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Wildfire management decisions outweigh mechanical treatment as the keystone to forest landscape adaptation

Tucker J. Furniss[1*], Nicholas Povak[2,3], Paul F. Hessburg[2,4], R. Brion Salter[2], Zhuoran Duan[5] and Mark Wigmosta[5,6]

Abstract

Background Modern land management faces unprecedented uncertainty regarding future climates, novel disturbance regimes, and unanticipated ecological feedbacks. Mitigating this uncertainty requires a cohesive landscape management strategy that utilizes multiple methods to optimize benefits while hedging risks amidst uncertain futures. We used a process-based landscape simulation model (LANDIS-II) to forecast forest management, growth, climate effects, and future wildfire dynamics, and we distilled results using a decision support tool allowing us to examine tradeoffs between alternative management strategies. We developed plausible future management scenarios based on factorial combinations of restoration-oriented thinning prescriptions, prescribed fire, and wildland fire use. Results were assessed continuously for a 100-year simulation period, which provided a unique assessment of tradeoffs and benefits among seven primary topics representing *social*, *ecological*, and *economic* aspects of resilience.

Results Projected climatic changes had a substantial impact on modeled wildfire activity. In the *Wildfire Only* scenario (no treatments, but including active wildfire and climate change), we observed an upwards inflection point in area burned around mid-century (2060) that had detrimental impacts on total landscape carbon storage. While simulated mechanical treatments (~3% area per year) reduced the incidence of high-severity fire, it did not eliminate this inflection completely. Scenarios involving wildland fire use resulted in greater reductions in high-severity fire and a more linear trend in cumulative area burned. Mechanical treatments were beneficial for subtopics under the *economic* topic given their positive financial return on investment, while wildland fire use scenarios were better for *ecological* subtopics, primarily due to a greater reduction in high-severity fire. Benefits among the *social* subtopics were mixed, reflecting the inevitability of tradeoffs in landscapes that we rely on for diverse and countervailing ecosystem services.

Conclusions This study provides evidence that optimal future scenarios will involve a mix of active and passive management strategies, allowing different management tactics to coexist within and among ownerships classes. Our results also emphasize the importance of wildfire management decisions as central to building more robust and resilient future landscapes.

Keywords Carbon, Climate change, Decision support systems, Forest landscape models, LANDIS-II, Landscape ecology, Resilience, Temperate forests, Wildfire

*Correspondence:
Tucker J. Furniss
tucker.furniss@uwyo.edu
Full list of author information is available at the end of the article

Resumen

Antecedentes El manejo moderno de tierras enfrenta incertidumbres sin precedentes relacionadas con el clima futuro, los nuevos cambios en los regímenes de fuegos, y retroalimentaciones ecológicas no anticipadas. El mitigar esta incertidumbre requiere de una aproximación al manejo de paisajes cohesivo, que utilice métodos simples para optimizar los beneficios, mientras se evaden riesgos sobre un futuro incierto. Usamos para ellos un modelo de simulación del paisaje basado en procesos (LANDIS-II), para pronosticar el manejo del bosque, su crecimiento, los efectos del clima, y dinámica de futuros fuegos, y filtramos los resultados usando una herramienta de soporte de decisiones, lo que nos permitió examinar las retroalimentaciones entre estrategias de manejo alternativas. Desarrollamos escenarios plausibles de manejo futuro basados en combinaciones factoriales de prescripciones de restauración mediante raleos, quemas prescriptas, y el aprovechamiento de incendios naturales. Los resultados fueron determinados de manera continua en un período simulado de 100 años, lo cual proveyó una valoración única de retroalimentaciones y beneficios entre siete tópicos primarios que representaron aspectos sociales, ecológicos y económicos de la resiliencia.

Resultados El cambio climático proyectado tuvo un impacto substancial en el modelado de la actividad de incendios. En el escenario de solamente incendios (sin tratamientos, pero incluyendo los efectos de incendios y el cambio climático), observamos un punto de inflexión ascendente en un área que se quemaría alrededor de mediados de este siglo (2060), que mostró impactos detrimentales en el almacenamiento de carbono a nivel de paisaje. Cuando simulamos los tratamientos mecánicos (~ 3% del área por año), si bien se redujo la incidencia de fuegos de alta severidad, esta inflexión no se eliminó completamente. Los escenarios que implicaron el uso de incendios naturales produjo una gran reducción en incendios severos y una tendencia más lineal en la acumulación del área quemada. Los tratamientos mecánicos fueron beneficiosos para los subtópicos que estaban bajo el tópico económico, dados sus retornos financieros relacionados con la inversión, mientras que el escenario de uso de los incendios naturales fue mejor para el subtópico ecológico, primariamente por una mayor reducción en los incendios de gran severidad. Los beneficios entre los subtópicos sociales fueron mixtos, reflejando la inevitabilidad de las retroalimentaciones en los paisajes de los que dependemos para los diversos y contrabalanceados servicios ecosistémicos.

Conclusiones Nuestros resultados proveen de evidencia de que el mejor escenario a futuro es el que implica una mezcla de estrategias pasivas y activas, lo que permitirá la coexistencia dentro y entre distintas clases de propiedad, y reconociendo la importancia de las decisiones de manejo del fuego como una actividad central en los esfuerzos para construir, a futuro, paisajes más robustos y resilientes.

Background

Land management in the modern era faces unprecedented uncertainty regarding future climatic changes, novel disturbance regimes, and unanticipated ecological feedbacks (Millar et al. 2007; Millar and Stephenson 2015; Hessburg et al. 2015, 2021; Schuurman et al. 2022). Wildfire poses both a challenge and a solution to these projected changes (Dombeck et al. 2004; North et al. 2015), and building climate-adapted forest landscapes will require restoring active wildfire regimes and reducing the fire deficit across much of the intermountain west (Moritz et al. 2014; Schoennagel et al. 2017; Hessburg et al. 2019). A challenge to this is that most landscapes of the intermountain west comprise a mosaic of public and private lands, large wildland areas, and extensive development in the wildland-urban interface (WUI). Employing a truly adaptive landscape management strategy requires participation across boundaries at scales large enough to restore a dynamic mosaic of forest and non-forest vegetation types that contribute to the resilience and self-regulation of active fire landscapes (Hessburg et al. 2015; Larson et al. 2022; Ager et al. 2022).

Recent investments in restorative forest treatments (e.g., US Forest Service Wildfire Crisis Strategy; USDA Forest Service 2022) are a necessary and long overdue part of the solution (Belavenutti et al. 2021), but fuel treatments alone are likely insufficient to alter fire regimes in the wildland-dominated landscapes of the west (North et al. 2015; Hessburg et al. 2015). Fuel treatments can reduce fire risk and improve resilience within the treated area (Stephens et al. 2012; Furniss et al. 2022a), but building resilient landscapes requires a multifaceted approach incorporating a combination of mechanical treatments, prescribed (Rx) fire, and wildland fire use (Miller 2003; van Wagtendonk 2007; North et al. 2012, 2015; Calkin et al. 2015; Stephens et al. 2016). Restoring natural wildfire regimes is a central part of the solution (Young and Ager 2024), as we are simply unable to duplicate the spatial scale and ecological complexity of wildfire effects (e.g., Furniss et al. 2020) with even our most sophisticated silvicultural tools.

Intact wildfire regimes function as a self-stabilizing ecological feedback process, contributing to landscape resilience by maintaining a shifting mosaic of forest structure and age classes across the landscape (Hessburg et al. 2005, Berkey et al. 2021; Povak et al. 2023). Landscape-scale resilience is therefore an emergent property of complex and interconnected systems, and it is only evident at spatial scales greater than individual forest patches and temporal scales greater than individual fires (Falk et al. 2019; Hessburg et al. 2019). We cannot fully evaluate the resilience of a landscape without evaluating forest succession and disturbance dynamics at these grander scales (tens of thousands of hectares; tens or hundreds of years). This is where landscape simulation models excel, as they facilitate simulation of land management, forest growth, and disturbance dynamics at spatio-temporal scales that are not feasible with field-based studies (e.g., Ager et al. 2022; Young et al. 2022; Furniss et al. 2023; Povak et al. 2023).

Landscape simulation models can be used to simulate different management paradigms over long (10–100 year) timescales, enabling us to evaluate feedbacks and unanticipated dynamics that may emerge (Loehman et al. 2017; Scheller et al. 2019; Ager et al. 2020; Keane et al. 2022). Numerous studies have successfully used simulation modeling to compare the effects of different land management strategies, often in factorial arrangements, on future landscape resilience (Loudermilk et al. 2014; Keane et al. 2018; Krofcheck et al. 2019; Ager et al. 2022; Abelson et al. 2022; Young and Ager 2024). A common challenge that these studies face is in distilling the output of these complex models, as results may vary widely in both space and time. Decision support systems (DSSs) are often used here to synthesize the outputs, compare results across different simulated management strategies, and to make results more actionable for managers that are developing landscape adaptation strategies (Vogler et al. 2015; Abelson et al. 2022; Povak et al. 2020, 2022; Day et al. 2024).

In a recent study, Furniss et al. (2023) used a spatial decision support model to explore tradeoffs and synergies (sensu Maron and Cockfield 2008) in space, identifying areas in a large study domain in north-central Washington State that have the greatest potential for treatments to be effective. In this study, we use that same decision support model to explore tradeoffs in time over a 100-year simulation window, and we evaluate factorial combinations of treatment types to evaluate which alternative landscape management strategies optimize socio-ecological benefits. Specifically, we used a landscape simulation modeling approach to provide a time-series of landscape-level resource benefits provided by several alternative management strategies ranging in the frequency, intensity, and type of treatments applied to the landscape.

We used this simulation model and decision support system to investigate several questions related to management strategies designed to improve future landscape health and ecosystem functioning. These guiding questions included:

1) How do climate adaptation-oriented mechanical treatments, Rx fire, and wildland fire use compare in their potential to improve landscape resilience?
2) How do these different management tactics compare in their potential to produce benefits among a wide range of social, economic, and ecological values?
3) In landscapes dominated by wildlands (as in the present study), can thinning and Rx fire in a portion of the landscape stabilize future wildfire regimes across the landscape as a whole?

We hypothesized that future management scenarios involving thinning alone would perform best among *Economic* topic areas, while thinning plus Rx fire would perform well among *Social* and *Ecological* topic areas. We expected scenarios involving wildland fire use scenarios to perform best among *Ecological* topic areas. We also expected that thinning plus Rx fire would produce significantly better results than a "no treatment" scenario involving no management other than future wildfire activity calibrated to current levels of suppression effectiveness.

Methods

Study area

This study was conducted in a large landscape (4524 km^2) on the east side of the Cascade Range in Washington State (Fig. 1). The study domain was defined by the hydrological boundaries of the Wenatchee and Entiat River sub-basins. The model was run on a landscape that included a 5-km outer buffer (6078 km^2 total area) to simulate possible edge effects and immigration of wildfires, and this buffer was then trimmed prior to our analysis.

The study domain is characteristic of many mountainous landscapes of the interior Pacific Northwest, with steep terrain, high heterogeneity in forest communities, and historically active fire regimes (Hessburg et al. 2019). Climate in this region is humid continental with warm, dry summers and cold, wet winters. Further details about the study region may be found in Furniss et al. (2022b).

Simulation modeling

We simulated forest dynamics, tree growth, regeneration, and wildfire dynamics using LANDIS-II (Scheller et al. 2007) with the NECN (Scheller et al. 2011) and SCRPPLE extensions (Scheller et al. 2019). LANDIS-II

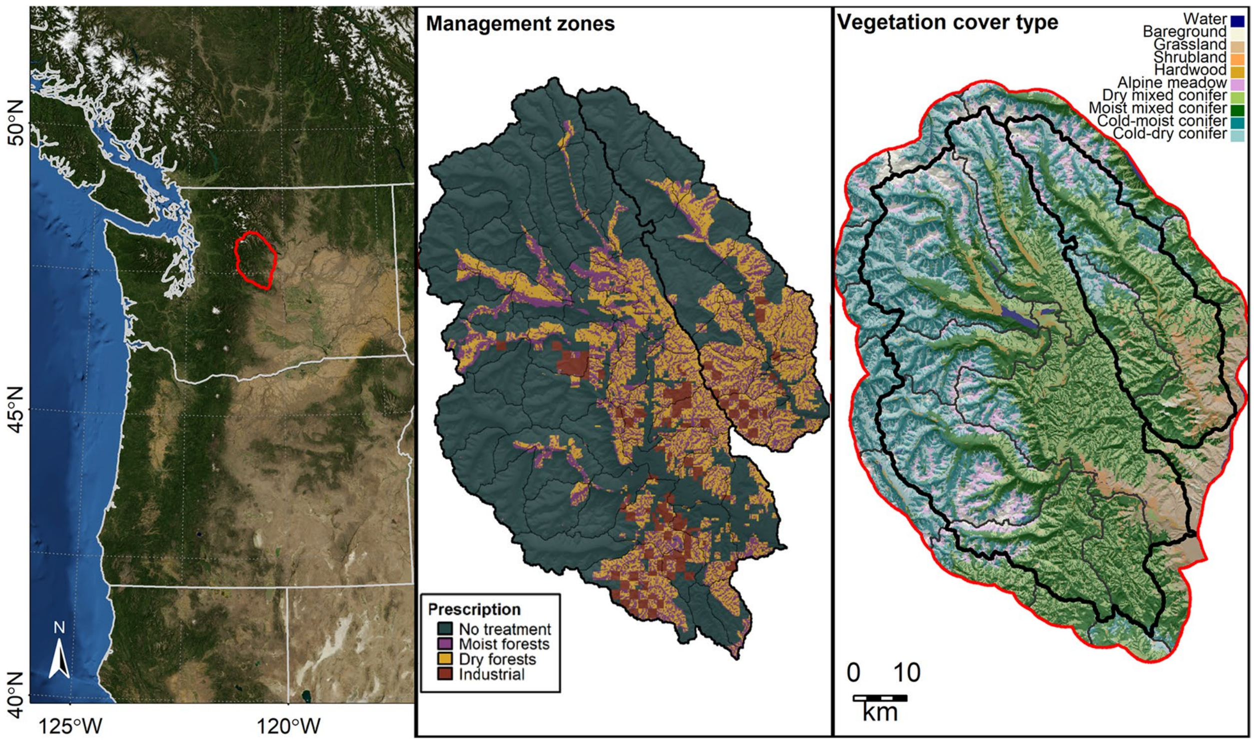

Fig. 1 Location of the study domain on the east slopes of the Washington Cascades (left). The study landscape is dominated by wilderness and roadless areas (54%), with the remainder comprising a mix of actively managed forests, private industrial timber lands, and wildland-urban interface (center). Vegetation in the study domain is heterogeneous, spanning from grass and shrub-dominated vegetation types in the lowlands to subalpine forests and alpine vegetation at the upper elevations (right). The dominant forest types on the landscape are dry and moist mixed-conifer, dominated by ponderosa pine and Douglas-fir, respectively, that occur on opposing aspects throughout most of the mid-elevations. The thick black lines in the right panel denote the boundaries of the Wenatchee and Entiat sub-basins, while the red perimeter represents a 5-km buffer that was included in the simulations to control for edge effects

is a spatially interactive forest landscape model that has been widely used to simulate climate effects on forest ecosystems and wildfire dynamics (Flatley and Fulé 2016; Loudermilk et al. 2017; Flanagan et al. 2019; Krofcheck et al. 2019). We coupled LANDIS-II with DHSVM (Wigmosta et al. 1994), a spatial distributed hydrology model for mountainous terrains that we then used to evaluate hydrologic functioning under various future management scenarios. Outputs from these models were analyzed in a decision support framework that leveraged fuzzy logic to integrate numerous ecological indicator metrics and evaluate positive and negative changes in overall ecosystem functioning (Reynolds et al. 2014; Povak et al. 2022, 2023; Furniss et al. 2023).

The initial vegetation layer for our LANDIS-II model was derived from TreeMap (Riley et al. 2021), a full-coverage raster of imputed Forest Inventory and Analysis (FIA) plot codes that could be used to develop tree lists for each 90-m pixel in the landscape. Edaphic characteristics were generated from the NRCS gSSURGO database (Soil Survey Staff 2020), and topographic layers were derived from the USGS 3D Elevation Program (Stoker and Miller 2022).

Wildfire ignitions were calibrated using the Fire Program Analysis Fire-Occurrence Database (FPA-FOD; Short 2017), and fire size and severity were calibrated to observed wildfire activity in the Monitoring Trends in Burn Severity (MTBS) database (Eidenshink et al. 2007). We used this combined empirical dataset (FPA-FOD and MTBS) to calibrate model behavior to observed patterns in wildfire frequency, area burned, and patch size distributions by severity class (Furniss et al. 2022a, b). We used the FPA-FOD alone to calibrate the frequency of small fires (< 400 ha) which are not present in the MTBS dataset. Simulated ignitions that did not spread produced fires that were 0.81 ha in size, an unavoidable consequence of the grain size of our 90-m raster grid.

We ran the wildfire and harvest extensions (SCRPPLE and Biomass Harvest, respectively) at an annual timestep, while the forest succession extension (NECN) had to be run at a 10-year timestep due to computational limitations. Each succession timestep took 3–5 h to run, so we used 10-year timesteps to keep each simulation within a reasonable runtime (~48 h per simulation). Changing to 5- or 1-year timesteps would have vastly increased our processing time, reducing our ability to run the required number of scenarios and iterations of each scenario.

Regeneration was simulated using species-specific seed dispersal kernels and establishment probabilities which are based on available light, which is in turn determined by vegetation structure and composition at each site. Seed dispersal is determined by the presence of mature cohorts in adjacent cells, with maximum dispersal distance and probability given by species-specific parameters. Subsequent growth and mortality is determined by additional parameters that give the range of optimal climatic conditions for each species. This is the primary way that tree growth and mortality respond to different climate inputs. Further details about regeneration and vegetation succession may be found in published documentation for NECN (Scheller et al. 2011). A comprehensive description of our LANDIS-II model development and calibration work, including species parameters, can be found in Furniss et al. (2022b).

Management scenarios

To compare the tradeoffs between alternative management strategies, we designed six different management scenarios by using additive combinations of wildfire, mechanical harvest, Rx fire, and wildland fire use (hereafter, WFU). These eight scenarios were as follows: (1) *Wildfire Only*, (2) *Wildfire + WFU*, (3) *Wildfire + Rx*, (4) *Wildfire + Rx fire + WFU*, (5) *Wildfire + Harvest*, (6) *Wildfire + WFU + Harvest*, (7) *Wildfire + Rx + Harvest*, (8) *Wildfire + Rx fire + WFU + Harvest*. Additionally, we ran a *No Disturbance* scenario that simulated forest growth in the absence of wildfire and harvest, which we used to quantify the upper limit of biomass accumulation in the absence of all disturbances. All scenarios were run under a RCP8.5 climate change forecast (details under "Climate data," below). We refer to these scenarios without the RCP8.5 prefix for readability.

We ran five iterations of each management scenario to account for variability due to stochastic timing and spatial extent of treatment patches and wildfires. The number of simulations was chosen to provide a reliable estimate of uncertainty while remaining computationally feasible, a common tradeoff among simulation modeling studies. We generated simulation envelopes using the maximum and minimum values from the five iterations for each metric, and we used the average value to generate a mean trend line for each management scenario.

Vegetation pathway groups (PWGs)

The LANDFIRE biophysical settings (BpS, https://landfire.gov/bps.php) raster was used to allocate PWGs across the study area and to assign broad vegetation types (Povak et al. 2022). These data represent vegetation types that were likely present prior to Euro-American colonization, based on the biogeoclimatic conditions and characteristic disturbance regime (Rollins 2009). We used the BpS group level attribute to assign each 90-m cell into the following categories: water, snow/ice, rock, barren, grassland, shrubland, hardwood/riparian, alpine meadow, dry or moist mixed conifer forest, and dry or moist cold conifer forest conditions. The cold forest and mixed conifer forest BpS classes were further differentiated into dry-mixed (DMC), moist-mixed (MMC), cold-dry (CDC), or cold moist (CMC) conifer forest conditions based on topographic position, aspect, and elevation. Further details about the classification heuristic may be found in Furniss et al. (2023). The vegetation PWG map was not used to limit species composition or define successional trajectories. It was simply used as to create ecologically and biophysically similar areas (termed "ecoregions" in LANDIS-II) for downscaling the 4-km climate inputs. We defined these areas using a spatial intersection of vegetation PWG and HUC10-level watershed, resulting in 177 unique ecoregions that were used to extract area-weighted means from the 4-km future climate surfaces (details in "Climate data," below). Ecoregion assignment was static through time.

Management patches

We developed topographically entrained management patches using a 30-m digital elevation model (DEM) from the USGS National Elevation Data repository. Patches were primarily defined using a landscape topographic template as described by Hessburg et al. (2015) to spatially allocate forest restoration treatments across the study area. This template was further subdivided by hydrologic divides, land ownership, and land use allocation. Hydrologic divides were derived from nested Hydrologic Unit Codes (HUC) 10 (~20–80,000 ha) and 12 (~10–40,000 ha, Seaber et al. 1987).

All raster-based input layers were resampled to 90-m resolution, and a minimum mapping unit (MMU) of 4 ha (five contiguous cells) was applied to create management treatment patches. All raw and derived input spatial layers were clipped to the study area. The spatial patches and attributes were then processed through a series of spatial intersections where the MMU was enforced at each step to best maintain the integrity of the input data.

Treatments

For scenarios involving mechanical harvest, we simulated low and variable density thinning-based restoration treatments (Graham et al. 1999) using the Biomass Harvest extension (Gustafson et al. 2000). We partitioned the landscape into wildlands, actively managed public lands, and industrial timber lands (Fig. S1, Table S1). We further sub-divided actively managed public lands into dry forests and moist forests. This produced four management zones within which we applied a single treatment prescription. Treatments occurred at the patch-level, where patches were selected at random and evaluated for their eligibility for treatment. If eligible, treatments were applied, and additional patches were selected until the target treatment rate (% area per year) was reached. Ineligible patches included patches in wildland areas and patches that had been recently treated (10 years for dry forests, 30 years for moist forests). We used random patch selection because there was not a way to optimize patch selection using an ecological basis in this version of the Biomass Harvest extension. Patches were developed by grouping pixels that shared similar ownership, topographic setting, and PWG.

In dry forests, treatments were designed to reduce surface fuels, retain medium and large sized trees, and to shift composition toward climate- and fire-adapted species (Hessburg et al. 2015; Stephens et al. 2013). This was achieved by thinning from below, removing young stems of all species and mature stems of shade-tolerant species. Slash and non-live surface fuels were reduced by 90% to simulate post-harvest pile and broadcast burning, but these simulated pile-burns were not counted when summarizing annual area burned. Treatments were applied to adjacent patches until treatment areas were between 20 and 100 ha to reduce wildfire risk at scales larger than individual patches. Target treatment area was 3% $\cdot$ year^{-1} to achieve fuel reduction efforts as quickly as possible.

The moist forest treatment was designed to increase heterogeneity and diversify habitat by creating small gaps and openings. This involved variable density thinning (75% reduction) among all size classes, for immature trees < 120 years old, across all species present in small patches (< 3 ha). Harvest gap size was set at 30% of each forest patch. Surface fuels were reduced by 50% to simulate slash piling and burning. The target treatment area was set at 1% $\cdot$ year^{-1} of available patches to maintain a sustainable level of biomass extraction throughout the simulation period.

Industrial forest lands were treated with clearcutting on a 35–50-year rotation to simulate the trend of moving toward short rotation industrial forestry in the twenty-first century. The treatment rate was set at 4% $\cdot$ year^{-1}, and surface fuels were reduced by 50% to represent slash piling and burning.

Wildfire suppression and wildland fire use scenarios

We tuned the suppression levels in our *Wildfire Only* scenario to match the fire event size and severity patch size distributions based on empirical fire activity from 1984 to 2019 found in the monitoring trends in burn severity (MTBS, Eidenshink et al. 2007) dataset. To calibrate frequency of fires smaller than 400 ha, we used the spatial wildfire occurrence (FPA-FOD; Short 2017) dataset. During this period, suppression was the default response to wildfire, and suppression efforts were applied to most fire events. As such, we applied an intermediate amount of suppression effort using the SCRPPLE extension to create a “suppression-as-usual” fire suppression scenario. Under this scenario, suppression was most effective under mild and moderate fire weather conditions, natural ignitions were suppressed with the same vigor as accidental ignitions, and suppression efforts were strongest in developed areas and in the WUI. The level of suppression in the model was calibrated in conjunction with the other fire spread parameters to produce a simulated fire regime consistent with observed fire activity in terms of fire frequency, severity, and patch size distributions (Furniss et al. 2022b). This scenario should therefore be thought of as a “suppression-as-usual” suppression strategy, which is notably different from a “no action” strategy. Instead, it may be thought of as an intensive suppression scenario, with its own set of merits and consequences.

We simulated alternative future wildfire management scenarios by redistributing how suppression was applied, both geographically and temporally. We first defined four suppression zones on the landscape, and we applied variable levels of suppression depending on ignition type, fire weather index (FWI), and location on the landscape (Table S2). For management scenarios involving wildland fire use (*WFU*), we reduced suppression effort by 95% under mild weather conditions and 25% under moderate weather conditions to allow more natural wildfire ignitions to burn when weather conditions were not severe. Under extreme weather conditions, slightly more suppression effort was applied (average of 10%), representing the increased availability of resources that could be saved by letting most wildfires burn with minimal intervention. The net effect of this redistribution was that less suppression was applied overall in the WFU scenarios, while slightly more suppression was applied to ignitions occurring under extreme weather conditions. This approach is consistent with other recent studies that have used the suppression parameters in SCRPPLE to simulate alternative future wildfire management scenarios (e.g., Abelson et al. 2022).

Our implementation of WFU is not necessarily representative of wildland fire use as implemented in real-world landscapes. Instead, it was intended to be an idealized form of WFU that could be possible in a future “post-suppression” wildfire management paradigm. The assumption that WFU could make suppression more effective under extreme weather conditions is contingent upon the idea that suppression resources stay the same (or increase) and are deployed with lower frequency but greater intensity by having increased availability of suppression resources that would be diverted from other areas throughout the region where fires were allowed to burn under moderate weather conditions. This assumption requires wildland fire use to be the default response across the region. Wildland fire use has never been tested at such a broad scale (van Wagtendonk 2007) and doing so would require a paradigm shift in wildfire management policy, culture, and legal liability (North et al. 2015).

Climate data

We generated future climate inputs using the MACAv2-METDATA CCSM4 dataset (Abatzoglou and Brown 2012), a spatially downscaled dataset containing daily climate forecasts at a 4-km resolution for the contiguous United States. We developed a baseline climate scenario by resampling historical climate from 1980 to 2010, with 3-year temporal autocorrelation (future years were drawn in sets of 3 re-ordered historical years) to create a synthetic forecast representing contemporary climate normals. This baseline climate forecast was not intended to predict plausible future weather streams, rather it provided a baseline with which we could compare the RCP8.5 climate forecast that we used to simulate the effects of climate change. We chose to use the RCP8.5 emissions scenario to simulate climate change as evidence suggests that this scenario will continue to be a good fit for anticipated climate changes for at least the next several decades (Schwalm et al. 2020).

Hydrology modeling

We used the Distributed Hydrology Soil Vegetation Model (DHSVM; Wigmosta et al. 1994) to simulate streamflow and snowpack dynamics at a daily resolution for the full 100-year simulation period. By updating the vegetation layers in DHSVM annually, we were able to create dynamic vegetation inputs that responded to forest growth, treatments, and wildfire events in LANDIS-II. We updated four vegetation parameters in DHSVM at annual intervals: canopy height, canopy fractional coverage, leaf area index (LAI), and vegetation type. LANDIS-II outputs are only available every 10 years (LAI, biomass, and age). Thus, we used linear interpolation of the decadal outputs to estimate intermediate values for each year. We ran DHVSM with a 90-m cell size to match the spatial resolution of the LANDIS-II model.

We modeled height and fractional coverage (which are not directly available from LANDIS-II) using generalized linear mixed effects models using the lme4 package in R (Bates et al 2015). We used FIA plot data to fit these models, and we applied the models to LANDIS-II outputs to estimate canopy height and cover for DHSVM (Fig. S1). The canopy height model used ln(age) and ln(biomass) to predict individual tree height, with random intercepts and slopes for age by species and PWG ($R^2 = 0.78$). Cover height for each cell was calculated as the 90th percentile of individual tree height. The fractional cover model used a third-order polynomial of stand biomass, stand age, and elevation to predict fractional coverage, with random slope and intercepts for biomass by PWG ($R^2 = 0.67$).

The DHSVM model was calibrated using annual meteorology data derived from the 1/16 degree (~6×6 km grid cells) Livneh dataset (Livneh et. al. 2015). Initial snow parameters were calibrated using empirical data from nearby SNOTEL stations (Trinity Snow Telemetry site). The model was then further calibrated using streamflow records (USGS gauges 12,456,500, 1,245,800) for the Wenatchee and Entiat sub-basins from the water years 1997–2003 and 1966–1971, respectively. Future climate forecasts were derived from the MACA Livneh climate dataset (Abatzoglou and Brown 2012).

Decision support system

We evaluated the performance of each management scenario using a custom decision support tool (DST) designed to assess ecological functioning and ecosystem services among seven primary topic areas: Sustainable Biomass, Economics, Carbon Storage, Water, Wildfire, Forest Health, and Landscape Integrity. We selected these topics to represent a broad range of important ecosystem services that are of central importance to managers and local stakeholders throughout the western US (Povak et al. 2023). For each topic area, we developed a set of 3 to 7 indicator metrics (e.g., C storage and fluxes for Carbon, peak snow water equivalent and late season flow volume for Water, etc.) that were used to assess the quality of ecosystem health and functioning (Table S3, also see Furniss et al. 2023). For each indicator metric, we assigned a logical premise that was evaluated using fuzzy logic to translate metric values into "strength-of-evidence" (SOE) scores, which use a −1 to +1 scale to represent the degree to which each metric satisfies a proposition. Fuzzy logic may be thought of as simply a way to standardize disparate unit scales onto a −1 to 1 scale, in contrast to Boolean logic which only allows values of 0 and 1. With fuzzy logic, scores can range from −1 to 1 with a SOE score of +1 indicates strong support for a proposition (e.g., carbon sequestration is maximized), a score of 0.75 indicating strong support (e.g., carbon sequestration is high), and a SOE score of −1 indicates poor support for the same proposition (e.g., carbon sequestration is minimized). Importantly, we centered all SOE scores relative to the *Wildfire Only* scenario so that positive values indicated that a given scenario performed better than the *Wildfire Only* scenario, while a negative score indicated that the *Wildfire Only* scenario outperformed the treatment scenario.

We grouped the primary topics into three partially overlapping groups (also see Table S3) representing key facets of resilience: *Economic* (Economics and Sustainable Biomass), *Social* (Sustainable Biomass, Carbon, Water, and Wildfire), and *Ecological* (Water, Wildfire, Forest Health, and Landscape Integrity). When all primary topics were grouped together, we referred to the SOE scores as *Overall* benefits.

All metrics were initially evaluated spatially using raster outputs from LANDIS-II and DHSVM. We then used these spatial maps to build a *spatial* DST that allowed us to evaluate what parts of the study landscape had the greatest potential for treatment synergy (Furniss et al. 2023). To evaluate trends in ecosystem function over time, and to compare the effects of various alternative management scenarios, we built an *aspatial* DST by aggregating the spatial SOE scores at the patch, HUC12, and PWG level. We summarized these scores using area-weighted averages of HUC12 scores to generate landscape-level scores, for each scenario, in each year. In contrast to the spatial DST that quantified potential benefits at the end of the simulation, these aspatial SOE scores allowed us to evaluate how potential benefits changed throughout the simulation period, at the landscape scale.

We further evaluated SOE scores for each topic at simulation year 10, 50, and 100 to distill general patterns over time. We plotted these scores using heatmaps, with scenarios assigned to rows and topics assigned to columns. We built dendrograms for the scenarios to generate groupings of similar scenarios. We used the *heatmap.2* (v3.1.3) function in R with the default clustering parameters (Warnes et al. 2022).

Software versions

Landscape simulations were generated with LANDIS-II v7.0 (Scheller et al. 2007) using the NECN v6.8 (Scheller et al. 2011), SCRPPLE v3.2.1 (Scheller et al. 2019), and Biomass Harvest v4.4 (Gustafson et al. 2000) extensions. All data pre-processing, post-processing, and subsequent analyses were performed in R v4.1.3 (R Core Team 2020) using *terra*, *whitebox*, *vegan*, and *tidyr* packages.

Results

Effects of climate change on wildfire and biomass dynamics

In the absence of wildfire and mechanical harvesting, biomass accumulated over the full 100-year simulation period, and climate effects on projected biomass accretion were negligible (Fig. 2). When we added wildfire disturbance, stark differences between future climate scenarios became evident. While area burned per year under the baseline climate scenario was relatively steady (i.e., average annual area burned was similar at the beginning and the end of the simulation), there was a notable increase in area burned between under the RCP8.5 climate scenario, particularly for moderate- and high-severity classes (Fig. 3). Cumulative area burned diverged around years 2060–2070 where annual area burned under the RCP8.5 scenario began to increase more rapidly compared to area burned under the baseline climate. Average area burned (*Wildfire Only* scenario, RCP8.5 climate) before the inflection point (2020–2060) was 1687 ha $\cdot$ year^{-1}, while after the inflection (2080–2120) it grew to 11,237 ha $\cdot$ year^{-1}. Consequently, the vast majority of area burned (and area burned at high severity) occurring during the latter half of the simulation (21% from 2020 to 2070 versus 79% from 2070 to 2120). This inflection point was evident even when the climate forecast was shuffled (i.e., random ordering of years from the RCP8.5 climate projection; Fig. S2), indicating that the inflection was not caused by an underlying trend in the RCP8.5 climate forecast (dotted line in Fig. S2).

These increases in wildfire activity had a significant impact on aboveground biomass in all vegetation types (Fig. S3). Under the baseline climate scenario, potential biomass losses from wildfire did not offset forest growth, allowing biomass to accumulate throughout the simulation period (albeit at a lower rate compared to the *No Disturbance* scenario; Fig. 2). Under the RCP8.5 scenarios, however, biomass levels in all tree-dominated vegetation types peaked around 2060, then declined for the rest of the simulation (Fig. S3). The timing of this biomass decline aligns with the inflection point observed in moderate- and high-severity area burned (Fig. 3), suggesting that direct climate effects on biomass (hence carbon storage) were negligible and were instead primarily mediated by future wildfire dynamics. The reduced biomass may also be an indication of wildfire-driven type conversion, which would result in a persistent reduction in carbon storage potential even if future wildfire activity were to stabilize, but we were not able to test that directly.

Management impacts on ecosystem functions and services

We generated landscape-level mean SOE scores to evaluate potential benefits under each treatment scenario over the entire 100-year simulation period. Recall that positive values indicated that a given treatment scenario performed better than the *Wildfire Only* scenario (with RCP8.5), while negative values indicated a poorer than *Wildfire Only*.

Primary topic results revealed intuitive short-term and long-term tradeoffs between management scenarios

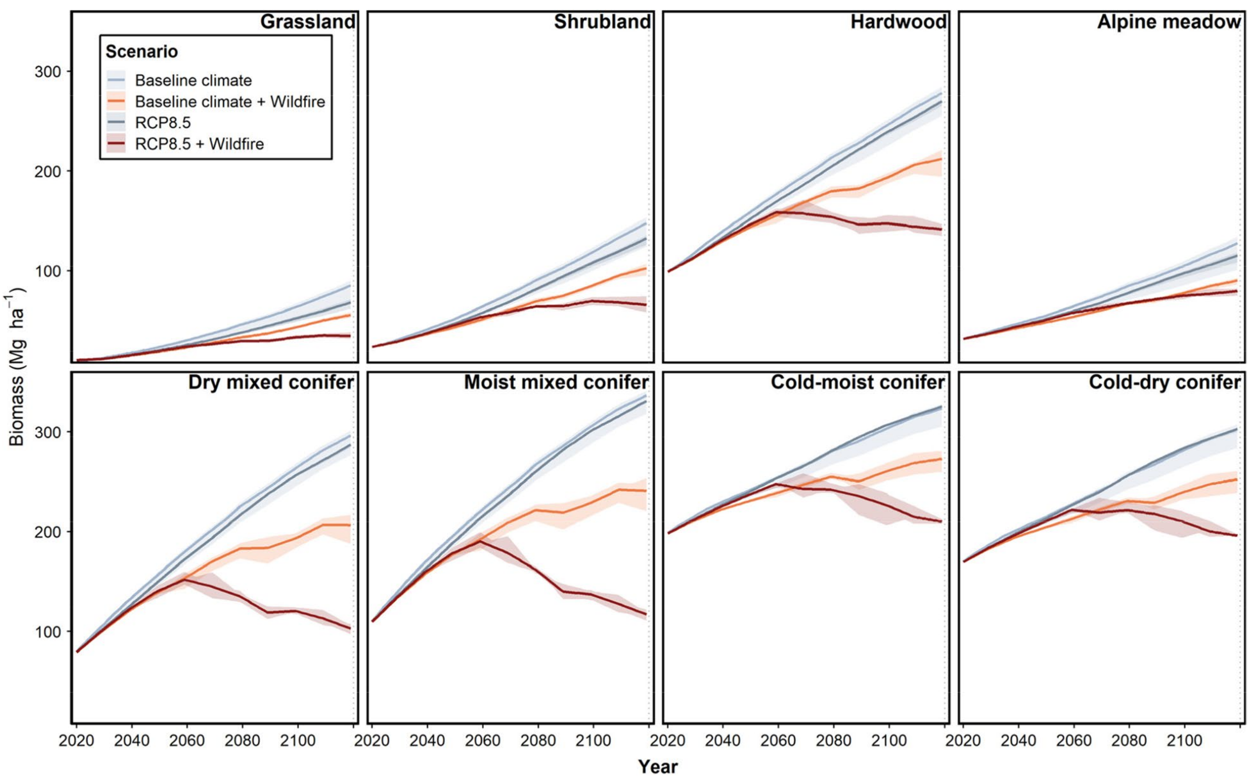

Fig. 2 Biomass accumulation per vegetation type under a *No Disturbance* scenario (cool colors) and the *Wildfire Only* scenario (warm colors). Each scenario was run under two climate forecasts: a baseline forecast representing late twentieth century climate ("Baseline climate") and a more realistic forecast based on a RCP8.5 emission scenario ("RCP8.5"). Direct effects of climate change on biomass accumulation were minimal. Wildfire had a substantial impact on biomass under the baseline climate scenario (orange lines), and an even greater impact under the RCP8.5 scenario (red lines)

(Fig. 4). In the short term (2020–2040), scenarios involving forest thinning (green lines in Fig. 4) generally performed best among Economic, Sustainable Biomass, and Water topics, with reduced benefits among the ecological categories including Forest Health, Carbon Storage, and Landscape Integrity. Existing timber stocks were depleted relatively quickly in the context of ongoing wildfires and small available treatable area, which reduced the size of potential benefits for the latter part of the simulations (Fig. 4).

Longer term benefits among all primary topics were strongly influenced by the inflection point in wildfire activity under the *Wildfire Only* scenario (under the RCP8.5 climate scenario). The rapid increase in area burned under *Wildfire Only* around 2060 (Fig. 3) led to an overall decline in benefits among most topics, and this decline contrasted with relative increases in the benefits among the other management scenarios (Fig. 4).

High interannual variability in area burned statistics, and a limited number of iterations of each scenario, precluded identifying significant differences among management scenarios at an annual resolution (Fig. 4). However, main treatment effects were observed for cumulative area burned by severity class (Fig. 3). Harvest treatments resulted in a slight reduction in cumulative area burned at high severity, while WFU produced a much more significant decrease in cumulative area burned at both moderate and high severity (Fig. 3).

When *Overall* benefits were assessed, all treatment scenarios except *Wildfire + Rx fire* performed better than the *Wildfire Only* by the end of the simulation (Fig. 5). *Economic* benefits were greatest in the scenarios involving harvest, but these benefits declined after available biomass for harvest was depleted in the context of ongoing wildfires and small treatable area (~ 2050; Fig. 5). *Social* benefits were greatest for scenarios that involved Harvest and/or WFU, which was surprising given that these scenarios tended to have the lowest benefits around mid-century. This dip was primarily driven by the depletion of carbon stocks associated with harvesting and elevated wildfire activity (Figs. 3, S2, S3). Yet as carbon and biomass stores recovered and area burned under the *Wildfire Only* scenario began to rise (Fig. 3), benefits associated with the treatment scenarios began to increase rapidly.

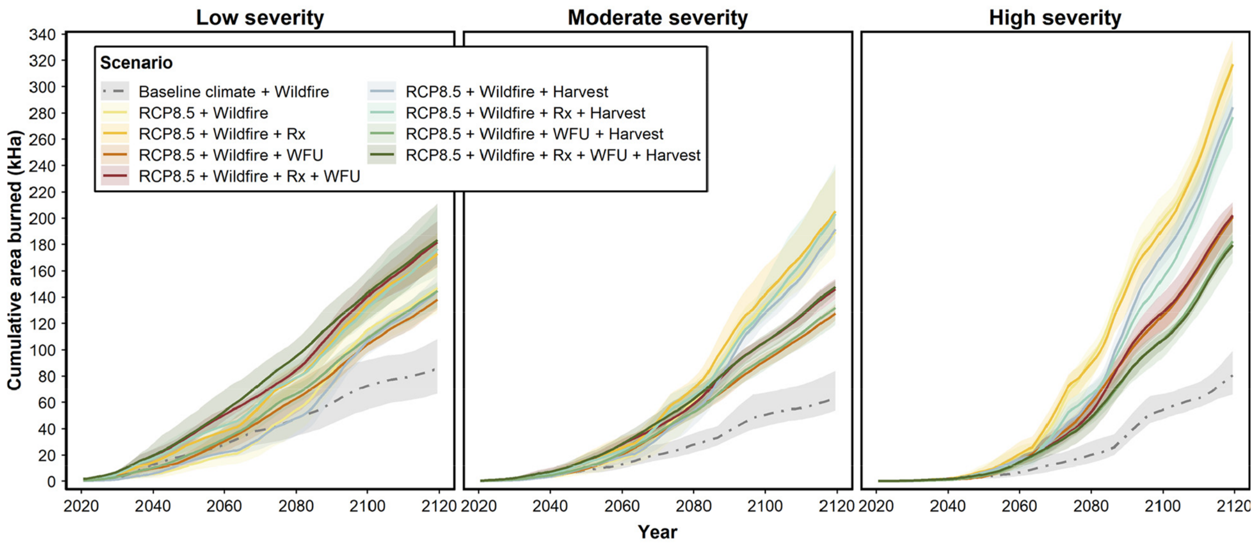

Fig. 3 Simulated area burned by severity class under historical conditions ("Baseline climate"), future ("RCP8.5") climate, and alternative management scenario (*Wildfire Only* = "RCP8.5 + Wildfire"). Model uncertainty is represented by the simulation envelopes (shaded regions) which were generated by running five iterations of each scenario. The shaded regions represent the highest and lowest values, while the solid lines represent mean values from the five simulation runs. Cool colors indicate scenarios with mechanical harvest treatments, while warm colors indicate scenarios without harvest. Darker colors indicate scenarios with wildland fire use (WFU). Differences in area burned at moderate and high severity were pronounced for the WFU scenarios, while harvest scenarios conferred a slight reduction in area burned at high severity

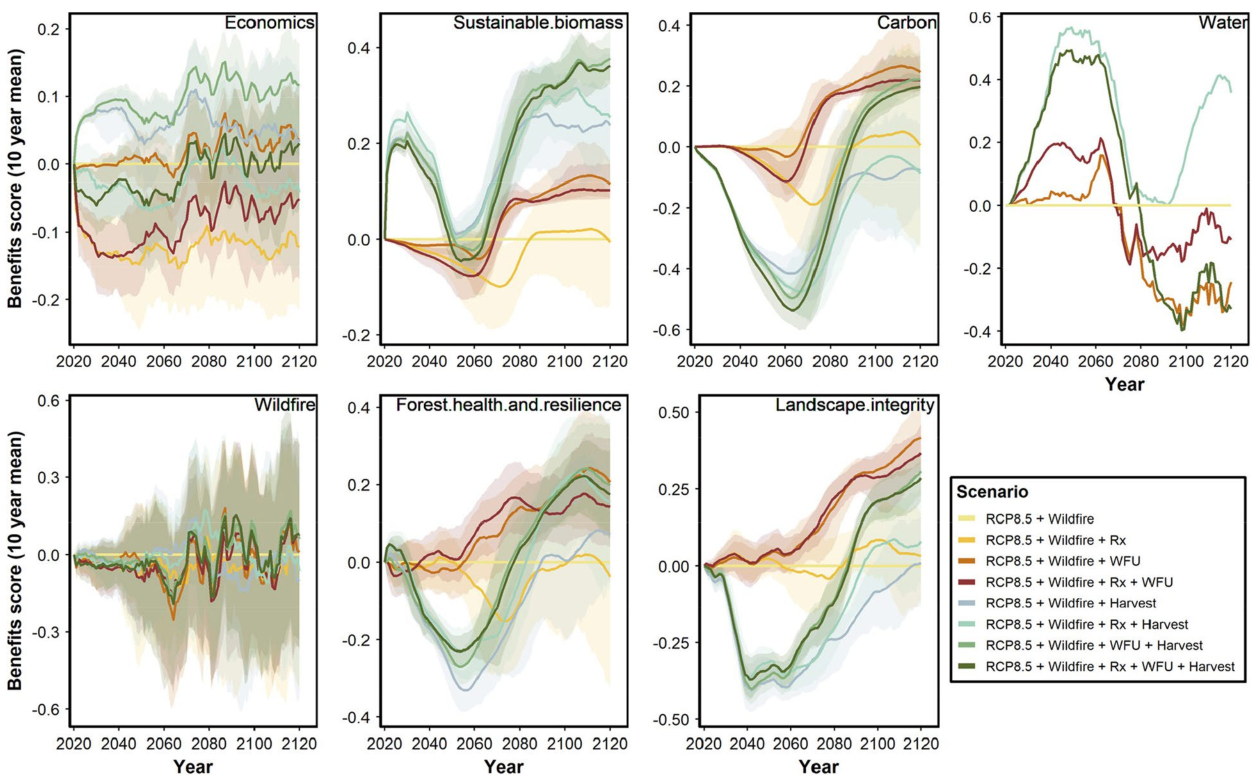

Fig. 4 Potential treatment benefits among seven primary topics for eight alternative future management scenarios. Benefits were assessed relative to the "no treatment" (*Wildfire Only*) scenario. Model uncertainty is represented by the simulation envelopes (shaded regions) which were generated by running five iterations of each scenario. The shaded regions represent the highest and lowest values, while the solid lines represent mean values from the five simulation runs

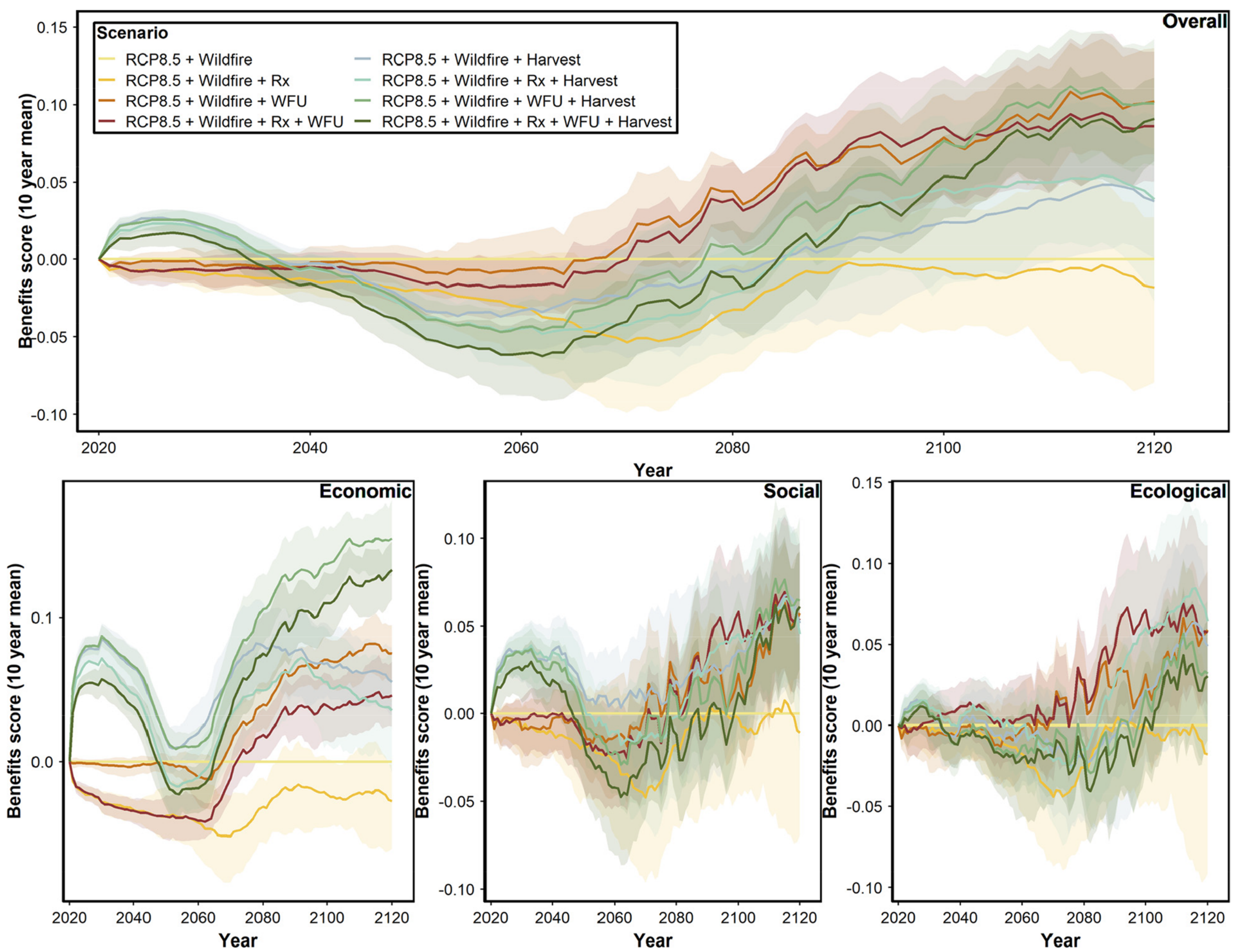

Fig. 5 Potential treatment benefits for eight alternative future management scenarios. Benefits were assessed relative to the "no treatment" scenario (*Wildfire Only*). Model uncertainty is represented by the simulation envelopes (shaded regions) which were generated by running five iterations of each scenario. The shaded regions represent the highest and lowest values, while the solid lines represent mean values from the five simulation runs

Ecological benefits showed a similar trend, although the mid-century dip was not as evident (Fig. 5).

To investigate the relative influence of Harvest versus WFU treatments, we examined the reduction in area burned due to harvest (i.e., *Wildfire Only* minus *Wildfire + Harvest*; *Wildfire + WFU* minus *Wildfire + WFU + Harvest*). Interestingly, mechanical treatments (*Harvest*) reduced area burned relative to the *Wildfire Only* scenario, but only if WFU was not applied. In the WFU scenarios, the addition of mechanical harvest did not have a discernable effect on area burned (Figs. S4 and 3).

Discussion

Scenarios involving harvest did perform best among the *Economic* categories as we expected, but the addition of Rx fire did not improve benefits to *Social* and *Ecological* topics. Wildland fire use emerged as the single most influential management tactic, and scenarios involving WFU performed well among all categories because it was most effective at curbing the amount of future high-severity fire. This was a surprising result, and it highlights the importance of wildfire as a foundational process governing the functioning and health of forest landscapes. We were also surprised by the variability in benefits across the 100-year simulation period. Even though our simulations applied the same management strategies throughout the entire simulations, future landscapes and the benefits they conferred were vastly different at year 50 versus year 100. These extended timeframes carry a great deal of uncertainty, of course, but the point remains that management actions with short-term benefits can be inconsequential or even detrimental in the long term (Young and Ager 2024). This is an important perspective for land managers and policymakers to consider. Estimating the consequences of current actions over decadal and century timescales is not easy, but it is necessary when managing large landscapes with the potential for feedbacks and complex disturbance dynamics.

Future wildfire dynamics

Future wildfire dynamics and low available treatment area were central to the interpretation of all results of this simulation modeling study. The *Wildfire Only* management scenario under the RCP8.5 climate change demonstrated a positive feedback cycle that began mid-century (~ 2060), driving a marked increase in high-severity wildfire (Figs. 3, S2). Importantly, this feedback was not evident among all management scenarios, indicating that it was caused by something that differed between scenarios rather than something intrinsic to the model itself. The inflection point was present in the *Wildfire Only* scenario and given that our DST results were assessed in contrast to the *Wildfire Only* scenario, the impacts of these emergent wildfire dynamics were pervasive.

The inflection point in future area burned was a striking result of this study. For context, average area burned under RCP8.5 climate before the inflection (2020–2060) was 1687 ha·year^{-1}, corresponding to represent the 60th percentile of area burned under the baseline climate scenario, which was calibrated to empirical fire activity. Average area burned per year after the inflection point, however, was 11,237 ha · year^{-1}, corresponding to the 98th percentile of area burned under a historical climate. In other words, an average fire year during the later half of the century would represent the most severe fire year from the first half of the century. This demonstrates the potential for wildfire to create positive feedbacks that can have profound and lasting impacts on the structure, function, and resilience of large landscapes.

There are two plausible reasons for this inflection point. First, the climate forecast could have an inflection in temperature around this period, and the inflection in fire activity may simply be responding to that increase in temperature (i.e., first order effects of climate on fire spread rates). Second, the inflection could be due to a positive feedback cycle between area burned and resultant patterns of landscape contagion and susceptibility to large fire spread. Both of these explanations have support from empirical studies (Halofsky et al. 2011; Abatzoglou et al. 2021; Povak et al. 2024), providing some reassurance that this trend was not an anomaly of our model.

We distinguished between these two explanations using the randomly shuffled RCP8.5 scenario. If the inflection point was climate driven, cumulative area burned for that scenario would have been linear (because we removed any underlying structure in the climate data by shuffling the years). Instead, we saw that both shuffled and non-shuffled RCP8.5 scenarios exhibited an inflection point (Fig. S2), indicating a tipping point where positive feedbacks between wildfire and surface fuels began to rapidly accelerate reburn frequency. This finding is consistent with recent empirical work that has documented increasing wildfire activity due to both climate and fuels (Coop et al. 2020; Hagmann et al. 2021; Abatzoglou et al. 2021; Povak et al. 2023; Prichard et al. 2023), and it is further evidence for the importance of pattern and structure in determining the contagious potential of wildfire (Povak et al. 2023). The exogenous influence of climate was clearly important as well, but these results indicate that climate alone did not account for the wildfire regime change that can emerge when high-severity fire initiates a positive feedback cycle with endogenous controls on fire behavior.

These dynamics are a feature, not a fault, of simulation modeling approaches with dynamic fire models (e.g., Ager et al. 2022; Young et al. 2022; Prichard et al. 2023). As wildfire activity is determined by process-oriented algorithms within a given model, fire regimes are allowed to evolve over the simulation period rather than being constrained by a pre-defined fire size distribution. Dynamic fire modeling allows simulated fire activity to respond to changes in fuels, climate, and landscape patterns, capturing dynamics that are foundational to the emergence of wildfire regimes in real landscapes (Agee 1998; Scholl and Taylor 2010; Hessburg et al. 2019).

Alternative management scenarios

Our *Harvest* treatments produced benefits in the form of economic returns and biomass production, but even these restoration-oriented thinning treatments did little to alter projected trends in wildfire activity. Treatments were primarily effective over the next several decades before existing biomass stores were depleted (around 2050), after which point treatments continued but were less economically viable. Around this time, simulated wildfire activity began to increase rapidly. Despite the *Harvest* treatments reducing surface fuels, total area burned under the *Wildfire + Harvest* scenario was not substantially lower than the *Wildfire Only* scenario (Fig. 3).

The near-term impacts of harvest were overwhelmed by the self-regulation of wildfire that eventually emerged in the WFU scenarios (Fig. 3). Interestingly, this led to more similarity between the WFU scenarios compared to the Harvest scenarios by the end of the simulation period (Fig. 6). In other words, the *Wildfire + Harvest* scenario was more similar to the *Wildfire Only* scenario than it was to the *Wildfire + Harvest + WFU* scenario. Similarly, *Wildfire + WFU* was more similar to the *Wildfire + WFU + Harvest* than to *Wildfire Only* scenario (Fig. 6). Harvest effects were prominent early in the simulation, but the effects of wildfire use eventually grew to dominate the scenario differences by the end of the century.

Wildland fire use

Wildland fire use (*WFU*) scenarios had profound impacts on wildfire activity that permeated to all other landscape metrics. Allowing more wildfire to burn in the wildlands produced benefits among the Water topic, at least for the first half of the century (Fig. 4). Benefits to other topic areas were slow to emerge, but the reduced amount of high-severity wildfire in the *WFU* scenarios (Fig. 3) eventually translated into greater carbon storage (Fig. S3), Landscape integrity (Fig. 4), and Ecological benefits (Fig. 5). This finding is particularly notable because most of the carbon is stored in the upper elevation wilderness areas (~200 Mg ha^{-1} in "Cold Moist Conifer" vs. ~100 Mg ha^{-1} in "Moist Mixed Conifer") where the *WFU* scenarios involved less suppression effort under *all* circumstances, even during extreme fire weather conditions. These results underscore the importance of wildfire management as a primary tool in the management toolbox (North et al. 2015; Barros et al. 2018; Young et al. 2022; Ager et al. 2022), highlighting the potential for managed wildfire use to alter fire regimes and mitigate high-severity area of future fires (e.g., Barros et al. 2018; Young and Ager 2024). Choosing how and when to suppress wildfire is the primary tactic available in large landscapes with substantial proportions of wilderness and roadless areas (Miller 2003; van Wagtendonk 2007; North et al. 2012; Stephens et al. 2016), and this study demonstrates that those wildfire management decisions can match or even exceed the impact of more active management tactics such as thinning and Rx fire.

Mechanical treatments

Interestingly, mechanical adaptation treatments (*Harvest*) only reduced area burned in the absence of a *WFU* suppression paradigm (Fig. S4). In the *WFU* scenarios, mechanical harvest resulted in a slight reduction in area burned (mean value was below 0), but this trend was not significantly different (simulation envelope overlapped 0). These results suggest that while active management can mediate future wildfire behavior, the effects of different management tactics are not necessarily cumulative, indicating diminishing returns in benefits. The same level of benefits was achieved through restoration via either mechanical methods (*Harvest* scenarios) or through alternative wildfire management paradigm (*WFU* scenarios), but applying harvest *and* WFU as well did not produce additional benefits (Fig. 5). The *Wildfire + WFU* scenario was equivalent in overall benefits to the *Wildfire + WFU + Harvest* scenario, as applying harvest increased benefits among Economic and Sustainable biomass topics while reducing benefits to Carbon and Landscape integrity (Fig. 4). Results indicate that tradeoffs among management strategies are inevitable. Therefore, managers and policy makers must decide how

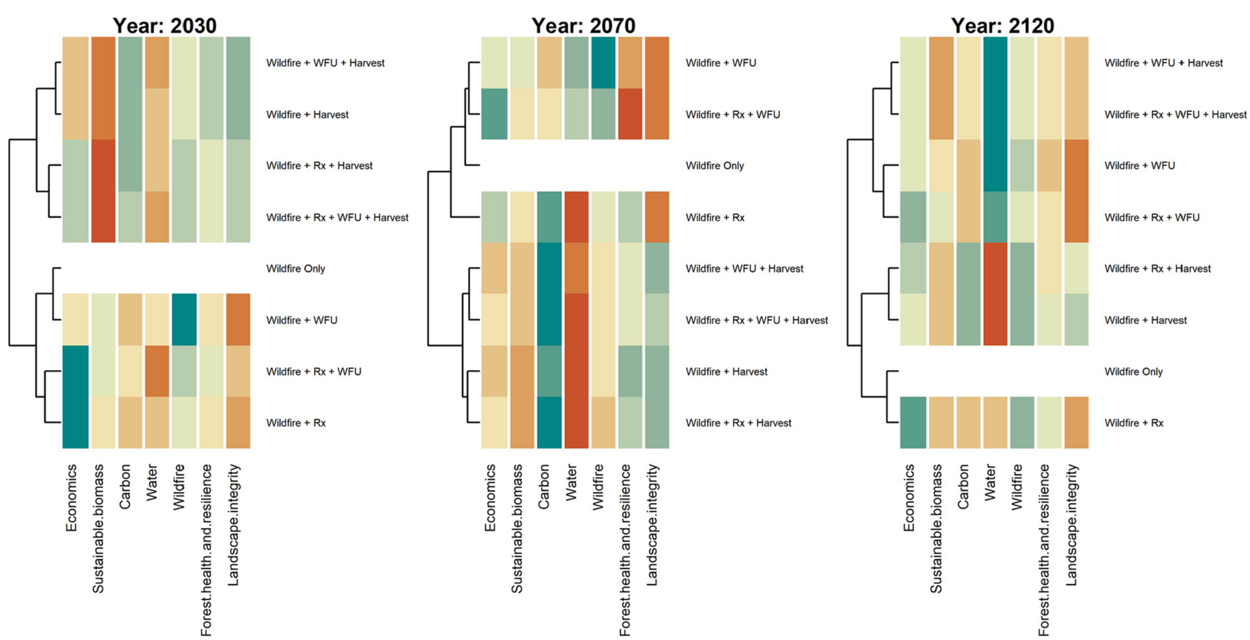

Fig. 6 Heatmap and dendrogram showing benefits among the seven primary topics (red = strong support, blue = weak support) and clustering of scenarios based on dissimilarity at three timesteps (simulation year 10, 50, and 100)

to distribute benefits, identify opportunities to manage for multiple resources at once, and determine when and where to prioritize benefits among certain topics (e.g., Ager et al. 2016; Povak et al. 2022; Furniss et al. 2023).

Prescribed fire

The Rx fire scenarios showed very little distinction from their comparison scenarios without Rx fire. This result was surprising, given that the rate of Rx fire was equal to the rate of harvest being applied (~ 5000 ha·year^{-1}). One explanation is that Rx fire was applied to the wildlands as well as the actively managed parts of the landscape, so the Rx fire treatments were more diffuse and therefore perhaps less impactful to overall landscape functioning. We scaled this annual rate to approximate the actual amount of Rx fire being applied in this landscape today. Our findings suggest that this level of Rx fire is wholly insufficient to alter wildfire behavior in such a large landscape. Rx fire is an effective management tool to reduce fuels at the patch-scale but generating benefits for landscape resilience will likely require far more Rx fire application and/or more wildland fire use.

Wildfire, fuel reduction, and carbon storage

Mechanical fuel reduction efforts mediated wildfire severity (Fig. 3), but these deferred losses to wildfire were offset by C losses due to harvest. This resulted in similar levels of residual biomass between the *Wildfire Only* and *Wildfire + Harvest* scenarios at the end of the simulation period (Fig. S3). This provides an interesting complement to prior studies that have shown restoration treatments (e.g., thinning + Rx fire) to be an effective way to increase forest C storage by mitigating future wildfire severity (Loudermilk et al. 2017; Young and Ager 2024). This potential for long-term benefits to forest C storage is well-established in the literature, but achieving net C gains requires carbon losses due to treatments to be effectively offset by reduced fire-related C emissions and increased productivity of residual trees. The efficacy with which restoration treatments reduce fire severity is contingent upon many factors including the timing and location of treatments (Loudermilk et al. 2014; Krofcheck et al. 2019), landscape configuration and forest conditions, and dominant fire regimes. Achieving net C gains through restoration treatments is therefore most likely in areas that are vulnerable to high-severity fire (Krofcheck et al. 2019), forests with high densities of small trees, and in places that will strategically impede fire flow.

In this study, simulated thinning treatments did not reduce fire severity enough to offset the C losses due to the thinning treatments themselves (Figs. 3, 4). In other words, scenarios without mechanical harvest resulted in higher C storage potential, with the *Wildfire + WFU* scenario showing the greatest C storage at the end of the simulation (Fig. S3). We may have achieved net C gains if simulated thinning treatments had a greater impact on fire severity and area burned, as was evident in the WFU scenarios (Fig. 3). It is also possible that post-treatment growth responses were not well represented in the model, which would have also influenced simulated carbon storage. Nonetheless, this result from our simulations reflects a real-world challenge in mitigating wildfire activity using thinning treatments: wildfire is not a deterministic process. Many treated areas never see fire, and other treated areas may burn at high severity due to top-down influences. Treatments can effectively mitigate fire severity, but it is difficult to know exactly when and where treatments may be most likely to maximize their intended benefits.

Interannual variability

For both Wildfire and Water topics, interannual variability between years was far greater than variability between management scenarios (Fig. S5). Differences between scenarios were evident when we used the *Wildfire Only* scenario as a reference, but examining the raw SOE scores revealed a great deal of noise from year to year. This noise may be largely attributed to annual climate fluctuations, as both Wildfire and Water topics were very sensitive to the timing of precipitation and within-year temperatures (via increased wildfire activity and decreased snowpack retention, respectively). Additionally, we were not able to generate simulation envelopes for the Water topic because we only performed a single DHSVM run per scenario due to computational limitations. Since DHSVM is a deterministic model and the climate stream fed into DHSVM was the same for all scenarios, all the scenarios tracked each other very closely (Fig. S5). The Wildfire topic, in contrast, was driven by wildfire activity in LANDIS-II which is stochastic and therefore produced noticeable differences between different runs of the same scenario (hence the wide simulation envelopes). For example, one iteration of *Wildfire Only* may have had a big fire year in year 10 while another iteration had a big fire year in year 11, leading to wide simulation envelopes and making differences between scenarios on a year-to-year basis difficult to detect (Fig. 4). We were able to tease out differences between management scenarios by evaluating cumulative area burned by severity which allowed differences in wildfire behavior to accumulate through time, highlighting the differences between scenarios that were evident over long enough time scales (Fig. 3).

Tradeoffs in space and time

Our simulation modeling revealed that ecosystem responses to future management scenarios are highly dynamic, and potential benefits are unstable over time. Fluctuations in ecosystem functioning point to the importance of underlying feedbacks and destabilizing processes in shaping future landscapes. These second-order landscape dynamics were evident in the inflection point in area burned under *Wildfire Only*, the rise and fall of available biomass under the *Harvest* scenarios, and the high Carbon scores for the *WFU* scenarios. These results emphasize the importance of adaptive land management strategies that periodically re-assess management tactics in response to ever-changing ecological challenges. They also provide a way to visualize the uncertainty that managers and policy makers must reconcile (e.g., Miller 2007; Lynch et al. 2022), demonstrating how scenarios that appear best in the short term can yield less-desirable outcomes over longer time spans (e.g., Young and Ager 2024).

Limitations and future research

Caution must be exercised when interpreting the results of decision support systems. The relative ranking of various scenarios is highly sensitive to the selection of evaluation metrics and the structure of the DST logic model. Results of the DST modeling are sensitive to the number of topics and the weight given to each of the topics in the final assessment. This is a strength of fuzzy logic models: they can be adapted to reflect stakeholder values and the relative importance of different topics of interest. It is likely that these seven topics would not carry equal weight if this model were to be applied in a management context. Equal weight was applied by using union operators in the logic model (Reynolds et al. 2014). Accordingly, the overall benefits scores associated with each management scenario would change to reflect the concerns and values of managers and the local community. We used the *Social*, *Economic*, and *Ecological* groupings to get at this, as these topic groupings reflect what the decision support model results would look like if it were to include only a subset of topics.

Another difficulty in interpreting our results is that the fuzzy logic model translated absolute values into a relativized scale, which is necessary to be able to aggregate diverse units of measurement into the primary topic areas. However, this translation may obscure the magnitude of treatment effects because we set the fuzzy logic breakpoints to the 10th and 90th percentiles of observed delta values to represent the middle 80th percentile range of values. For the mean annual flow metric, for example, differences in mean annual flow between scenarios each year were very small, yet these small differences still received scores ranging from − 1 to 1. This allowed us to evaluate differences between scenarios, but it obscured the fact that year-to-year variability in mean annual flow was far greater than the within-year variability due to scenario differences (Fig. S5).

This study builds upon a growing body of research leveraging decision support systems to evaluate tradeoffs and synergies among important ecological and social values, both in space and over time, to project future landscape dynamics and management effects (Reynolds et al. 2014; Abelson et al. 2022; Maxwell et al. 2022; Povak et al. 2022; Furniss et al. 2023). A significant advancement made here is the integration of LANDIS-II with a distributed hydrology model (DHSVM), enabling us to quantify impacts of forest treatments on snowpack and streamflow dynamics. An important next step will be to make this integration more accessible, perhaps through the development of a new model extension, and to consider ways to couple the models to improve hydrology dynamics (hence water availability) within LANDIS-II.

Conclusions

We found that most alternative future management scenarios produced discernable benefits among *Economic*, *Social*, and *Ecological* primary topic areas. These gains were both robust and fragile, with the *Wildfire Only* scenario having the greatest overall performance part way through the simulation (2040–2070), then declining as positive feedbacks in wildfire activity under this scenario caused a steep increase in high-severity fire. Simulated management actions were able to mitigate this high-severity fire feedback, with both mechanical forest treatments and wildland fire use tactics reducing high-severity area burned and resulting in better overall landscape health. Unsurprisingly, mechanical treatments were more beneficial for *Economic* categories while wildland fire use alone was better for some of the *Ecological* topics. Benefits for the *Social* topics were somewhere in between, reflecting the inevitability of tradeoffs among countervailing needs such as carbon storage and streamflow enhancement. These tradeoffs highlight the need for diverse and cohesive landscape management strategies, as no single management scenario will produce optimal results across the board.

Tradeoffs are at the very core of wicked problems; positive outcomes in some areas yield negative cascades in others. Disentangling these problems requires managers and stakeholders to identify shared values, priorities, and tolerable tradeoffs, and to apply a mix of methods that reflect the diversity of desired benefits associated with various management strategies. This study demonstrates what these future scenarios can look like, underscoring the importance of both active and passive management strategies—and wildfire management decisions in particular—in building more robust and resilient future landscapes.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-024-00339-y.

Supplementary Material 1.

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Authors' contributions
TJF, PFH, and NAP conceived of the study. TJF performed the majority of analysis and prepared the first draft. MW and ZD performed the hydrology modeling, and RBS helped collect and prepare foundational data layers. PFH and MW provided funding. All authors contributed to writing and editing of the final manuscript.

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Data availability
This study leveraged existing datasets, all of which have been cited appropriately in the "Methods" section. No new data was collected for this study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Department of Ecosystem Science and Management, University of Wyoming, Laramie, WY, USA. [2]USDA Forest Service, Pacific Northwest Research Station, Wenatchee, WA, USA. [3]USDA Forest Service, Pacific Southwest Research Station, Placerville, CA, USA. [4]School of Environmental and Forest Sciences, University of Washington, Seattle, WA, USA. [5]Pacific Northwest National Laboratory, Richland, WA, USA. [6]School of Civil and Environmental Engineering, University of Washington, Seattle, WA, USA.

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