

Wildfires managed for restoration enhance ecological resilience

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Abstract. Expanding the footprint of natural fire has been proposed as one potential solution to increase the pace of forest restoration programs in fire-adapted landscapes of the western USA. However, studies that examine the long-term socio-ecological trade-offs of expanding natural fire to reduce wildfire risk and create fire resilient landscapes are lacking. We used the model Envision to examine the outcomes that might result from increased area burned by what we call “restoration” wildfire in a landscape where the ecological benefits of wildfire are known, but the need to suppress high-risk fires that threaten human values is also evident. Our study area, in the eastern Cascades of Oregon, USA, includes the Deschutes National Forest where large tracts of mixed conifer forest structure are outside the historical range of variation and characterized by multi-layer, closed-canopy stands. We found that simulation of one restoration wildfire per year in addition to high-risk wildfires in the regular fire season and over the course of 50 yr resulted in a 23% increase in total area burned, but the same probability of fire-on-fire interactions. This translated into 0.3% of the national forest burned by restoration wildfire per year and had a small impact in area burned by high-risk fires albeit more likely in extreme fire years. Smoke production doubled in the restoration scenario relative to the scenario without restoration wildfire, but still resulted in minimal smoke production in most years. Restoration fires burned with low- to mixed-severity and led to a steady reduction in canopy cover and increase in resilient forest structure in dry-forest types. Habitat for the federally protected northern spotted owl declined with the inclusion of restoration fire, while habitat for species that use recently burned forest stands (e.g., black-backed woodpecker) increased. Our results suggest that restoration wildfire can improve forest resilience and contribute to restoration efforts in fire-adapted forests, but there are trade-offs (wildlife habitat, smoke, area burned in fire-sensitive forest types), and the level of restoration fire use we simulated is unlikely to have a significant impact on the occurrence of high-severity wildfires.

Key words: Envision; fire use; FlamMap; forest landscape modeling; managed fire; socio-ecological trade-offs; state-and-transition model; wildfire feedbacks.

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INTRODUCTION

Ecologists, managers, and policymakers increasingly recognize the need to expand the footprint of natural fires to restore fire-adapted forest

ecosystems in the western United States. Management of natural (i.e., from lightning) ignitions for ecological benefit, hereafter restoration wildfire, is advocated to reduce hazardous fuels, improve habitat, and restore seral stand structure, thus

contributing to increased forest health and resilience (North et al. 2015b, Stephens et al. 2016). Numerous studies have documented the fire resilient ponderosa pine (*Pinus ponderosa*) and dry-mixed conifer forests that covered vast areas prior to Euro-American settlement, and how fire suppression, logging, and grazing practices contributed to stand densification and changes in species composition and structure (e.g., Agee 1993, Haugo et al. 2015, Hessburg et al. 2016, Collins et al. 2017, Reilly et al. 2017). The change in surface and canopy fuels in concert with climate and human impacts has resulted in longer fire seasons and frequent, large, and severe fires in western forests (Westerling et al. 2006, Dennison et al. 2014, Jolly et al. 2015, Balch et al. 2017), a trend that is expected to extend into the 21st century (Flannigan et al. 2013, Barbero et al. 2015).

Part of the growing interest in restoration wildfire stems from financial and operational constraints that limit the frequency and extent of mechanical treatments in restoration programs (North et al. 2015a, Barros et al. 2017). Landscape fragmentation regarding ownership, capacity to treat among different communities, and the public's limited acceptance of mechanical actions also constrain the implementation of large-scale treatment programs (Toman et al. 2014, Paveglio et al. 2015). In addition, fire plays an ecological function in fire-adapted ecosystems that cannot be replicated by mechanical fuel reduction treatments; for example, fire controls the opening of serotinous cones and seed dispersal, cycles carbon, and nutrients through vegetation and organic layers, and creates habitat (Hutto et al. 2016). However, concerns about smoke impacts to communities, loss of protected habitat, and limited public support for the use of fire, among other factors, have limited restoration fire outside wilderness areas (Miller 2014).

Leveraging restoration fire as a strategy to create and maintain long-term health and resilience in fire-adapted forests has the potential to create a self-limiting landscape for future fires, via fire-vegetation feedbacks. Modeling and empirical studies have documented fire-on-fire interactions (Prichard et al. 2017), that is, when wildfires occur in close succession, and create negative feedbacks in fire spread and intensity (van Wagtendonk et al. 2012, Parks et al. 2014, Coop et al. 2016, Harvey et al. 2016, Holsinger et al. 2016,

Ager et al. 2017a). Other studies have explored how the dynamics of spatial fire interactions can alter post-fire vegetation recovery (Stevens-Rumann and Morgan 2016, Stevens-Rumann et al. 2016) and can moderate future fire activity by limiting fuel load and availability to burn (Prichard et al. 2017). Forest landscape modeling studies have suggested the benefits of restoration wildfire in terms of economics (Houtman et al. 2013) and risk reduction (Finney et al. 2007), and have shown how an increase in area burned from a restoration fire policy could potentially shift forest structure and composition toward desired conditions (Miller 2007). Empirical studies have demonstrated the benefits of restoration wildfire in terms of reduced fire suppression costs (Dale et al. 2005), improved runoff ratio (Boisrame et al. 2017), and fire resilience (Holden et al. 2010) when compared to unburned areas. Managed (restoration) wildfire programs in wilderness areas and national parks have been used for more than 40 yr with much success (Miller 2014). Restoration fire in forests that historically experienced frequent fire resulted in forest structure and composition similar to the pre-fire suppression conditions (Collins and Stephens 2007, Huffman et al. 2017), and fire severity patterns that are within the natural range of variation of western coniferous forests (Meyer 2015). Collectively, evidence from modeling and empirical studies suggests that by managing more acceptable wildfire today, that is, restoration fire, managers can increase forest resilience to disturbance and reduce the occurrence of extensive and severe fires in the future.

Although there is a consensus that restoration fire can contribute to meeting the ecological objectives of federal forests in the western USA (Wildland Fire Leadership Council 2014), questions remain about how specific wildfire policies may unfold in real landscapes and over time. Prior studies on managed fire impacts were primarily conducted within wilderness areas or focused on a limited set of metrics (e.g., severity or changes in forest structure), and have not considered other potential socio-ecological impacts including habitat for protected species, potential fire hazard, and smoke production. Thus, the long-term practicality of restoration wildfires regarding the social, operational, biophysical constraints (e.g., suitable ignitions), and ecological outcomes has not been

well studied, partly because such experimental design requires complex simulation frameworks that model forest landscape dynamics under alternative wildfire policies.

To address this gap, we used simulation modeling to examine potential changes in fire regimes and socio-ecological trade-offs associated with increased use of restoration wildfire. The study area was a 1.2 million ha fire-prone landscape on the east flank of the Cascade Mountains in central Oregon, USA. We used the agent-based landscape model Envision (Bolte 2018, Spies et al. 2017) to simulate wildfire activity under a forest and management policy that focuses on the suppression of high-risk fires (high-risk scenario) and then examined the effects of including restoration wildfires over the course of 50 yr (restoration scenario). We define high-risk fire as area burned by any wildfire that could exceed acceptable social and ecological loss, with the acknowledgment that a portion of such fire could also provide for restoration (Reilly et al. 2018). Restoration wildfires were simulated as one event per year over the course of 50 yr, under moderate fire weather and in locations where an ecological benefit is expected, and threats to high-valued resources are minimized. We compared the high-risk and restoration scenarios in terms of area burned, fire severity, potential fire hazard, forest resilience, forest structure, smoke production, and habitat for avian species of relevance to the region. We hypothesized that increasing restoration wildfires could reduce potential fire hazard and improve forest resilience at the landscape scale, but would have no impact on high-severity fire or the likelihood of large fires because the frequency of this fire type remains low.

METHODS

Study area and model overview

The study area (Fig. 1A) corresponds to roughly 1.2 million ha of public, state, and private land in central Oregon, USA, and it has been described in previous work (Barros et al. 2017, Spies et al. 2017). Potential forest types include subalpine forest along the crest of the Cascades, moist-mixed conifer in the montane zone, dry-mixed conifer, lodgepole pine (*Pinus contorta*) and ponderosa pine forest at lower elevation, and

juniper (*Juniperus occidentalis*) woodlands to the east (see Appendix S1: Table S1 for a description of species associated with potential forest types).

Approximately 60% of the study area corresponds to the Deschutes National Forest (DNF), 20% to the Confederated Tribes of Warm Springs, and the remaining area is distributed among private industrial, private non-industrial, state, and homeowner ownerships. Wildland urban interface (WUI) and scattered dwellings account for 10% of the study area (SILVIS Lab 2012).

We used Envision to model vegetation succession and forest disturbance (wildfire and forest management) in the study area over a 50-yr period. The model has previously been used to investigate the impact of increasing levels of fuel management (Barros et al. 2017) and wildfire (Ager et al. 2017a) on future fire regimes. Spies et al. (2017) used Envision to examine outcomes of alternative forest management scenarios for fire, socioeconomic, and ecosystem service metrics in the study area. The model initially developed by Bolte et al. (2006) includes succession, forest management, wildfire, and wildfire effects submodels, and runs on an annual time step and at the spatial scale of individual decision units (IDU) polygons (Fig. 2). Individual decision units range from 1 to 8 ha and were obtained based on the spatial intersection between vegetation classes, county tax-lot boundaries, and development zone boundaries (see Spies et al. 2017 for a detailed description). The wildfire submodel uses lists of fires (firelists) generated outside Envision using a spatiotemporal ignition prediction model (Preisler et al. 2004, Preisler and Ager 2013) hereafter referred to as Fire Generator. Envision outputs include evaluative metrics that describe changes to landscape structure, ecosystem services, and wildfire descriptors at the landscape scale and for individual fire events (Fig. 2).

Succession submodel

Each IDU is associated with a vegetation structural state characterized by cover type, average tree size, canopy cover, and number of canopy layers (Appendix S1: Table S2). Vegetation succession is modeled through changes in a given IDU state, based on state-and-transition models for the region following Halofsky et al. (2014a). State-and-transition models are collections of empirical rules that describe the deterministic

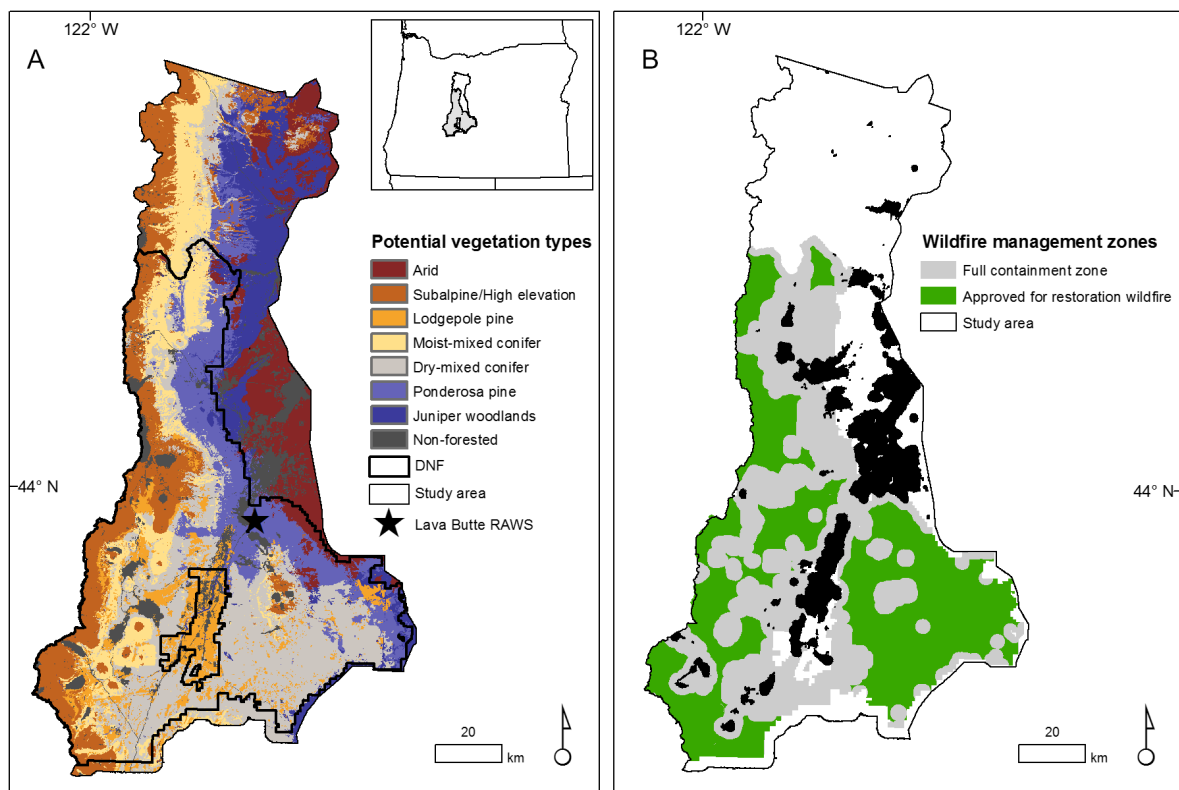


Fig. 1. Location of the study area in central Oregon, USA, and distribution of potential vegetation types (based on Halofsky et al. 2014b, A), and wildfire management zones on the Deschutes National Forest (DNF, B). The latter includes regions where natural ignitions can be managed as restoration wildfire (green), whereas, in the remaining area (gray), all ignitions are managed for full containment. Areas approved for restoration wildfire were delineated based on information from DNF managers in addition to a 2-km buffer around the wildland urban interface (SILVIS Lab 2012) and scattered dwellings.

and stochastic transitions between alternative vegetation states. Deterministic transitions reflect vegetation growth and are based on the forest's initial age and the passage of time, triggering a change in one or more of the state attributes and consequently a transition into a new state (sometimes referred to as phases). Deterministic transitions are also triggered by any disturbance that alters the IDU's state attributes, but not all disturbances simulated with Envision will do so (Appendix S1: Table S3). For example, thinning will reduce canopy cover and number of layers (leading to a new state), whereas a surface fire removes surface fuels without alterations to cover type, tree size, number of layers, or canopy cover. Stochastic transitions represent interaction processes such as the establishment of seral species or understory development leading to

changes from an initial single stand state to a multistory state, and these are conditional on the probability of occurrence (Halofsky et al. 2014a).

Surface fuels, canopy fuels, and initial conditions

In addition to vegetation state, we described each IDU regarding its slope, aspect, elevation, surface, and canopy fuels (Appendix S1: Table S4). Surface fuels were described by fuel models that correspond to standard classifications of fuel bed characteristics (fuel type, load, and structure) commonly used to model wildfire behavior and spread (Anderson 1982). We used information from the existing fuel model layer developed for the DNF and LANDFIRE 2008 fuel model data (LANDFIRE 2013) elsewhere.

Canopy fuels were described by canopy bulk density, canopy cover, canopy base height, and

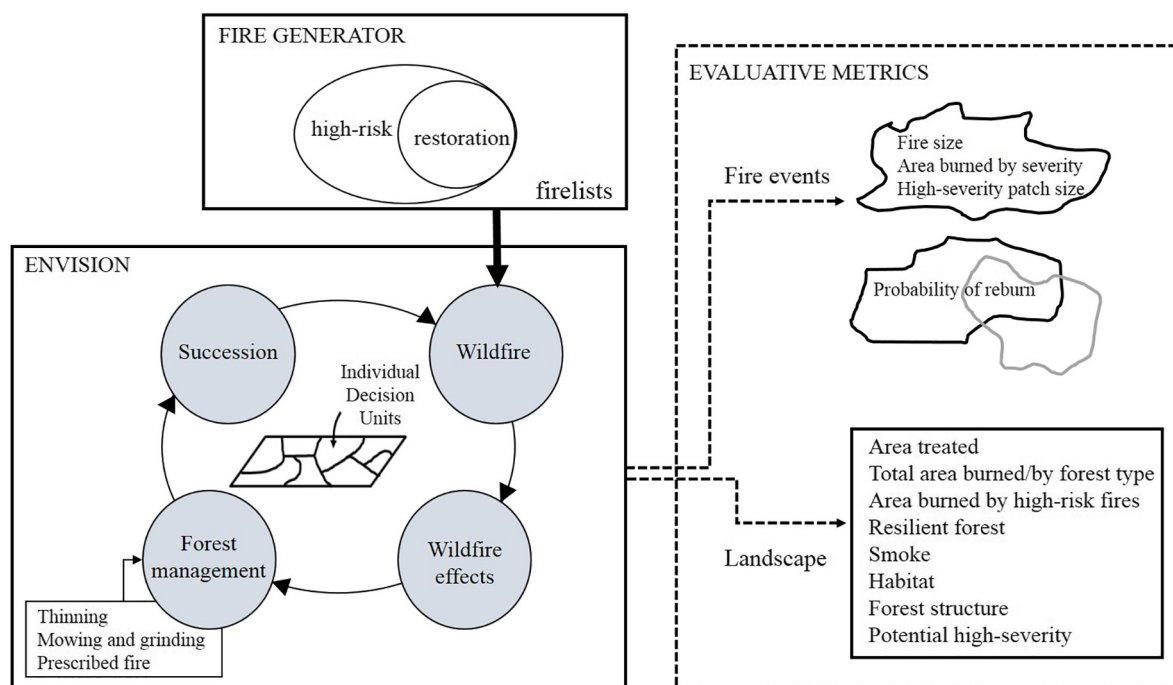


Fig. 2. Envision overview including the four submodels (succession, wildfire, wildfire effects, and forest management) and the Fire Generator model used to create lists of fires that are inputs for the wildfire submodel. Evaluative metrics include analysis of fire events and changes through time in landscape attributes.

total stand height, all of which were calculated with the Forest Vegetation Simulator (FVS; Dixon 2002). Forest Vegetation Simulator is a simulation system that models forest growth in response to natural succession, disturbance, and forest management. The model uses tree lists to record and track both stand and individual tree attributes through simulation cycles. We used expert knowledge to select tree lists in FVS, representative of the structural attributes in each vegetation state in Envision. We obtained canopy fuel variables through FVS runs for each set of lists and assigned the corresponding canopy fuels to IDUs based on the IDU's state. Initial vegetation state attributes were based on the 2006 Gradient Nearest Neighborhood data (Ohmann et al. 2011) and updated up to 2012 (first simulation year) to reflect historical wildfires (see Spies et al. 2017 for more details).

Wildfire submodel

The wildfire submodel in Envision (Appendix S2: Fig. S1) consists of an application that shares the same code libraries and functionalities

of the FlamMap program (Finney 2006). FlamMap simulates fire growth (fire perimeters) and fire intensity (flame length) over a landscape that results from converting polygon-based IDU information on surface fuels, canopy fuels, and topography into an ASCII grid with 90-m spatial resolution. It relies on the minimum travel time algorithm, a mathematical model that is the basis for fire growth and behavior calculations in several wildfire modeling applications used in the USA and elsewhere (Finney et al. 2011, Alcasena et al. 2015, Oliveira et al. 2016, Lozano et al. 2017). Additional parameters required by FlamMap are energy release component (ERC), wind speed, wind direction, and fuel moisture of live and dead fuels. ERC is an index and component of the National Fire Danger Rating System (Bradshaw et al. 1983) and calculated based on the multi-day moisture of live and dead fuels. ERC relates to potential fire severity and is a good predictor of area burned (Preisler et al. 2008).

The wildfire submodel runs in both dynamic and static settings (Appendix S2: Fig. S1). Static runs calculate potential flame length under fixed

weather conditions for every burnable pixel in the gridded landscape. Dynamic runs simulate the growth and intensity of individual fire events covering one or multiple fire seasons. Individual fire events and associated information needed to run the wildfire model were compiled in firelists that are derived from the Fire Generator.

Fire Generator

The Fire Generator is a collection of mathematical models developed to predict ignition probability, ignition location, and expected fire size based on historical fires in the study area (Appendix S2: Fig. S2). The model has been thoroughly described in Ager et al. (2017a, b), and A. Ager et al. (*unpublished manuscript*), and we provide a brief description here, emphasizing the adaptations implemented to model restoration fire. Model development used information on location, day of year, cause, fire size, and ERC associated with historical ignitions (1992–2009) that generated fires larger than 10 ha (Short 2014). These account for 2% of historical ignitions but 90% of the burned area in the study area.

The Fire Generator uses a stream of synthetic daily ERC values to generate firelists that are used in dynamic runs by the wildfire submodel. Synthetic ERC streams replicate the historical inter-annual variability in ERC for the study area and were generated by an autoregressive model based on historical daily ERC (1961–2011) from the Lava Butte Remote Automated Weather Station (RAWS; Fig. 1A). Daily ERC streams are read by the Fire Generator to generate firelists as follows. First, we modeled ignition probability as a binary function of location, ERC, and day of year. Second, when ignition probability = 1, we estimated the probability of said ignition generating a fire ≥ 10 ha based on location and ERC. Ignitions with predicted fire size ≥ 10 were compiled in a firelist and expected fire size calculated as a function of ERC.

In addition to year, day of year, ERC, location, and expected fire size, firelists also include wind speed, azimuth, fuel moisture, and burn period for each ignition record. For each ERC value, we sampled wind data from the historical distribution of wind gusts on days when area burned was > 500 ha. We calculated fuel moisture for each combination of fuel model and ERC as an average over historical values. Burn period (in

minutes) corresponds to the simulation time for each ignition, and it relates non-linearly with simulated fire size. Burn period was estimated through a calibration process by which all ignitions were simulated in Envision at initial conditions (first simulation year), and the resulting fire size was compared with the fire size estimated by the Fire Generator. Final burn period was obtained by adjusting the original burn period proportionally to the difference between fire size obtained with Envision and expected fire size predicted by the Fire Generator.

Fire Generator adaptations to simulate restoration wildfire

To simulate the proposed restoration strategy, we adapted the Fire Generator to include all ignitions in the historical record, that is, including ignitions that generated fires < 10 ha and were previously excluded (Appendix S2: Fig. S2). Our objective was to capture the frequency, location, and seasonality of ignitions that were likely to have occurred under weather conditions that facilitated suppression and constitute potential candidates for restoration wildfire. We further restricted the number of potential restoration ignitions based on cause, location, and ERC. Specifically, we excluded all human-caused ignitions, ignitions starting on days when ERC is > 60 , ignitions outside the DNF or inside the DNF but within the DNF full suppression zone (Fig. 1B). The DNF's full suppression zone was defined based on information from managers and includes the area where all ignitions were considered high-risk, in addition to a 2-km protection buffer surrounding WUI, isolated dwellings, and private land-tenures (Fig. 1B).

Because historical records of restoration fires were not sufficient to generate a baseline of fire size, we relied on information from fire and forest managers to set maximum fire size for any restoration fire at 20,000 ha. Note that maximum fire size is an estimate based on initial conditions. Final fire size for any ignition depends on the spatiotemporal interactions between fires, treatments, and succession at the time step the ignition is simulated. Also, we intended to simulate the occurrence and spread of restoration fires under mild weather conditions to (1) approximate the conditions under which fire managers are more likely to manage fires for ecological benefit, and (2)

minimize the likelihood of severe fire effects. In other words, we restricted restoration fires only to ignite and spread on days when ERC was <60 . This constraint was implemented by estimating burn period for restoration fires based on the number of consecutive days with low ERC, using the synthetic daily ERC stream used to generate firelists. For each restoration ignition, we calculated burn period by adding eight hours for each post-ignition day where ERC was <60 , up to a maximum of 5000 min. The maximum burn period limit was set to guarantee that restoration wildfires did not grow larger than the imposed maximum fire size (20,000 ha) and stayed contained within the restoration area (Fig. 1B). For high-risk ignitions, we sampled wind speed from a gust wind distribution, which was not adequate to model conditions under which restoration fires occur. For the latter, we randomly sampled wind speed from values ranging 1–16 km/h based on information provided by fire managers.

Wildfire effects submodel

The wildfire effects submodel classifies fire severity at the IDU level and simulates changes to the IDU state, surface, and canopy fuels (Appendix S2: Fig. S3). Outputs from dynamic fire runs include fire perimeters for each ignition and flame lengths associated with burned IDUs. An IDU is classified as burned when a fire perimeter overlaps $>50\%$ of its area. The wildfire effects submodel uses flame length for each burned IDU in combination with the IDU's pre-fire state, to classify fire severity in one out of three severity classes based on expected tree mortality: surface fire, mixed-severity fire, and stand-replacing fire. We used the FVS-Fire and Fuels Extension (FFE; Reinhardt and Crookston 2003) to calculate flame length thresholds above which a given structural state would have $\leq 20\%$ (surface fire), 20–80% (mixed-severity), and $>80\%$ (stand-replacing) tree mortality. The wildfire effects submodel then cross-references modeled flame length with the pre-fire state thresholds and assigns a fire severity class to burned IDUs.

The extent to which wildfire affects an IDU depends on the IDU's pre-fire state and fire severity. For example, stand-replacing fire will modify multiple structure attributes (e.g., canopy cover, number of layers), leading to a new post-disturbance state. Mixed-severity fires can alter

an IDU's vegetation structure, and surface fires rarely do so. The fire effects submodel also updates the fuel model in burned IDUs. If the fire triggered a transition to a new state, the IDU would be assigned the fuel model of the new state. Otherwise, changes in fuel model will follow the rules shown in Appendix S1: Table S3. Fuel model returns to the pre-disturbance fuel model 10 yr after wildfire or until a new transition is triggered. At the end of each time step, fuel models and vegetation states (if a transition was triggered) are updated for all burned IDUs, and the information is carried over to the management submodel.

Management submodel

In Envision, forest management was implemented through a submodel that selects IDUs for treatment based on a set of user-defined treatment allocation rules that include constraints, preferences, and annual area targets, specific to each management activity and ownership. Currently, Envision can simulate mechanical thinning, prescribed fire, mowing and grinding, clear-cutting, and multiple levels of harvest intensity. In the DNF, treatment allocation criteria (constraints and preferences) followed the current management practices and were based on the Land and Resource Management plan (USDA Forest Service 1990) and interviews with local managers (Spies et al. 2017). In each time step, the management submodel selected potential IDUs for treatment based on constraints that define the ecological and operational conditions associated with each treatment activity (Appendix S2: Table S1). The selected IDUs were ranked based on user-defined weighted preferences that prioritize units for treatment (Appendix S2: Table S1). Treatments were applied to higher-ranking IDUs until annual area treated reached a predefined target, or until there was no additional IDUs that matched the treatment constraints. Similar to wildfire, changes in the IDU state and fuel model depend on management intensity and the IDU's pre-management state. Actions that alter size class, canopy cover, and layering trigger a transition to a new post-management vegetation state. All management actions alter the IDU fuel model, even if no change in state is triggered, and last for five years after which the fuel model returns to the pre-treatment model.

Scenarios

We used Envision to model two alternative wildfire management scenarios: a high-risk wildfire scenario (high-risk) and a restoration wildfire scenario (restoration). In the high-risk scenario, we only simulated high-risk wildfires. In the restoration scenario, we simulated the use of restoration wildfire while maintaining the same high-risk fires that characterize a typical fire season. Therefore, firelists for the restoration scenario include the same high-risk ignitions as in high-risk, plus one restoration wildfire per year. Each restoration wildfire can potentially burn up to 20,000 ha/yr of the DNF, a significant increase relative to historical data showing that on all the national forests of the Pacific Northwest, the area burned by managed fire was 3542 ha/yr between 2002 and 2007 (NIFC 2011).

In real landscapes, each fire event can be simultaneously high-risk and restoration; that is, different parts of the fire can be managed for different objectives, and these can vary throughout a fire event. However, for this simulation exercise, we categorized each fire event in the restoration scenario as high-risk or restoration wildfire in its entirety. This simplification is acceptable because the objective is to increase area burned by restoration wildfire regardless of whether it is derived from a single event assumed entirely as restoration wildfire (as simulated in our study)

or multiple fire events managed with multiple management strategies (as in real landscapes).

We ran the wildfire submodel in the dynamic setting using 15 firelists that enable alternative realizations of fire scenarios. Each firelist consisted of 50 yr and was created based on an alternative synthetic ERC stream and thus has a unique set of ignitions and associated information—location, day of year, ERC, wind speed, and direction. To assess yearly landscape-scale potential flame length that resulted from the simulations, we also ran the wildfire submodel for each year in the static setting and assumed ERC = 60, wind speed = 29 km/h, and azimuth = 220°. Forest and fuel management had the same allocation rules and annual rates of treatment for both scenarios (Appendix S2: Table S1). Yearly treatment targets in the DNF were defined based on information from managers and corresponded to an overall target of 8500 ha/yr distributed as follows: 50% thinning, 30% mowing and grinding, and 20% as prescribed fire.

Evaluative metrics

We used Envision to evaluate the outcome of the high-risk and restoration scenarios according to the metrics in Table 1, including summaries of the treatment area, individual fire events, and landscape-level metrics of social and ecological effects. We reported area treated per year in each

Table 1. Description of evaluative metrics used to compare restoration and high-risk scenarios including the method of calculation and type of output data used, that is, individual fire events or landscape summaries.

Evaluative metric	Description and unit	Method
Area treated	Total area treated per year (ha)	Average per year over all replicates
Fire size	Area of each fire event (ha)	Average over all individual fire events and replicates
Area burned by severity class	Area burned at different severities (ha)	
High-severity patch size	Frequency of stand-replacing fire patch sizes	
Fire-on-fire interactions	Probability of reburn	
Area burned	Total area burned (ha)	
Area burned by high-risk fires	Area burned by high-risk fires (ha)	
Smoke production	Smoke production† (Mg)	
Habitat	Area of habitat for avian species (ha)	Difference between the restoration and high-risk scenarios per year and over 50 yr
Forest structure/resilient forest	Area of cover-size layering/forest types (ha)	
Area burned by severity/forest type	Area burned by severity class and forest type (ha)	
Potential high-severity	Area of potential fire burning as stand-replacing (ha)	

† In atmospheric particulate matter class of <2.5 µm and referred to as PM2.5.

treatment action (thinning, mastication, and prescribed fire) and compared it to area burned by restoration fire. We hypothesized that because restoration wildfires occur under controlled ERC and wind speed, they would be smaller, less severe, and more fragmented than high-risk fires. Therefore, we compared individual restoration and high-risk fire events using summaries of fire size, total area burned by severity class, and the size distribution of stand-replacing patches. We tested for differences between the size distributions of stand-replacing patches using the Wilcoxon rank sum test ($\alpha = 0.05$) using MatLab R2016b (Mathworks 2016).

To examine the potential to which a fire can limit the growth of future fires, we quantified the number of spatial intersections between fire perimeters (fire-on-fire interactions) within a 10-yr timespan. The 10-yr period was defined based on previous literature suggesting that interactions among reburned areas are limited after 10 yr (Collins et al. 2009, Parks et al. 2015, 2016, Prichard et al. 2017). We used fire-on-fire intersection data to test the hypothesis that the probability of intersection will be higher in restoration than in high-risk because the former has more fires (50 additional fires for each simulation replicate) and more area burned. For each pair of intersecting fires, we recorded the year of each event and used these data to calculate, for each scenario, the probability that an ignition will generate a fire that is intersected by a subsequent fire ($P_{\text{reburn}10}$; Eq. 1):

$$P_{\text{reburn}10} = \frac{\text{Number of ignitions with at least 1 interaction in a 10-yr period}}{\text{Total number of ignitions}} \quad (1)$$

where $P_{\text{reburn}10}$ is the probability that any given ignition generates a fire that will be overlapped at least once in the following 10 yr.

To analyze socio-ecological trade-offs between the two scenarios, we calculated the annual differences between restoration and high-risk scenarios for the following metrics: total area burned, area burned by forest type, area burned exclusively by high-risk fires, smoke production, habitat for avian species, forest structure, forest resilience, and potential for high-severity fire. Annual differences between the two scenarios were calculated using mean values over 15 replicates of the amount of area (ha) associated with each variable

except for smoke, where the response variable was smoke production (Mg). Total area burned described overall area burned by all simulated fires in each scenario, that is, high-risk fires in high-risk and high-risk plus restoration fires in restoration. We also calculate the area burned by high-risk fires only, which quantifies the effect of restoration wildfire in reducing area burned by fires that pose a threat to high-value resources.

We modeled smoke production as a function of area burned at different fire severities and vegetation states. We used FVS-FFE to calculate smoke emissions (kg/ha) for each vegetation state and severity class—surface, mixed, and stand-replacing fire. We modeled only emissions of particulate matter $<2.5 \mu\text{m}$ (hereafter, class PM_{2.5}) which are known for having adverse impacts on human health. Smoke emissions increase with fire severity, that is, for any given vegetation state, stand-replacing fire has greater smoke emission per unit of area burned than a surface fire. Smoke production at the landscape scale (Mg) resulted from multiplying IDU area by the corresponding smoke emission based on fire severity.

We calculated changes over time in the amount of resilient forest, which we defined as moist-mixed conifer, dry-mixed conifer, or ponderosa pine forest types where tree dbh is $>50 \text{ cm}$, and canopy cover is 10–40%, or tree dbh is $\geq 38 \text{ cm}$, and canopy cover is 40–60% in a single layer (Spies et al. 2017). Our resilient forest definition excludes subalpine forest and characteristics of the shrub or surface fuel layers. It is intended to approximate the structure of relatively open dry forests containing mature and old fire-tolerant trees that were maintained by frequent ($<25 \text{ yr}$), low-severity fire in this region (Reilly et al. 2018).

We described the change in nesting and roosting habitat suitability for the northern spotted owl (*Strix occidentalis caurina*, hereafter NSO) based on the habitat model for eastern Oregon described in Spies et al. (2017). We also reported the differences in suitable habitat for the white-headed woodpecker (*Picoides albolarvatus*), the western bluebird (*Sialia mexicana*), the black-backed woodpecker (*Picoides arcticus*), the pileated woodpecker (*Hylatomus pileatus*), and the northern goshawk (*Accipiter gentilis*) based on wildlife models developed by Morzillo et al. (2014) and described by Spies et al. (2017). All of

the abovementioned species have different habitat needs and are described as species of conservation concern by management agencies or stakeholders in this region (Spies et al. 2017).

To detect changes in forest structure, we quantified differences in the area of subalpine, moist-mixed conifer, dry-mixed conifer, and ponderosa pine forest types in the following structure classes: meadows/shrublands, seedling/sapling, medium-closed, medium-open, large-giant-closed, and large-giant-open. Structure classes were defined based on canopy cover, size, and layering classes (Appendix S3: Table S1) and developed through an expert opinion process involving federal agency ecologists and other experts (Spies et al. 2017). We also quantified differences in area burned by severity class in each of the abovementioned vegetation types. Finally, we used outputs from static wildfire runs to calculate differences in potential area burned by stand-replacing fire for different forest types. The latter describes overall landscape susceptibility to high-severity fire.

RESULTS

Mechanical treatments and prescribed fire were implemented at consistent levels over the 50-yr simulation period (Appendix S4: Fig. S1). Treatment levels included approximately 4250 ha/yr of mechanical thinning, 2550 ha/yr of masticated areas, and 1750 ha/yr of prescribed fire. Both restoration and high-risk scenarios had the same amount of area treated per year but a different

spatial allocation of treated areas. For example, in some simulation years IDUs that were selected for thinning under high-risk where not available for thinning under the restoration scenario because restoration fires had burned them in previous years.

Average fire size of high-risk fires was 793 and 783 ha in the high-risk and restoration scenarios, respectively. The average and median restoration wildfire size was 2267 and 1392 ha, respectively. However, there was high variability in fire size of restoration wildfire among years and simulation runs. In some simulation years, fires were as small as two ha when the ignition fell in a recently treated area, or when ERC and wind speed were low. The most extensive restoration wildfire was 16,282 ha and approximately four times smaller than the largest high-risk fire that burned entirely within the DNF (61,195 ha). The area burned by high-risk fires was 8154 and 8046 ha/yr under the high-risk and restoration scenarios, respectively. On an annual percentage basis relative to the DNF's area, restoration wildfires burned 0.3% of the DNF, while high-risk fires burned 1.08% and 1.06% under high-risk and restoration scenarios, respectively.

As expected, when compared to high-risk fires, restoration wildfires burned with less severity than high-risk fires. Only 8% of the area burned by restoration fire was by stand-replacing fire, and this corresponded to almost three times less than the area burned as stand-replacing in high-risk fires (Fig. 3A). The size distribution of

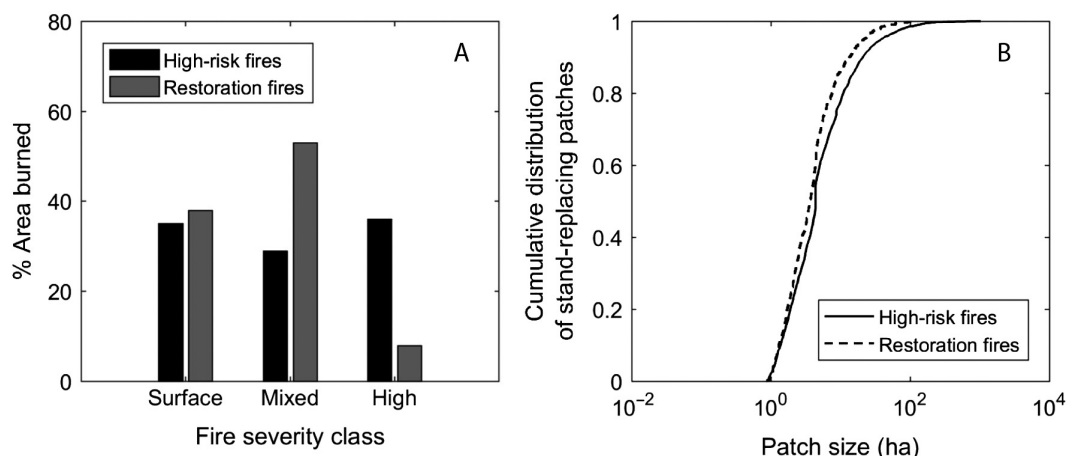


Fig. 3. Percentage of total area burned by fire severity class (A) and cumulative distribution of the proportion of high-severity patches (B) in high-risk (solid line) and restoration wildfires (dashed line).

stand-replacing fire patches (Fig. 3B) in forested areas was significantly different between the two types of fire, with restoration wildfires presenting smaller patches ($Z = 5.6$, $P < 0.001$). Average patch size was 6.25 and 11.59 ha for restoration and high-risk fires, respectively. The majority of ignitions (75%) were not intersected by any fire in the 10-yr period following ignition ($P_{\text{reburn}10} = 0.25$ for both scenarios).

Changes over time in landscape-level evaluative metrics

The restoration scenario had more fires and more area burned (1840 ha/yr, or a 23% increase) than the high-risk scenario. Most of the additional area burned was mixed-severity and surface fire (Fig. 4A). The effect of restoration wildfires on high-risk fires was small (Fig. 4B, black line), albeit more likely in years with more fire activity (Fig. 4B, red line). On average, high-

risk fires under the restoration scenario burned 55 ha/yr less than under the high-risk scenario. The maximum area burned reduction in a high-risk fire due to single, localized interaction with restoration fire was 30,855 ha.

Under the restoration scenario, resilient forest structure in fire-frequent forest types increased at an average of 1715 ha/yr up to simulation year 40 after which it declined sharply (Fig. 4C). There was an increase in smoke production of ~400 Mg/yr with restoration, with substantial variability among years and runs (Fig. 4D). This increase corresponded to a doubling of the smoke production in the high-risk scenario and was driven by years when smoke production from high-risk fires was low resulting in a substantial relative increase when restoration fires were simulated.

Habitat for the NSO was reduced an average of 2757 ha/yr for the restoration scenario (Fig. 5A).

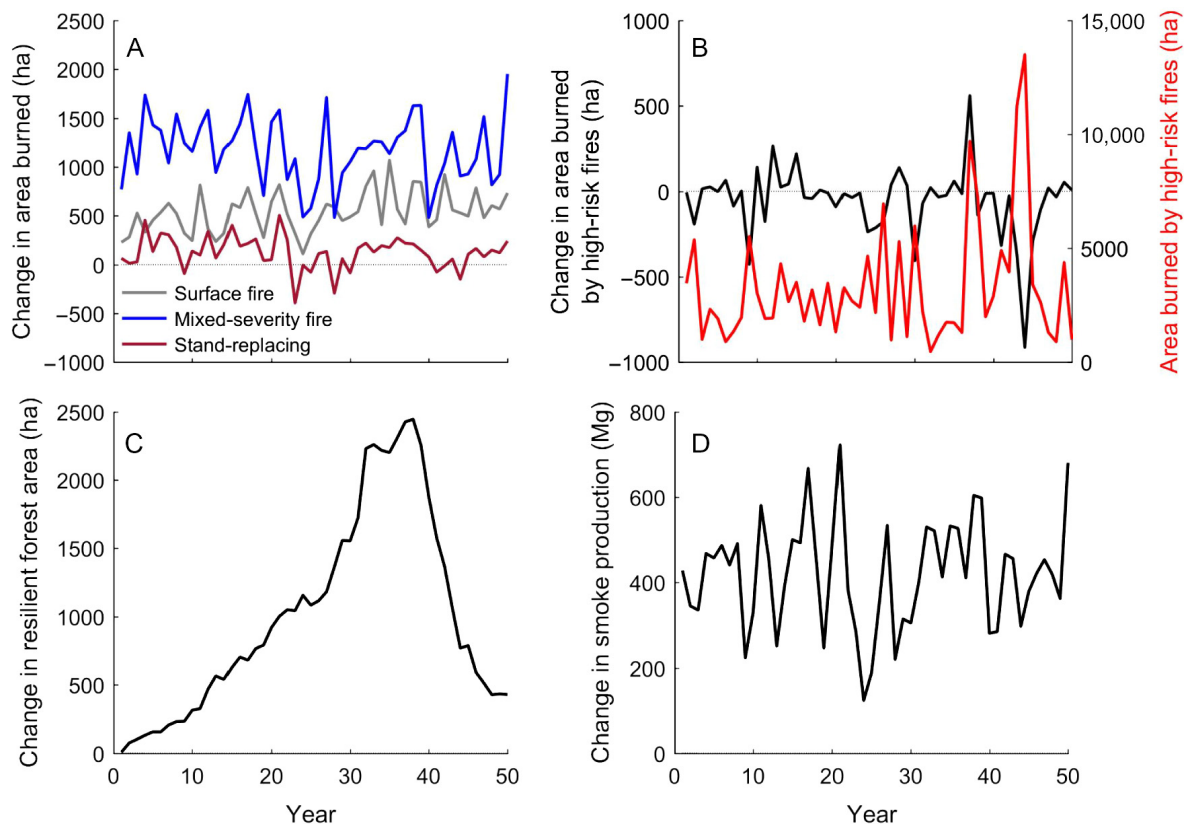


Fig. 4. Change (restoration–high-risk) in total area burned (high-risk + restoration wildfires) by severity class (A), area burned by high-risk fires (B, black line), area of resilient forest (C), and smoke production (D). Red line in panel B corresponds to total area burned by high-risk fires.

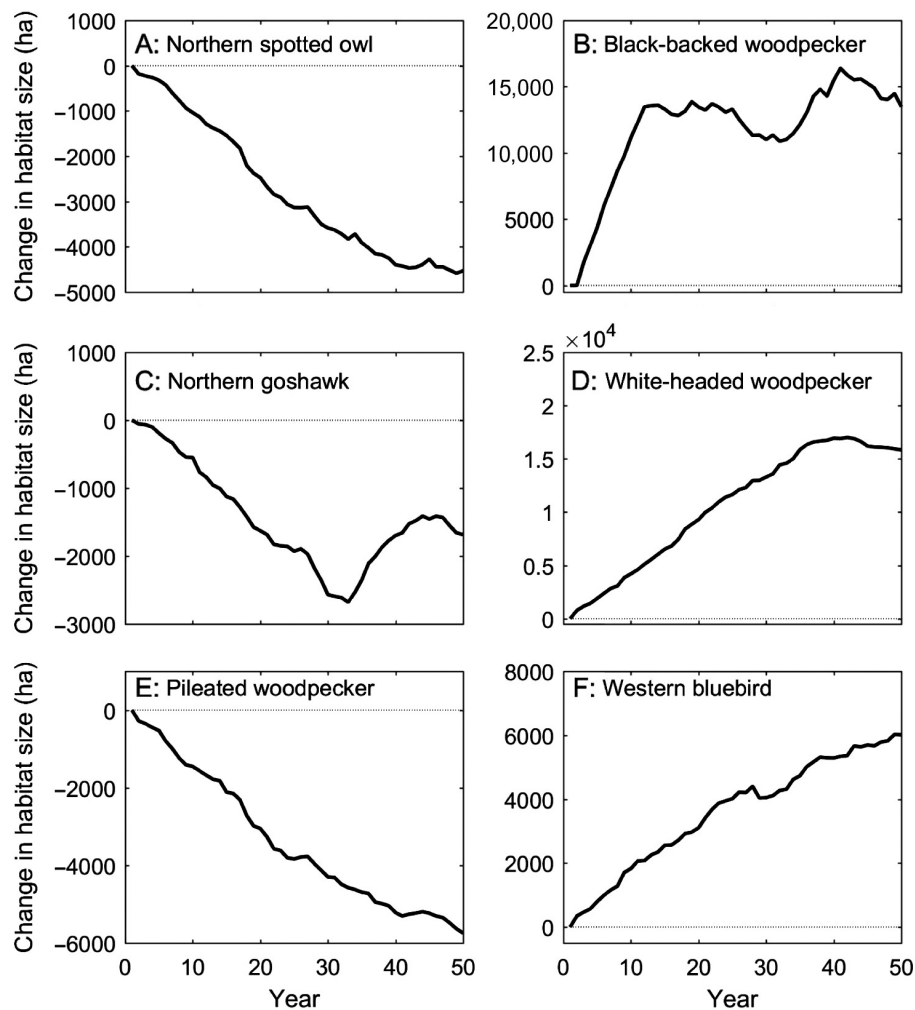


Fig. 5. Change in area of suitable habitat between the restoration and high-risk wildfire scenarios for selected avian species: northern spotted owl (A), black-backed woodpecker (B), northern goshawk (C), white-headed woodpecker (D), pileated woodpecker (E), and the western bluebird (F).

A decline in NSO habitat was not surprising considering that the species' habitat preference is for mature and late-successional stands of mixed conifer types, all of which were impacted by partial stand-replacement fires as modeled here. The restoration scenario led to an increase in habitat for avian species that use open forest stands or recently burned areas. Habitat for the black-backed woodpecker (Fig. 5B), white-headed woodpecker (Fig. 5D), and the western bluebird (Fig. 5F) increased—an average of 1175, 3594, and 1057 ha/yr, respectively. Habitat for the pileated woodpecker showed a steady decline of 3381 ha/yr over the course of 50 yr (Fig. 5E), while habitat

for the northern goshawk was negatively affected during the first three decades, after which it slowly started to recover (Fig. 5C).

The dry-mixed conifer forest type had the highest increase in area burned under the restoration scenario; an additional 781 ha/yr burned relative to the high-risk scenario, and mostly as mixed-severity fire (Fig. 6A). The effect of additional restoration wildfire was reflected in forest structure as shown by the increase in medium-open and giant-large-open dry-mixed conifer stands (Fig. 7D, F). This increase in open conditions was steady up to year 40, after which we observed a reduction particularly pronounced in the large-

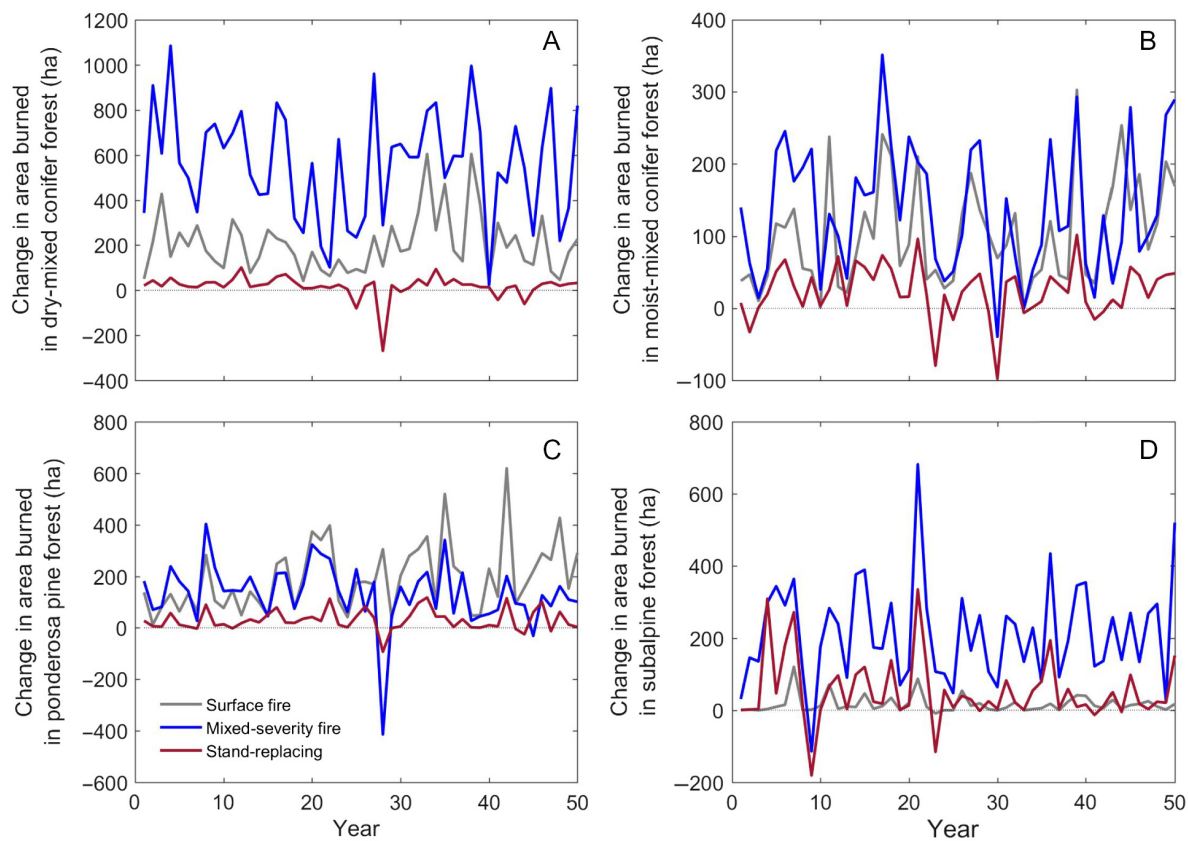


Fig. 6. Change (restoration–high-risk) in area burned by severity class in dry-mixed conifer (A), moist-mixed conifer (B), ponderosa pine (C), and subalpine forest (D).

giant class, and by year 50, there was no distinguishable difference between the two scenarios (Fig. 7F). Changes in area burned of moist-mixed conifer forest followed the same dynamic as in the dry-mixed conifer type although to a lesser extent; an additional 362 ha/yr burned relative to the high-risk scenario (Fig. 6B). Variation in the area of meadows and shrublands for both dry and moist-mixed conifer forest (Fig. 7A) resulted from stand-replacing fire in addition to mixed-severity fire in the pole, and small size classes (not shown) that trigger stands to transition into this early successional stage.

Ponderosa pine forest burned on average 356 ha/yr more in the restoration scenario than in high-risk, and mostly as surface and mixed-severity fire (Fig. 6C). In ponderosa pine stands, there was an increase in the area of medium-open stands (Fig. 7D), at the expense of medium-closed stands burning as mixed-severity (Fig. 6C). There

was also a reduction in large-giant-open ponderosa pine stands (Fig. 7F), concurrent with an increase in meadows (Fig. 7A), in response to the occasional stand-replacing fire in this forest type (Fig. 6C). Results showed no difference in the area of large-giant-closed ponderosa pine stands between the two scenarios (Fig. 7E).

Under the restoration scenario, there was an additional 282 ha/yr burned in subalpine forest, 75% of which burned as mixed-severity fire (Fig. 6D). Similar to other forest types, mixed-severity fire in subalpine forest led to an opening of the canopy in stands where size class was medium or large-giant (Fig. 7D, F). Only a small proportion of restoration wildfire (18%) burned as stand-replacing fire in the subalpine forest, which increased meadows and shrublands of that forest type (Fig. 7A).

Compared to the high-risk scenario, landscape-scale potential for high-severity fire under

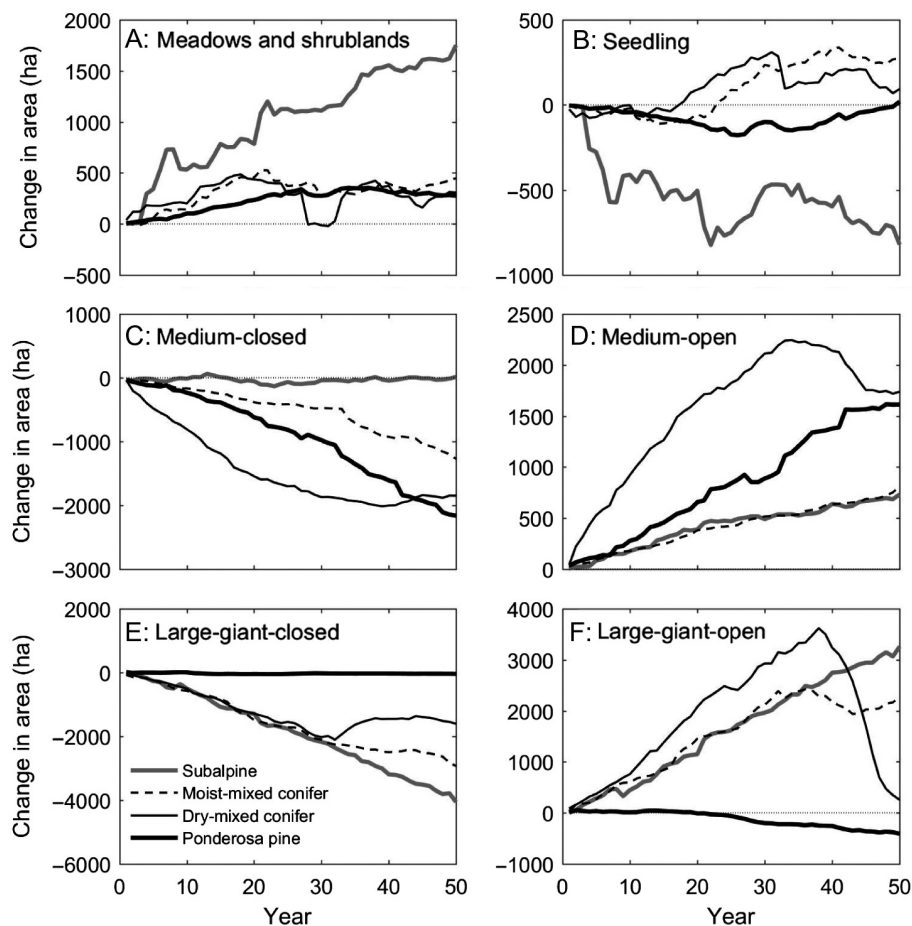


Fig. 7. Change (restoration–high-risk) in area of alternative forest structure classes: meadows-shrublands (A), seedling (B), medium-closed (C), medium-open (D), large-giant-closed (E), and large-giant-open (F), for different forest types. See Appendix S3: Table S1 for description of forest structure classes regarding size, canopy cover, and number of canopy layers.

the restoration scenario declined over time for all forest types but with different orders of magnitude (Fig. 8). Dry-mixed conifer and moist-mixed conifer showed the greatest reduction in potential area burned as high-severity fire—with reductions of 3363 and 2540 ha/yr, respectively. Ponderosa pine and subalpine forest showed the least reduction in potential high-severity fire, 554, and 946 ha/yr, respectively.

DISCUSSION

Our study suggests that restoration wildfire can decrease the potential for high-severity fire and increase the amount of resilient forest structure and habitat for species that benefit from

burned forest. However, a significant increase in restoration fire compared to what we modeled is needed to curb the current trend in fire activity at the landscape scale. In this study area, fire interactions remained rare and opportunities to increase levels of restoration fire may be limited by the lack of suitable ignitions and smoke concerns. The restoration scenario had little effect on high-risk fire size, and trade-offs associated with the restoration strategy were evident, such as increased smoke production, and habitat loss for species that favor dense, closed-canopy forests.

We modeled one restoration fire per simulation year corresponding to an average fire size of 2267 ha or 0.3% of the DNF burned per year. We selected one out of an average of five ignitions

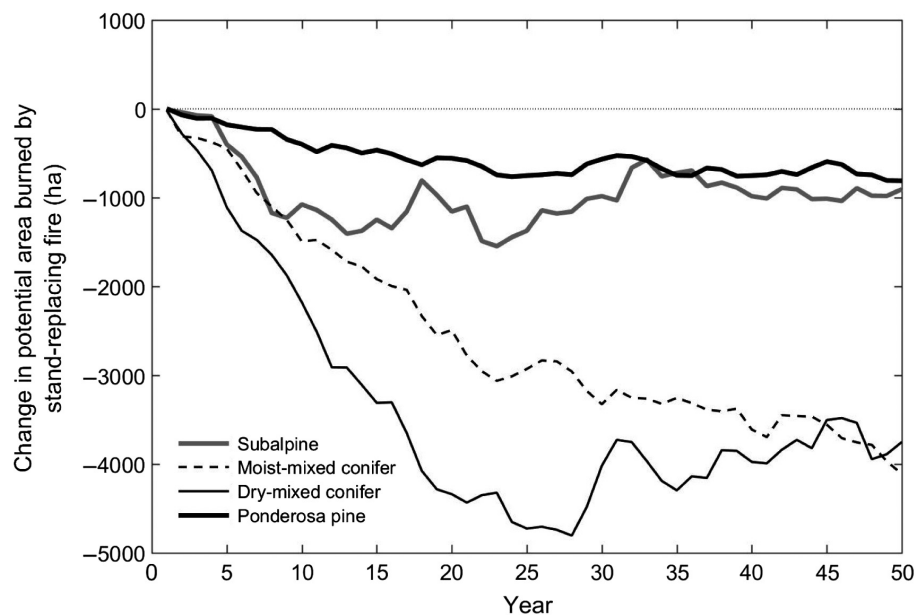


Fig. 8. Change in potential area burned by high-severity fire between scenarios (restoration–high-risk) for different forest types. Potential area burned by high-severity fire is a measure of overall landscape susceptibility to stand-replacing fire and calculated using static wildfire runs.

that met our criteria for restoration fire, suggesting that this landscape offers a potential fivefold increase in the number of restoration fires. However, the increase in area burned per fire would likely be lower because restoration ignitions are geographically limited, meaning that an increase by fivefold would lead to restoration fire returning to the same areas and potential negative fire feedbacks. From the simulations, we can identify four key findings that are potentially relevant for restoration wildfire policy on national forests. First, while the average reduction in area burned by high-severity fires under the restoration scenario was only minor, it was more likely in years with higher fire activity. Second, restoration wildfire reduced the potential for high-severity fire over the entire study area and increased resilience (as defined by forest structure) within a diversity of vegetation types by lowering crown fuels and creating patches of early successional forest. Third, increasing levels of restoration wildfire doubled smoke production over current levels. Fourth, restoration wildfire created different structural conditions in different forest types that reduced habitat for some wildlife species of concern but increased habitat for others.

Fire-on-fire interactions reduce area burned of high-risk fires by two mechanisms: (1) Ignitions occur in areas previously burned by restoration wildfire and do not spread, and (2) fires ignite outside the burned area and encounter a fire footprint with reduced fuels and spread rates. While we observed both mechanisms in our simulations, the frequency of interactions as was low and the same for both scenarios ($P_{\text{reburn10}} = 0.25$). Localized fire-on-fire interactions reduced area burned by high-risk fire under the restoration scenario by an average of 55 ha/yr, with the effects more likely in years with higher fire activity as observed in other studies (Syphard et al. 2011a,b, Loudermilk et al. 2014, Parks et al. 2015). Thus, under future fire scenarios characterized by more ignitions fire-on-fire interactions are expected to increase (Mann et al. 2016, Parisien et al. 2016).

In addition to direct fire-on-fire feedbacks, reduction in area burned by high-risk fire resulted from differences in the spatial distribution of treated areas between the two scenarios. Differences in spatial treatment allocation resulted in instances where high-risk fires under the restoration scenario started in recently

treated areas and became smaller than the corresponding ignition in the high-risk scenario. In the absence of restoration fires, both scenarios would have the same stands treated in each simulation year because both scenarios shared the constraints and priorities determining which areas to treat. However, under the restoration scenario, additional areas burned by restoration fire were excluded from management for 10 yr following fire, forcing the management sub-model to allocate fuel treatments in alternative stands that meet the treatment criteria. Because there is a surplus of areas to treat relative to the simulated treatment targets, this affects the spatial location and grain of treatment patches but not the amount of area treated, which was the same for both scenarios. However, under expanded levels of restoration fire, it is likely that fire and fuel treatments would compete for the same stands.

Our simulations indicated that restoration wildfire could change dry pine and mixed conifer forests to more resilient structural conditions by using low and mixed fire severity to reduce canopy fuels. These forest types exhibited cumulative, steady long-term trends, suggesting that these ecological benefits accrue and persist in contrast to the episodic nature of adverse outcomes such as smoke production. The increase in medium-sized open-canopy stands under the restoration scenario showed that the simulated restoration wildfire removed small, shade tolerant conifers like Douglas-fir and true firs (*Abies* spp.). Under natural conditions, fire-caused mortality of shade tolerant species reduces competition for resources and increases the vigor of large fire-resistant pines. It is important to note that even surface fire can cause mortality of large, old pines for a variety of reasons, including increased litter depth around the base of the trees resulting from litter accumulation after decades of fire exclusion (Agee 1993, Kolb et al. 2007). Because our state-and-transition model did not include mortality rates at the individual tree level, we may be overestimating the beneficial effects of fire on forests with older pine trees. However, open pine forests containing large diameter and tall, thick-barked fire-resistant trees that are maintained by low-severity fire are more resilient to fire, than pine forests with smaller trees and dense understories where surface and ladder

fuels have accumulated (Allen et al. 2002, Agee and Skinner 2005).

Under the restoration scenario, the area of large-giant-open dry-mixed conifer forest increased for the first four decades and declined afterward resulting in similar levels between the two scenarios around simulation year 50. In other words, around simulation year 50, the relative difference in the area of large-giant-open dry-mixed conifer between the two scenarios became negligible. This was likely due to the increase in area burned under the high-risk scenario concurrent with a decrease in area burned under the restoration scenario around the same time. The reduction in the relative difference between the two scenarios highlights that ignitions classified as high-risk can also help meet restoration goals in dry-forest, for example, open stands with large trees (Reilly et al. 2018). However, because of their location, cause, or weather conditions under which they occur, its risk to high-valued resources outweighs its potential restorative value.

The restoration scenario reduced the potential for high-severity fire over time for all forest types including subalpine forest. The moister subalpine forest is not included in our definition of resilient forest and is outside the scope of restoration programs. In our simulations, when restoration wildfire burned through subalpine stands, it did so as predominantly mixed-severity fire with small patches of stand-replacing fire. The latter led to transitions to early development stages in the moister subalpine forest that is in agreement with observed changes in forest structure conditions after wildfire for this forest type and this region (Reilly et al. 2018).

On a percentage change basis, with an additional 0.3% of the DNF burned with restoration wildfire (an increase of 23% in total area burned), we found a 10% reduction in potential high-severity fire across all forested vegetation types. In the Sierra Nevada, Stevens et al. (2016) found that when 13% of the landscape was treated with thinning, there was a 13–44% reduction in landscape vulnerability to high-severity fire as a function of treatment type, location, and amount of area treated. In areas with an existing resilient forest structure, restoration wildfire can be used to maintain the open-canopy structure (Huffman et al. 2018), by avoiding understory reinitiation

with shade tolerant species that would render the initial treatments useless (Ager et al. 2007, Naficy et al. 2010). While restoration wildfire requires extensive pre-planning (Seielstad 2014), it provides managers with additional flexibility due to the ability to quickly treat large areas. However, it is not possible to schedule these treatments, and their stochasticity will be a challenge for planning and management. Therefore, efforts to increase the scale and pace of restoration programs and maintain restored forest areas must take into account that levels of accomplished restoration fire are contingent on the frequency of lightning-caused ignitions occurring in the right place and under the right set of fire weather conditions.

One of the adverse outcomes of increased levels of restoration wildfire was smoke production, which on average doubled, despite high inter-annual variability. We report smoke production under the restoration scenario relative to the high-risk scenario, which in many years had very little burned area and thus little smoke production. As modeled in Envision, smoke production constitutes a measure of the expected increase in gross smoke production and does not necessarily reflect smoke impact to communities, which will depend on distance to fire and smoke dispersion patterns. The majority of these simulated fires occurred at a considerable distance from the WUI suggesting that in real landscapes, smoke exposure to populations may be reduced (Schweizer and Cisneros 2014). A more detailed simulation study of smoke dispersion (e.g., using the modeling framework BlueSky; Larkin et al. 2009) throughout fire spread days is required to adequately address concerns about how smoke produced under a restoration scenario would impact communities (McKenzie et al. 2006, Stevens et al. 2016). However, under a different restoration scenario with multiple restoration events burning on multiple national forests in a given region, even in remote areas, could potentially reduce air quality in communities that are distant from the fires.

Potential habitat declined steadily for both the northern goshawk and the NSO with a slight pick up after 30 yr for the northern goshawk due to the recovery of large-giant-closed stands of dry and moist-mixed conifer forest around the same time. This partial recovery of lost habitat

was not observed for the NSO suggesting that it was associated with forest types outside the middle elevation range that constitutes the NSO's preferred habitat conditions. Studies evaluating the response of spotted owls to high-severity fire show a variety of responses from generally positive to neutral or negative depending on the subspecies, type of forest burned, and the parameter evaluated (Ganey et al. 2017). Recent studies have shown that spotted owls may still use home ranges affected by high-severity fire provided that the patches of high-severity are small and within a diverse mosaic of low and moderate fire severity (Lee and Bond 2015, Comfort et al. 2016). This suggests that habitat suitability models based on changes in forest structure post-fire (as in Envision) may provide an incomplete characterization of the species' habitat needs. The steady decline (4000 ha) in vegetation conditions that support the NSO over the course of 50 yr is particularly relevant because its habitat protection is mandated by federal law (Agee and Edmonds 1992). The US Fish and Wildlife Service (USDI Fish Wildlife Service 2012) has recognized that forest ecosystem restoration and providing habitat for the NSO are competing goals in the eastern Cascades indicating that landscape approaches are needed to reconcile conservation conflicts. Protection of NSO's habitat can be addressed with planning efforts that include prioritizing high-risk ignitions near old-growth patches and employing point-protection suppression strategies to minimize exposure of identified habitat.

There are other potential benefits and risks associated with restoration wildfire not addressed in this study. For example, the risk of fires escaping the boundaries of public lands or leading to unexpected losses poses an essential barrier to increased levels of restoration wildfire (Doane et al. 2006). Restoration wildfire could also lead to loss of potential habitat for other species, loss of visual amenity values, cultural resources, timber products, and carbon stocks. Other potential ecological benefits of restoration fire include increased nutrient release and soil productivity, improved watershed condition, and costs avoided by limiting the application of unnecessary chemical retardants and construction of bulldozed firelines (Dale 2006). Ultimately, the decision to implement restoration

wildfire relies on the district fire manager and line officer perceptions of its value, risk profile (whether they are risk-takers or risk-averse), and potential career consequences (Black et al. 2008). Because forest restoration is a multi-generational challenge, decisions made in the present (e.g., to tolerate increased smoke production) require an understanding of the future benefits (e.g., healthier, more resilient forests) against the current and future costs. This highlights a scale mismatch (Cumming et al. 2006, Spies et al. 2014) between ecosystem feedbacks and social feedbacks, where short-term social costs are heavily weighted compared to long-term ecological and biophysical benefits, which may be less visible or valued. Both managers and the public perceive this mismatch and addressing it may be facilitated with agent-based landscape models that provide information on the complex interactions in coupled natural-human systems that we cannot easily parse and identify the biophysical barriers and socio-ecological trade-offs to restoration wildfire. In the long run, these tools can be used to build political, public support, and individual commitment to wildfire restoration programs.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online at: <http://onlinelibrary.wiley.com/doi/10.1002/ecs2.2161/full>