. Forest Ecology and Management 95:63–77.

Chamberlain, C. P., G. R. Cova, C. A. Cansler, M. P. North, M. D. Meyer, S. M. A. Jeronimo, and V. R. Kane. 2023. Consistently heterogeneous structures observed at multiple spatial scales across fire-intact reference sites. Forest Ecology and Management 550:121478.

Chandler, R., K. Kellner, I. Fiske, D. Miller, A. Royle, J. Hostetler, R. Hutchinson, A. Smith, M. Kery, M. Meredith, A. Fournier, A. Muldoon, and C. Baker. 2023. unmarked: Models for Data from Unmarked Animals. https://cran.r-project.org/web/packages/unmarked/index.html#:~:text=unmarked%3A%20Models%20for%20Data%20from,sampling%2C%20and%20double%20observer%20sampling.

Charnley, S., H. Gosnell, K. L. Wendel, M. M. Rowland, and M. J. Wisdom. 2018. Cattle grazing and fish recovery on US federal lands: can social–ecological systems science help? Frontiers in Ecology and the Environment 16:S11–S22.

Chiono, L. A., D. L. Fry, B. M. Collins, A. H. Chatfield, and S. L. Stephens. 2017. Landscape-scale fuel treatment and wildfire impacts on carbon stocks and fire hazard in California spotted owl habitat. Ecosphere 8:e01648.

Churchill, D. J., A. J. Larson, M. C. Dahlgreen, J. F. Franklin, P. F. Hessburg, and J. A. Lutz. 2013. Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring. Forest Ecology and Management 291:442–457.

Connell, J. H. 1978. Diversity in tropical rain forests and coral reefs. Science 199:1302–1310.

Converse, S. J., G. C. White, K. L. Farris, and S. Zack. 2006. Small mammals and forest fuel reduction: national-scale responses to fire and fire surrogates. Ecological Applications 16:1717–1729.

Coop, J. D., S. A. Parks, C. S. Stevens-Rumann, S. D. Crausbay, P. E. Higuera, M. D. Hurteau, A. Tepley, E. Whitman, T. Assal, B. M. Collins, K. T. Davis, S. Dobrowski, D. A. Falk, P. J. Fornwalt, P. Z. Fulé, B. J. Harvey, V. R. Kane, C. E. Littlefield, E. Q. Margolis, M. North, M. A. Parisien, S. Prichard, and K. C. Rodman. Wildfire-driven forest conversion in Western North American landscapes. BioScience 70:659–673.

Cova, G., V. R. Kane, S. Prichard, M. North, and C. A. Cansler. 2023. The outsized role of California's largest wildfires in changing forest burn patterns and coarsening ecosystem scale. Forest Ecology and Management 528:120620.

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

Dickinson, Y. L., and J. D. Cadry. 2017. An evaluation of tree marking methods for implementing spatially heterogeneous restoration. Journal of Sustainable Forestry 36:47–64.

Dickinson, Y., K. Pelz, E. Giles, and J. Howie. 2016. Have we been successful? Monitoring horizontal forest complexity for forest restoration projects. Restoration Ecology 24:8–17.

Dodson, E. K., and D. W. Peterson. 2010. Dry coniferous forest restoration and understory plant diversity: The importance of community heterogeneity and the scale of observation. Forest Ecology and Management 260:1702–1707.

Eidenshink, J., B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, and S. Howard. 2007. A Project for Monitoring Trends in Burn Severity. Fire Ecology 3:3–21.

Fahey, R. T., B. C. Alveshere, J. I. Burton, A. W. D'Amato, Y. L. Dickinson, W. S. Keeton, C. C. Kern, A. J. Larson, B. J. Palik, K. J. Puettmann, M. R. Saunders, C. R. Webster, J. W. Atkins, C. M. Gough, and B. S. Hardiman. 2018. Shifting conceptions of complexity in forest management and silviculture. Forest Ecology and Management 421:59–71.

Fahrig, L. 2017. Ecological Responses to Habitat Fragmentation Per Se. Annual Review of Ecology, Evolution, and Systematics 48:1–23.

Finney, M. A. 2001. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. Forest Science 47:219–228.

Fischer, J., and D. B. Lindenmayer. 2007. Landscape modification and habitat fragmentation: a synthesis. Global Ecology and Biogeography 16:265–280.

Fletcher, R. J., R. K. Didham, C. Banks-Leite, J. Barlow, R. M. Ewers, J. Rosindell, R. D. Holt, A. Gonzalez, R. Pardini, E. I. Damschen, F. P. L. Melo, L. Ries, J. A. Prevedello, T. Tscharntke, W. F. Laurance, T. Lovejoy, and N. M. Haddad. 2018. Is habitat fragmentation good for biodiversity? Biological Conservation 226:9–15.

Fletcher, R. Jr., L. Ries, J. Battin, and A. D. Chalfoun. 2007. The role of habitat area and edge in fragmented landscapes: definitively distinct or inevitably intertwined? Canadian Journal of Zoology 85:1017–1030.

Foggia, J. R., S. A. Rush, D. A. Miller, T. B. Wigley, and J. A. Martin. 2018. Effects of forest structure and harvest-induced edges on predation risk. Wildlife Society Bulletin 42:237–245.

Fontaine, J. B., and P. L. Kennedy. 2012. Meta-analysis of avian and small-mammal response to fire severity and fire surrogate treatments in U.S. fire-prone forests. Ecological Applications 22:1547–1561.

Fraixedas, S., Lindén, A., Piha, M., Cabeza, M., Gregory, R., and Lehikoinen, A. (2020). A state-of-the-art review on birds as indicators of biodiversity: Advances, challenges, and future directions. Ecological Indicators 118:106728.

Franklin, J. F., N. K. Johnson, and D. L. Johnson. 2018. Ecological Forest Management. First edition. Waveland Press, Long Grove, IL.

Franklin, M. J. M., R. E. Major, and R. A. Bradstock. 2023. Canopy cover mediates the effects of a decadal increase in time since fire on arboreal birds. Biological Conservation 277:109871.

Gaines, W. L., M. Haggard, J. F. Lehmkuhl, A. L. Lyons, and R. J. Harrod. 2007. Short-Term Response of Land Birds to Ponderosa Pine Restoration. Restoration Ecology 15:670–678.

Gaines, W. L., R. J. Harrod, J. Dickinson, A. L. Lyons, and K. Halupka. 2010. Integration of Northern spotted owl habitat and fuels treatments in the eastern Cascades, Washington, USA. Forest Ecology and Management 260:2045–2052.

Gallagher, C. V., J. J. Keane, P. A. Shaklee, H. A. Kramer, and R. Gerrard. 2019. Spotted owl foraging patterns following fuels treatments, Sierra Nevada, California. The Journal of Wildlife Management 83:487–501.

Golding, J. D., J. J. Nowak, and V. J. Dreitz. 2017. A multispecies dependent double-observer model: A new method for estimating multispecies abundance. Ecology and Evolution 7:3425–3435.

Guo, J., J. Gabry, B. Goodrich, A. Johnson, S. Weber, H. S. Badr, D. Lee, K. Sakrejda, M. Martin, Trustees of Columbia University, O. Sklyar, The R Core Team, J. Oehlschlaegel-Akiyoshi, J. Maddock, P. Bristow, N. Agrawal, C. Kormanyos, and B. Steve. 2023. rstan: R Interface to Stan. https://cran.r-project.org/web/packages/rstan/index.html.

Hadley, A. S., and M. G. Betts. 2016. Refocusing Habitat Fragmentation Research Using Lessons from the Last Decade. Current Landscape Ecology Reports 2016 1:2 1:55–66.

Hagmann, R. K., P. F. Hessburg, S. J. Prichard, N. A. Povak, P. M. Brown, P. Z. Fulé, R. E. Keane, E. E. Knapp, J. M. Lydersen, K. L. Metlen, M. J. Reilly, A. J. S. Meador, S. L. Stephens, J. T. Stevens, A. H. Taylor, L. L. Yocom, M. A. Battaglia, D. J. Churchill, L. D. Daniels, D. A. Falk, P. Henson, J. D. Johnston, M. A. Krawchuk, C. R. Levine, G. W. Meigs, A. G. Merschel, M. P. North, H. D. Safford, T. W. Swetnam, and A. E. M. Waltz. 2021. Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. Ecological Applications e02431.

Hanberry, B. B., B. J. Palik, and H. S. He. 2012. Comparison of historical and current forest surveys for detection of homogenization and mesophication of Minnesota forests. Landscape Ecology 27:1495–1512.

Hatfield, J. H., J. Barlow, C. A. Joly, A. C. Lees, C. H. de F. Parruco, J. A. Tobias, C. D. L. Orme, and C. Banks-Leite. 2020. Mediation of area and edge effects in forest fragments by adjacent land use. Conservation Biology 34:395–404.

Hessburg, P. F., J. K. Agee, and J. F. Franklin. 2005. Dry forests and wildland fires of the inland Northwest USA: Contrasting the landscape ecology of the pre-settlement and modern eras. Forest Ecology and Management 211:117–139.

Hessburg, P. F., D. J. Churchill, A. J. Larson, R. D. Haugo, C. Miller, T. A. Spies, M. P. North, N. A. Povak, R. T. Belote, P. H. Singleton, W. L. Gaines, R. E. Keane, G. H. Aplet, S. L. Stephens, P. Morgan, P. A. Bisson, B. E. Rieman, R. B. Salter, and G. H. Reeves. 2015. Restoring fire-prone Inland Pacific landscapes: seven core principles. Landscape Ecology 30:1805–1835.

Heyerdahl, E. K., L. B. Brubaker, and J. K. Agee. 2001. Spatial controls of historical fire regimes: A multiscale example from the interior west, USA. Ecology 82:660–678.

Hood, S. M., C. R. Keyes, K. J. Bowen, D. C. Lutes, and C. Seielstad. 2020. Fuel Treatment Longevity in Ponderosa Pine-Dominated Forest 24 Years After Cutting and Prescribed Burning. Frontiers in Forests and Global Change 3:78.

Horne, B. Van. 1983. Density as a Misleading Indicator of Habitat Quality. The Journal of Wildlife Management 47:893.

Howell, C. A., W. D. Dijak, and F. R. Thompson. 2007. Landscape context and selection for forest edge by breeding Brown-headed Cowbirds. Landscape Ecology 22:273–284.

Hutto, R. L. 2016. Should scientists be required to use a model-based solution to adjust for possible distance-based detectability bias? Ecological Applications 26:1287–1294.

Ireland, K. B., A. B. Stan, and P. Z. Fulé. 2012. Bottom-up control of a northern Arizona ponderosa pine forest fire regime in a fragmented landscape. Landscape Ecology 27:983–997.

Johnston, J. D., S. M. Greenler, M. J. Reilly, M. R. Webb, A. G. Merschel, K. N. Johnson, and J. F. Franklin. 2021. Conservation of Dry Forest Old Growth in Eastern Oregon. Journal of Forestry 119:647–659.

Kauffman, J. B., G. Coleman, N. Otting, D. Lytjen, D. Nagy, and R. L. Beschta. 2022. Riparian vegetation composition and diversity shows resilience following cessation of livestock grazing in northeastern Oregon, USA. PLOS ONE 17:e0250136.

Kellner, K. 2023, February 2. ubms: Bayesian Models for Data from Unmarked Animals using “Stan.” https://cran.r-project.org/web/packages/ubms/index.html.

Kennedy, M. C., and M. C. Johnson. 2014. Fuel treatment prescriptions alter spatial patterns of fire severity around the wildland-urban interface during the Wallow Fire, Arizona, USA. Forest Ecology and Management 318:122–132.

Koontz, M. J., M. P. North, C. M. Werner, S. E. Fick, and A. M. Latimer. 2020. Local forest structure variability increases resilience to wildfire in dry western U.S. coniferous forests. Ecology Letters 23:483–494.

Kupfer, J. A. 2006. National assessments of forest fragmentation in the US. Global Environmental Change 16:73–82.

Larson, A. J., and D. Churchill. 2012. Tree spatial patterns in fire-frequent forests of western North America, including mechanisms of pattern formation and implications for designing fuel reduction and restoration treatments. Forest Ecology and Management 267:74–92.

Latif, Q. S., J. B. Cannon, E. J. Chabot, and R. A. Sparks. 2022. Simulated treatment effects on bird communities inform landscape-scale dry conifer forest management. Ecological Applications 32:e2555.

Latif, Q. S., R. L. Truex, R. A. Sparks, and D. C. Pavlacky,. 2020. Dry conifer forest restoration benefits Colorado Front Range avian communities. Ecological Applications 30:e02142.

Laughlin, M. M., J. D. Bakker, D. J. Churchill, M. J. Gregory, T. DeMeo, E. C. Alvarado, and B. J. Harvey. 2023. Trends in forest structure restoration need over three decades with increasing wildfire activity in the interior Pacific Northwest US. Forest Ecology and Management 527:120607.

Laurance, W. F., and E. Yensen. 1991. Predicting the impacts of edge effects in fragmented habitats. Biological Conservation 55:77–92.

Lehmkuhl, J. F., M. Kennedy, E. D. Ford, P. H. Singleton, W. L. Gaines, and R. L. Lind. 2007. Seeing the forest for the fuel: Integrating ecological values and fuels management. Forest Ecology and Management 246:73–80.

Lelli, C., H. H. Bruun, A. Chiarucci, D. Donati, F. Frascaroli, Ö. Fritz, I. Goldberg, J. Nascimbene, A. P. Tøttrup, C. Rahbek, and J. Heilmann-Clausen. 2019. Biodiversity response to forest structure and management: Comparing species richness, conservation relevant species and functional diversity as metrics in forest conservation. Forest Ecology and Management 432:707–717.

Loepfe, L., J. Martinez-Vilalta, J. Oliveres, J. Piñol, and F. Lloret. 2010. Feedbacks between fuel reduction and landscape homogenisation determine fire regimes in three Mediterranean areas. Forest Ecology and Management 259:2366–2374.

Lowe, E. B., B. Iuliano, C. Gratton, and A. R. Ives. 2022. 'Scalescape': an R package for estimating distance-weighted landscape effects on an environmental response. Landscape Ecology 37:1771–1785.

Lyons-Tinsley, C., and D. L. Peterson. 2012. Surface fuel treatments in young, regenerating stands affect wildfire severity in a mixed conifer forest, eastside Cascade Range, Washington, USA. Forest Ecology and Management 270:117–125.

Matsuoka, S. M., C. L. Mahon, C. M. Handel, P. Sólymos, E. M. Bayne, P. C. Fontaine, and C. J. Ralph. 2014. Reviving common standards in point-count surveys for broad inference across studies. The Condor 116:599–608.

McCarthy, M. A., and H. P. Possingham. 2007. Active Adaptive Management for Conservation Manejo Adaptativo Activo para Conservar. Conservation Biology 21:956– 963.

McCollin, D. 1998. Forest edges and habitat selection in birds: a functional approach. Ecography 21:247–260.

Mederski, P. S. 2006. A comparison of harvesting productivity and costs in thinning operations with and without midfield. Forest Ecology and Management 224:286–296.

Moore, M. M., W. W. Covington, and P. Z. Fulé. 1999. Reference conditions and ecological restoration: A Southwestern ponderosa pine perspective. Ecological Applications 9: 1266–1277

Morrison, M. L., W. M. Block, M. D. Strickland, B. A. Collier, and M. J. Peterson. 2008. Wildlife Study Design. Second edition. Springer, New York, New York.

National Oceanic and Atmospheric Administration. 2023. U.S. Climate Normals Quick Access, Seneca, OR. 1991-2020. https://www.ncei.noaa.gov/access/us-climate-normals/#dataset=normals-monthly&timeframe=30&station=USC00357675

Newell, F. L., and A. D. Rodewald. 2011. Role of topography, canopy structure, and floristics in nest-site selection and nesting success of canopy songbirds. Forest Ecology and Management 262:739–749.

North, M., A. Brough, J. Long, B. Collins, P. Bowden, D. Yasuda, J. Miller, and N. Sugihara. 2015. Constraints on Mechanized Treatment Significantly Limit Mechanical Fuels Reduction Extent in the Sierra Nevada. Journal of Forestry 113:40–48.

Ohmann, J. L., and M. J. Gregory. 2011. Predictive mapping of forest composition and structure with direct gradient analysis and nearest- neighbor imputation in coastal Oregon, U.S.A. https://doi.org/10.1139/x02-011 32:725–741.

Opdam, P., R. Foppen, R. Reijnen, and A. Schotman. 1995. The landscape ecological approach in bird conservation: integrating the metapopulation concept into spatial planning. Ibis 137:S139–S146.

Paveglio, T. B., M. S. Carroll, A. M. Stasiewicz, and C. M. Edgeley. 2019. Social fragmentation and wildfire management: Exploring the scale of adaptive action. International Journal of Disaster Risk Reduction 33:131–141.

Pfeifer, M., V. Lefebvre, C. A. Peres, C. Banks-Leite, O. R. Wearn, C. J. Marsh, S. H. M. Butchart, V. Arroyo-Rodríguez, J. Barlow, A. Cerezo, L. Cisneros, N. D'Cruze, D. Faria, A. Hadley, S. M. Harris, B. T. Klingbeil, U. Kormann, L. Lens, G. F. Medina-Rangel, J. C. Morante-Filho, P. Olivier, S. L. Peters, A. Pidgeon, D. B. Ribeiro, C. Scherber, L. Schneider-Maunoury, M. Struebig, N. Urbina-Cardona, J. I. Watling, M. R. Willig, E. M. Wood, and R. M. Ewers. 2017. Creation of forest edges has a global impact on forest vertebrates. Nature 2017 551:7679 551:187–191.

Prichard, S. J., P. F. Hessburg, R. K. Hagmann, N. A. Povak, S. Z. Dobrowski, M. D. Hurteau, V. R. Kane, R. E. Keane, L. N. Kobziar, C. A. Kolden, M. North, S. A. Parks, H. D. Safford, J. T. Stevens, L. L. Yocom, D. J. Churchill, R. W. Gray, D. W. Huffman, F. K. Lake, and P. Khatri-Chhetri. 2021. Adapting western North American forests to climate change and wildfires: 10 common questions. Ecological Applications 31:e02433.

Prichard, S. J., and M. C. Kennedy. 2014. Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. Ecological Applications 24:571–590.

Radcliffe, D. C., J. D. Bakker, D. J. Churchill, E. C. Alvarado, D. W. Peterson, M. M. Laughlin, and B. J. Harvey. 2024. How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests? Forest Ecology and Management 553:121594.

Ralph, J. C., S. Droege, and J. R. Sauer. 1995. Managing and Monitoring Birds Using Point Counts. Page In: Ralph, C. John; Sauer, John R.; Droege, Sam, technical editors. 1995. Monitoring bird populations by point counts. Gen. Tech. Rep. PSW-GTR-149. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station: p. 161-168.

Roberts, C. P., V. M. Donovan, S. M. Nodskov, E. B. Keele, C. R. Allen, D. A. Wedin, and D. Twidwell. 2020. Fire legacies, heterogeneity, and the importance of mixed-severity fire in ponderosa pine savannas. Forest Ecology and Management 459:117853.

Robertson, B. A., and R. L. Hutto. 2006. A framework for understanding ecological traps and an evaluation of existing evidence. Ecology 87:1075–1085.

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

Rodríguez, A., H. Andrén, G. Jansson Rodríguez, A. Andrén, H. Jansson, A. Rodríguez, H. Andrén, and G. Jansson. 2001. Habitat-mediated predation risk and decision making of small birds at forest edges. Oikos 95:383–396.

Rosenberg, K. V., A. M. Dokter, P. J. Blancher, J. R. Sauer, A. C. Smith, P. A. Smith, J. C. Stanton, A. Panjabi, L. Helft, M. Parr, and P. P. Marra. 2019. Decline of the North American avifauna. Science 366:120–124.

Saab, V. A., Q. R. Latif, W. M. Block, and J. G. Dudley. 2022. Short-term benefits of prescribed fire to bird communities of dry forests. Fire Ecology 18:1–19.

Schulte, L. A., D. J. Mladenoff, T. R. Crow, L. C. Merrick, and D. T. Cleland. 2007. Homogenization of northern U.S. Great Lakes forests due to land use. Landscape Ecology 22:1089–1103.

Schwilk, D. W., J. E. Keeley, E. E. Knapp, J. McIver, J. D. Bailey, C. J. Fettig, C. E. Fiedler, R. J. Harrod, J. J. Moghaddas, K. W. Outcalt, C. N. Skinner, S. L. Stephens, T. A. Waldrop, D. A. Yaussy, and A. Youngblood. 2009. The national Fire and Fire Surrogate study: effects of fuel reduction methods on forest vegetation structure and fuels. Ecological Applications 19:285–304.

Smith, W. B. 2002. Forest inventory and analysis: a national inventory and monitoring program. Environmental Pollution 116:S233–S242.

Spies, T. A., J. W. Long, S. Charnley, P. F. Hessburg, B. G. Marcot, G. H. Reeves, D. B. Lesmeister, M. J. Reilly, L. K. Cerveny, P. A. Stine, and M. G. Raphael. 2019. Twenty-five years of the Northwest Forest Plan: what have we learned? Frontiers in Ecology and the Environment 17:511–520.

Stephens, S. L., M. A. Battaglia, D. J. Churchill, B. M. Collins, M. Coppoletta, C. M. Hoffman, J. M. Lydersen, M. P. North, R. A. Parsons, S. M. Ritter, and J. T. Stevens. 2020. Forest Restoration and Fuels Reduction: Convergent or Divergent? BioScience 71:85–101.

Stephens, S. L., S. W. Bigelow, R. D. Burnett, B. M. Collins, C. V. Gallagher, J. J. Keane, D. A. Kelt, M. P. North, L. J. Roberts, P. A. Stine, and D. H. Van Vuren. 2014. California Spotted Owl, Songbird, and Small Mammal Responses to Landscape Fuel Treatments. Bioscience 64:893–906.

Stephens, S. L., J. D. McIver, R. E. J. Boerner, C. J. Fettig, J. B. Fontaine, B. R. Hartsough, P. L. Kennedy, and D. W. Schwilk. 2012. The Effects of Forest Fuel-Reduction Treatments in the United States. BioScience 62:549–560.

Stephens, S. L., J. J. Moghaddas, C. Edminster, C. E. Fiedler, S. Haase, M. Harrington, J. E. Keeley, E. E. Knapp, J. D. McIver, K. Metlen, C. N. Skinner, and A. Youngblood. 2009. Fire treatment effects on vegetation structure, fuels, and potential fire severity in western U.S. forests. Ecological Applications 19:305–320.

Stephens, S. L., and L. W. Ruth. 2005. Federal Forest-Fire Policy in the United States. Ecological Applications 15:532–542.

Terraube, J., F. Archaux, M. Deconchat, I. van Halder, H. Jactel, and L. Barbaro. 2016. Forest edges have high conservation value for bird communities in mosaic landscapes. Ecology and Evolution 6:5178–5189.

Tewksbury, J. J., S. J. Hejl, and T. E. Martin. 1998. Breeding productivity does not decline with increasing fragmentation in a western landscape. Ecology 79:2890–2903.

Tinker, D. B., C. A. C. Resor, G. P. Beauvais, K. F. Kipfmueller, C. I. Fernandes, and W. L. Baker. 1998. Watershed analysis of forest fragmentation by clearcuts and roads in a Wyoming forest. Landscape Ecology 13:149–165.

Tscharntke, T., J. M. Tylianakis, T. A. Rand, R. K. Didham, L. Fahrig, P. Batáry, J. Bengtsson, Y. Clough, T. O. Crist, C. F. Dormann, R. M. Ewers, J. Fründ, R. D. Holt, A. Holzschuh, A. M. Klein, D. Kleijn, C. Kremen, D. A. Landis, W. Laurance, D. Lindenmayer, C. Scherber, N. Sodhi, I. Steffan-Dewenter, C. Thies, W. H. van der Putten, and C. Westphal. 2012. Landscape moderation of biodiversity patterns and processes - eight hypotheses. Biological Reviews, 87:661–685.

Turner, M. G., R. H. Gardner, M. G. Turner, and R. H. Gardner. 2015. Introduction to Landscape Ecology and Scale. Pages 1–32 Landscape Ecology in Theory and Practice. Springer New York.

Vega-García, C., and E. Chuvieco. 2006. Applying local measures of spatial heterogeneity to Landsat-TM images for predicting wildfire occurrence in Mediterranean landscapes. Landscape Ecology 21:595–605.

Wardell-Johnson, G., and P. Horwitz. 2000. The recognition of heterogeneity and restricted endemism in the management of forested ecosystems in south-western Australia. Australian Forestry 63:218–225.

White, A. M., E. F. Zipkin, P. N. Manley, and M. D. Schlesinger. 2013. Simulating avian species and foraging group responses to fuel reduction treatments in coniferous forests. Forest Ecology and Management 304:261–274.

Wiens, J. A. 1989. Spatial Scaling in Ecology. Functional Ecology 3:385.

Williams, B. K. 2011. Adaptive management of natural resources—framework and issues. Journal of Environmental Management 92:1346–1353.

Wilson, J. S., and P. J. Baker. 1998. Mitigating fire risk to late-successional forest reserves on the east slope of the Washington Cascade Range, USA. Forest Ecology and Management 110:59–75.

Woolsey, G. A., W. T. Tinkham, M. A. Battaglia, and C. M. Hoffman. 2024. Constraints on Mechanical Fuel Reduction Treatments in United States Forest Service Wildfire Crisis Strategy Priority Landscapes. Journal of Forestry:1–17.

Wotton, S. R., M. A. Eaton, D. Sheehan, F. B. Munyekenye, I. J. Burfield, S. H. M. Butchart, K. Moleofi, D. Nalwanga-Wabwire, P. K. Ndang'ang'a, D. Pomeroy, K. J. Senyatso, and R. D. Gregory. 2020. Developing biodiversity indicators for African birds. Oryx 54:1–12.

Zuur, A. F., E. N. Ieno, N. J. Walker, A. A. Saveliev, and G. M. Smith. 2009. Mixed effects models and extensions in ecology with R. First edition. New York, NY.

Conclusions

Ecological forest management involves incorporation of multiple objectives on broad temporal and spatial scales (Franklin et al. 2018). The work in this dissertation offers several insights for managers, policy makers and other stakeholders interested in long-term ecological forest management of dry forests. Major themes of this dissertation include the long-term effectiveness of thin-plus-burn treatment on opening stand structure and reducing canopy fuel, the value of comparing long-term treatment outcomes against desired conditions in addition to pre-treatment values, the long-term impacts of drivers that vary within a treatment type, and the value of large treated and un-treated patches providing for interior habitat to dry forest songbirds.

Given limited resources for treatment (North et al. 2015, Woolsey et al. 2024), long-term stewardship of dry forests involves assessing tradeoffs between conducting frequent treatment maintanance over smaller areas vs. extensive treatment application over larger areas (Finney et al. 2007). By suggesting that thin-plus-burn treatments sustain some but not all desired effects on dry forest fuel profiles and stand structure for 2 or more decades following implementation, the work in the first three chapters of this dissertation supports the context-dependence of decisions about maintenance of thin-plus-burn treatments. In contexts with extensive un-treated areas available for treatment, managers may prioritize treating un-treated areas over maintaining stands treated with thin-plus-burn 1-2 decades after treatment. However, in stands that are of high value or adjacent to human structures, rapid surface fuel accumulation documented in Chapter 3 may be of concern, potentially warranting maintenance by as soon as 5 years following treatment. Long-term impacts of maintenance treatments have received relatively little study, but it is plausible that woody surface fuel and litter will show lower rates and magnitudes of post-treatment accumulation following maintenance treatment, due to the already reduced canopy fuel existing before maintenance treatment. Therefore, long-term patterns of fuel succession following maintenance treatment are a potentially valuable avenue for future research.

Chapter 1 highlighted some limitations of comparing long-term treatment outcomes against pre-treatment conditions, and Chapter 2 showed an example of comparison of long-term outcomes against desired conditions. Comparisons of long-term outcomes against pre-treatment conditions may be valuable for managers interested in more spatially-extensive treatment strategies and comparing tradeoffs between maintenance treatments in previously treated stands vs. initial treatment of previously un-treated stands. However, desired conditions are likely a more useful point of reference for higher value stands and high consequence areas. Therefore, in Chapter 2, I compared treatments against metrics which were developed based on Fire and Fire Surrogate goals (McIver and Weatherspoon 2010), shedding light on the inability of treatments to meet goals for basal area survival in a modelled wildfire. However, it is unclear whether these Fire and Fire Surrogate study goals developed more than 20 years ago reflect current management goals, and it is challenging to established desired conditions that reflect diverse management contexts. Future work more thoroughly exploring management goals and using these to produce metrics of treatment success could be useful for increasing the relevance of long-term treatment research to managers.

Chapter 1 illustrated that general patterns of fuel succession following common treatment types have been established, but wide variance within treatment categories indicated opportunities to study the long-term effects and management implications of drivers that vary within treatment type. Chapters 2 and 3 of this dissertation suggested that treatment intensity is an important driver that may create fine-scale (<1 ha) heterogeneity in the long-term, especially for stand structure. More intense treatments may be used on a stand scale to increase long-term effects of treatment on basal area and density, or variation in treatment intensity on a local (<1 ha) scale may be used to promote long-term heterogeneity in stand structure conditions. While some compensatory responses of fuel profiles to greater treatment intensity were shown in Chapter 3, these did not fully mitigate the long-term benefits of greater intensity by 15 years following treatment implementation. Future work exploring treatment intensity over large productivity gradients would be useful for increasing understanding of where more intense treatment may be expected to produce desired long-term fuel profile and stand structure responses (Jain et al. 2012).

The value of interior dense-forest habitat to common songbirds highlighted in Chapter 4 and known for rarer bird species (e.g., Stephens et al. 2014) presents a challenge from a fuel management perspective, but is important to accommodate in an ecological forest management perspective. Risks to un-treated forest patches and adjacent values can be reduced by disrupting the spatial continuity of fuel in the surrounding area and choosing less fire-prone topographic positions such concave features (Camp et al. 1997, Rodman et al. 2023). The value of interior open-forest habitat patches to at least one common songbird species supports large patch size of treated stands, a finding which is largely congruent with wildfire management needs (Prichard and Kennedy 2014, Kennedy and Johnson 2014). In addition, lower intensity treatment within dense-forest patches may reduce potential for severe wildfire, and lower intensity treatments intended to protect dense-forest habitat are a potentially value avenue for further research focusing both on biodiversity and fuel responses (Stephens et al. 2014, Chiono et al. 2017).

This dissertation and work that builds to this literature can help managers, researchers, and policy makers interested in developing long-term treatment regimes. By continuing to expand the scales of our inquiries into fuel treatment effects, researchers may be able to provide a more complete toolkit of decision support tools in dry forest stewardship, increasing our chance of facilitating dry forest resilience through a time of a changing climate, expanding human development, and uncharacteristically high fuel loads.

References

Camp, A., C. Oliver, P. Hessburg, and R. Everett. 1997. Predicting late-successional fire refugia pre-dating European settlement in the Wenatchee Mountains. Forest Ecology and Management 95:63–77.

Chiono, L. A., D. L. Fry, B. M. Collins, A. H. Chatfield, and S. L. Stephens. 2017. Landscape-scale fuel treatment and wildfire impacts on carbon stocks and fire hazard in California spotted owl habitat. Ecosphere 8:e01648.

Finney, M. A., R. C. Seli, C. W. McHugh, A. A. Ager, B. Bahro, and J. K. Agee. 2007. Simulation of long-term landscape-level fuel treatment effects on large wildfires. International Journal of Wildland Fire 16:712.

Franklin, J. F., N. K. Johnson, and D. L. Johnson. 2018. Ecological Forest Management. First edition. Waveland Press, Long Grove, IL.

Jain, Theresa B., Mike A. Battaglia, Han-Sup. Han, Russell T. Graham, Christopher R. Keyes, Jeremy S. Fried, and Jonathan E. Sandquist. 2012. A comprehensive guide to fuel management practices for dry mixed conifer forests in the northwestern United States Gen Tech Rep RMRS-GTR-292, 331. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Kennedy, M. C., and M. C. Johnson. 2014. Fuel treatment prescriptions alter spatial patterns of fire severity around the wildland-urban interface during the Wallow Fire, Arizona, USA. Forest Ecology and Management 318:122–132.

McIver, J. D., and C. P. Weatherspoon. 2010. On conducting a multisite, multidisciplinary forestry research project: Lessons from the national fire and fire surrogate study. Forest Science 56:4–17.

North, M., A. Brough, J. Long, B. Collins, P. Bowden, D. Yasuda, J. Miller, and N. Sugihara. 2015. Constraints on Mechanized Treatment Significantly Limit Mechanical Fuels Reduction Extent in the Sierra Nevada. Journal of Forestry 113:40–48.

Prichard, S. J., and M. C. Kennedy. 2014. Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. Ecological Applications 24:571–590.

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

Stephens, S. L., S. W. Bigelow, R. D. Burnett, B. M. Collins, C. V. Gallagher, J. J. Keane, D. A. Kelt, M. P. North, L. J. Roberts, P. A. Stine, and D. H. Van Vuren. 2014. California Spotted Owl, Songbird, and Small Mammal Responses to Landscape Fuel Treatments. Bioscience 64:893–906.

Woolsey, G. A., W. T. Tinkham, M. A. Battaglia, and C. M. Hoffman. 2024. Constraints on Mechanical Fuel Reduction Treatments in United States Forest Service Wildfire Crisis Strategy Priority Landscapes. Journal of Forestry:1–17.