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Research, part of a Special Feature on Adaptation in Fire-Prone Landscapes: Interactions of Policies, Management, Wildfire, and Social Networks in Oregon, USA

Using an agent-based model to examine forest management outcomes in a fire-prone landscape in Oregon, USA

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ABSTRACT. Fire-prone landscapes present many challenges for both managers and policy makers in developing adaptive behaviors and institutions. We used a coupled human and natural systems framework and an agent-based landscape model to examine how alternative management scenarios affect fire and ecosystem services metrics in a fire-prone multiownership landscape in the eastern Cascades of Oregon. Our model incorporated existing models of vegetation succession and fire spread and information from original empirical studies of landowner decision making. Our findings indicate that alternative management strategies can have variable effects on landscape outcomes over 50 years for fire, socioeconomic, and ecosystem services metrics. For example, scenarios with federal restoration treatments had slightly less high-severity fire than a scenario without treatment; exposure of homes in the wildland-urban interface to fire was also slightly less with restoration treatments compared to no management. Treatments appeared to be more effective at reducing high-severity fire in years with more fire than in years with less fire. Under the current management scenario, timber production could be maintained for at least 50 years on federal lands. Under an accelerated restoration scenario, timber production fell because of a shortage of areas meeting current stand structure treatment targets. Trade-offs between restoration outcomes (e.g., open forests with large fire-resistant trees) and habitat for species that require dense older forests were evident. For example, the proportional area of nesting habitat for northern spotted owl (*Strix occidentalis*) was somewhat less after 50 years under the restoration scenarios than under no management. However, the amount of resilient older forest structure and habitat for white-headed woodpecker (*Leuconotopicus albolarvatus*) was higher after 50 years under active management. More carbon was stored on this landscape without management than with management, despite the occurrence of high-severity wildfire. Our results and further applications of the model could be used in collaborative settings to facilitate discussion and development of policies and practices for fire-prone landscapes.

Key Words: *adaptation; ecosystem services; landscape; management; wildfire*

INTRODUCTION

Fire-prone landscapes (i.e., fire-dependent forest ecosystems with historically frequent, < 100-yr wildfire) are globally widespread and produce valuable ecosystem services, including wood fiber, fuel, recreation, regulation of carbon emissions, and biodiversity (Noss et al. 2006, Bowman et al. 2009). Coupled human and natural systems (CHANS) in fire-prone landscapes are characterized by complex interactions between fire-dependent natural systems and nearby rural and urban human communities where high-severity wildfire is undesirable. In some parts of the world, such landscapes are characterized as the "wildland-urban interface" (WUI), a transition or contact zone between unpopulated fire-adapted natural vegetation and populated areas having elevated levels of risk for loss of homes and lives to wildfire. The spatial extent of ecological and socioeconomic dynamics of fire-prone landscapes is broader than just the WUI, however, encompassing the full extent of wildlands in which the WUI is embedded (Pyne 2008, Ager et al. 2015). Although many studies of social-ecological interactions in fire-prone ecosystems have focused on the WUI, far fewer have focused on the larger landscape and system, of which the WUI is only one part.

The application of a CHANS approach can help reveal complexities and interactions in social-ecological systems that are not visible when ecological or social systems are studied in isolation or if spatial heterogeneity and temporal lags are not taken into account (Liu et al. 2007). Understanding of fire-frequent CHANS is limited by gaps in knowledge about fundamental social and ecological processes and how they interact, as well as a lack of models that integrate human and natural systems across spatial and temporal scales. Retrospective studies of individual fire events can be quite informative about how fuels management, vegetation, topography, and weather influence fire behavior (e.g., Thompson and Spies 2009), and how people respond to specific fires (McCaffrey et al. 2012). However, it is nearly impossible to evaluate the variability and cumulative effects of fire on landscapes managed under multiple alternative management scenarios or climate regimes without simulation models.

Here, we use an agent-based landscape model to explore how forest vegetation management alternatives and policies affect fire behavior and ecosystem services in a large multiownership fire-prone landscape in the eastern Cascade Mountains of Oregon, USA. Our questions and management issues are similar to those that prevail in many landscapes of the western United States and other countries where natural resource and amenity-based economies and communities are present within a fire-prone,

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multiownership forest landscape, and where the goals of actors include both wildfire protection and forest restoration (Stephens and Ruth 2005, Reinhardt et al. 2008). Historical forest policies (e.g., fire suppression) have had a major effect on forest landscapes and ecosystems (Langston 1995, Stine et al. 2014). One of our goals was to develop tools that could be used to evaluate new policies and potentially avoid future undesirable or unintended outcomes of wildfire management actions.

Although many landscape models linking vegetation dynamics, management activity, climate, and fire behavior have been developed (e.g., Beukema et al. 2003, Chew et al. 2004, Keane et al. 2004, Scheller et al. 2007, O'Connor et al. 2011), relatively few models have been used to evaluate policy scenarios on multiowner landscapes over large scales (see Gustafson et al. 2007, Spies et al. 2007). For instance, most prior efforts to model fire-prone landscapes have lacked adequate representation of human decision making with respect to land management actions. Only recently have landscape models been developed to evaluate the spatial and temporal effects of land management across multiple ownerships on fire and ecosystem services over large areas (e.g., Millington et al. 2008, Scheller et al. 2011, Syphard et al. 2011, Loudermilk et al. 2013, Conlisk et al. 2015).

We used an existing agent-based modeling framework, Envision (Bolte et al. 2006), to link fire behavior, human decision making, and landscape outcomes related to wildfire, forest landscape conditions, and ecosystem services (Spies et al. 2014), and to examine broader social and ecological effects of different federal management strategies across all ownerships. Our main objective was to evaluate how alternative forest management strategies might affect wildfire, vegetation dynamics, human exposure to fire, biodiversity, and ecosystem services across a multiownership landscape. More specifically, we ask: (1) Do current or alternative accelerated restoration scenarios on federal lands, and associated linked changes on private corporate forestlands, reduce the occurrence of high-severity fire and fire hazard across the entire landscape compared with a scenario of no federal management? And (2) What are the social and ecological trade-offs, if any, associated with alternative forest management actions and wildfire? The social and ecological values and perspectives in this landscape are broad and diverse but fall into two main areas: fire protection (homes and forest values and forest restoration; Fischer and Jasny 2017) and ecosystem services, including timber production and wildlife habitat. We evaluated outcomes related to these perspectives, paying particular attention to critical social-ecological issues on federal lands, which dominate the landscape (nearly 40% of forest area). The major goals on federal lands are to protect homes in the WUI, restore fire-resilient forest structures, maintain dense forest habitat (which is sensitive to loss from fire) for the northern spotted owl (*Strix occidentalis;* listed under the U.S. *Endangered Species Act;*), and provide timber to support local communities and forest management infrastructure.

We focus on aggregate effects across all ownerships and plan to explore differences and spatial interactions among ownerships and climate change in subsequent work. Ager and colleagues describe the creation of the fire subcomponent of the model by linking existing fire models to Envision, and then use the model to explore fire feedbacks (Ager, Barros, Day et al. *unpublished manuscript* hereafter Ager et al. *unpublished manuscript*). Barros et al. (2017) examine how fuel treatments on federal lands affect fire size and behavior. Charnley et al. (2017) focus on how adaptation strategies to fire-prone landscapes differ among large landowners (e.g., federal, state, and corporate).

METHODS

Study area

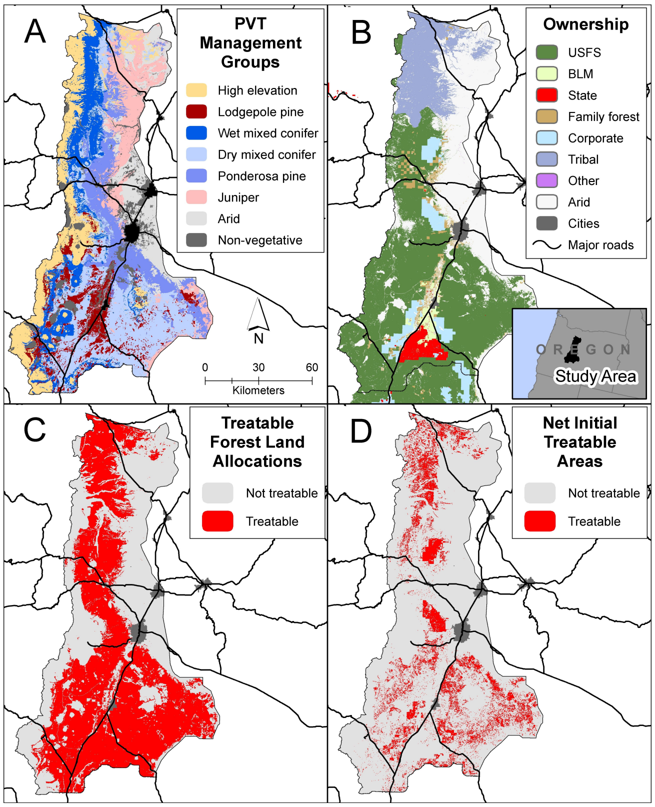
The 12,529-km² study area is characterized by mountainous topography and steep environmental gradients running from cool, wet subalpine mountain forests to moist and dry mixed-conifer and pine forests to semi-arid juniper woodlands that occur on more gently sloping topography at lower elevations (Fig. 1; Appendix 1 and 2). These forest types have different pre-EuroAmerican fire regimes (Agee 1993) and vary in effects of fire exclusion and logging (Merschel et al. 2014). Forest ownership patterns are also heterogeneous but dominated by federal lands. Landowners' management objectives include wilderness experiences, producing timber, and maintaining residential homesteads (Spies et al. 2014). The WUI occupies a relatively small area (9.7%) within the larger region, but receives substantial attention from policy makers and forest managers. Historical land-use activities have left a strong imprint on the vegetation and fire regimes. Euro-American activities, which began in the mid-1880s, included grazing, logging, road building, and disruption of Native American resource use practices (Robbins 1997, Hessburg and Agee 2003). The disruption of Native American cultures would also have reduced fire ignitions, though natural ignitions from lightning are common in this region (Ager et al. *unpublished manuscript*). Studies of existing older pine and mixed-conifer patches indicate that the density of shade-tolerant understory trees (e.g., grand fir [*Abies grandis*]) has increased several fold since 1900, and the presence of large, old shade-intolerant pines has been reduced by as much as 70% as a result of partial cutting for timber (Merschel et al. 2014).

Management issues in the study region include: (1) balancing the potentially competing goals of restoring or managing forests for resilience to fire, protecting structures in the WUI, and meeting goals for producing timber and maintaining or restoring wildlife habitat (Spies et al. 2006); (2) maximizing effectiveness of limited funding for forest restoration and wildfire protection activities; and (3) engaging public land managers with stakeholder collaborative groups to advance the understanding of the need for landscape-scale restoration.

General model description

We follow the "overview, design concepts, and details" (ODD) protocol for describing our agent-based model (Grimm et al. 2010). Our model has two purposes: (1) to advance scientific understanding of the dynamics and interactions of forest management, fire, and vegetation across landscapes characterized by multiple owners; and (2) to contribute to management and collaborative restoration of fire-prone landscapes by serving as a tool for managers and stakeholders to evaluate ecological and social outcomes of different management, policy, and climate scenarios. Other components of the ODD template are described in Appendix 3.

Fig. 1. Maps of the study area in Oregon, USA indicating vegetation and ownership distributions. (A) Potential vegetation types (PVTs). (B) Land ownership. (C) Area subject to management after constraints (physical and land allocation only). (D) Initial (year 1) area subject to management that met vegetation and habitat structure constraints.

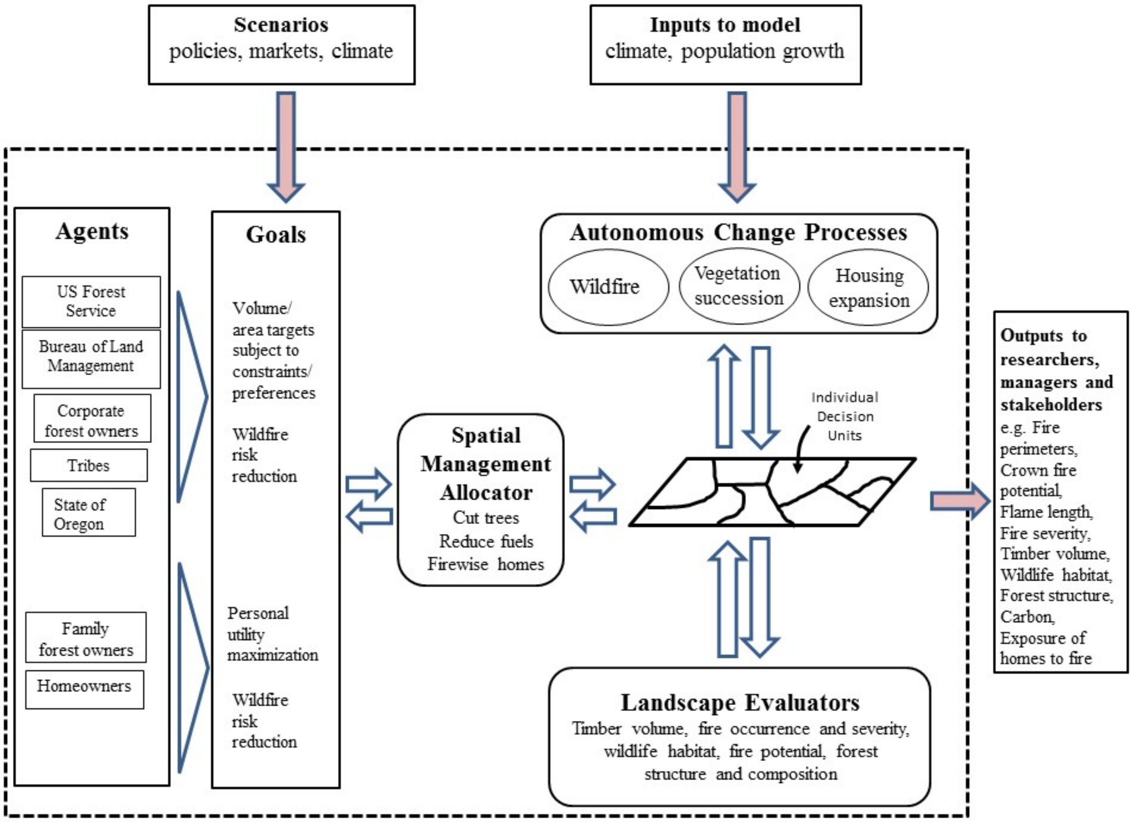


The conceptual model of the CHANS (Spies et al. 2014) was implemented using Envision (Bolte et al. 2006). Envision is a spatially explicit agent-based modeling framework that is able to simulate forest management and wildfire disturbances and changes in vegetation and fuel that, in turn, affect fire behavior, forest succession, and ecosystem services over long time frames (Fig. 2). By integrating models of forest succession, wildfire occurrence and spread, and forest management into a spatially explicit model, we can examine how these process interact over space and time and explore possible trade-offs among ecosystem services. We started with the existing Envision basic structure for actor decisions, forest succession, and wildfire, but modified these to add more management options, successional states, and pathways that are relevant to this forest region, as well as a wildfire submodel (see *Wildfire submodel*) that was customized for the historical ignitions, climate, and wildfire history of this landscape. Agents are the major landowners (see *Management submodel*) who initiate forest management activities (e.g., silviculture, prescribed fire) that affect vegetation and fuel conditions on the landscape delineated by individual decision units (IDUs). Agents are spatially distributed (Fig. 1B) across forested landscape characterized by variability in forest composition and structure (Fig. 1A). They make decisions about forest management (e.g., silviculture and prescribed fire) based on goals (see *Management submodel*). Wildfires are modeled by coupling a semiempirical mechanistic fire spread algorithm with a stochastic fire event simulator representing ignitions and weather. Fires occur and spread with variable behavior based on vegetation, topography, and weather. Changes in the environment (e.g., vegetation structure and composition) create feedbacks that influence human decisions about future management activities and wildfire behavior. For example, if forests grow into new successional stages or are burned by fire, the type and probability of management changes according to empirically developed rules (Appendix 4). Some of the human actors (family forest owners and homeowners) respond to the experience of nearby wildfire by changing their likelihood of conducting certain activities such as thinning and reducing fire hazard at homesites (Olsen 2017; Kline, White, Fischer, et al. *unpublished manuscript* hereafter Kline et al. *unpublished manuscript*). The actions of federal, tribal, and private corporate landowners are based on targets of timber volume produced or area treated, and preferences for certain vegetation types and landscape positions (e.g., distance to roads). Agent actions only affect other agents indirectly through the effect of management on an IDU as it might affect the spread of wildfire across many IDUs and ownerships. We also sought to incorporate the role of social networks in influencing actor decision making (Fischer and Jasny 2017); however, network dynamics are not included in the current model version. External influences such as changing federal policy and economic conditions are modeled as scenarios.

Succession, initial vegetation, and fuels

Vegetation succession was modeled using state-and-transition models that have been developed and applied in the eastern Cascades of Oregon (Hemstrom et al. 2007, Burcsu et al. 2014, Halofsky et al. 2014). Each vegetation state (vegetation class) is a combination of dominant cover type (based on dominant tree or shrub species) and structure stage (based on tree size, canopy cover, number of canopy layers). Vegetation succession and other state changes occur through deterministic and probabilistic transitions that were developed for 39 potential vegetation types (PVTs) from four ecoregions using expert opinion of agency ecologists and, in some cases, calibration with the Forest Vegetation Simulator (Burcsu et al. 2014, Dixon 2015; Appendix 2). PVTs represent environmental conditions that support different late-successional or climax vegetation (e.g., ponderosa pine [*Pinus ponderosa*], grand fir). The states and transitions were applied in a spatially explicit manner to IDUs. Deterministic successional transitions occur when a vegetation state reaches its maximum age. Each vegetation state also has the potential for one of several probabilistic transitions at each time step to introduce alternative successional pathways (e.g., understory development). Some probabilistic transitions must also meet a minimum threshold for time since previous transition or disturbance. For disturbances from fire and forest management, we did not use the probabilistic transitions built into the existing state-and-transition models. Instead, the timing and spread of wildfire was determined stochastically by the fire submodel, whereas forest management, including prescribed fire, was

Fig. 2. Conceptual model of components and interactions of the Envision model for forest landscapes in the eastern Cascades of Oregon, USA. Agents (landowners) have different goals that are implemented through a spatial management allocator that changes the structure of the vegetation on individual management units. The landscape is also affected by autonomous change processes. The landscape is characterized at different points in time by metrics of fire and ecosystem services. See Spies et al. (2014) for more discussion of this conceptual model.



scheduled and distributed based on separate disturbance rule sets. We did not implement the probabilistic transitions for insects and disease described previously (Burcsu et al. 2014) because we did not possess the information needed to model these processes spatially. Moreover, fire-insect interactions are rare in this region (Meigs et al. 2015).

We defined the landscape and vegetation structure of IDUs by the spatial extent of major vegetation classes (averaged over 4 ha), county tax-lot boundaries, and development zone boundaries identified from local land-use planning maps. IDUs < 1 ha were merged into similar adjacent IDUs, and IDUs > 8 ha were broken into a 4-ha grid pattern to allow for fine-scale representation of vegetation conditions likely to affect fire behavior. Initial vegetation conditions were modeled using an imputed spatial vegetation layer called Gradient Nearest Neighbor (GNN; Ohmann et al. 2011) that estimates the structure and composition of the live and dead woody vegetation based on 2006 Thematic Mapper satellite imagery, forest inventory plot data, and environmental data at a resolution of 30 m. Accuracy assessments for vegetation classes in GNN have been conducted for the study area using 4560 plots (http://lemma.forestry.oregonstate.edu/data/structure-maps). Overall accuracy for 11 structure classes at the pixel scale was 55%, and fuzzy accuracy (± 1 class) was 87%. These vegetation layers are not intended to be used for predicting the conditions on individual pixels, and accuracy improves with aggregation to coarser scales even at the scale of a few hectares (Matt Gregory, *personal communication*).

Fuel models (i.e., fuel conditions; Scott and Burgan 2005) were assigned to vegetation states based on a fuel model layer from the Deschutes National Forest (Lauren Miller, *personal communication*) and on Landfire-assigned fuel models (Rollins 2009; http://www.landfire.gov/viewer) for the rest of the study area. Often, multiple fuel models occurred within each IDU or vegetation state, so the majority fuel model was assigned to that state from spatial data layers. Fuel models change with changing vegetation states and disturbance. For disturbances (e.g., surface fire) that affect surface fuels but not the vegetation state or canopy fuels, fuel model variants were developed based on expert opinion (see Barros et al. 2017 for description of fuel models). A new fuel model is assigned after prescribed fire or surface wildfire, mixed-severity fire, high-severity fire, mowing and grinding, or timber harvest. The fuel model variant remains associated with the postdisturbance vegetation state for a set period of time or until the vegetation state transitions to a new state.

Wildfire submodel

We incorporated wildfire into Envision using the minimum travel time fire spread algorithm (Finney 2002) and a wildfire prediction system (Ager et al. *unpublished manuscript*). We initialized this wildfire submodel at the beginning of each Envision run. The spatial input data included fuel model, canopy cover, canopy height, canopy base height, and canopy bulk density. The wildfire submodel then read the fire list to be simulated along with fire-specific simulation parameters (e.g., weather, ignitions) from external files. A different fire list was used for each of the 15 replicates. Fires were simulated within the submodel, and the submodel then returned to the main Envision landscape model a grid of flame lengths, which was used to update the IDU polygons that burned based on vegetation information for each individual polygon (from vegetation class lookup files). The wildfire prediction system forecasted daily fire occurrence, location, and size using empirically derived relationships between energy release component (ERC), a measure of potential fire severity, and historic fires. Thus, the wildfire submodel was stochastic, and its effects emerged from the interactions of fire parameters and vegetation conditions at IDU and landscape scales.

The historical reference period for predicting fire occurrence was 1992–2009, a period characterized by relatively frequent, large fires. The statistical relationships between ERC and fire parameters were determined from 25 remote automatic weather stations (RAWS) in the study area that incorporated a range of historical values and fire sizes. Fire weather and fuel moistures were modeled independently from fire probabilities using data from the Lava Butte RAWS for the years 1987–2011. Wind direction was randomly sampled based on day of year. Wind speed was sampled from a probability distribution of maximum gust speed generated from the same Lava Butte data but restricted to days when fires exceeded 500 ha. Fuel moistures were averaged across historical ERCs by fuel size class (i.e., 1, 10, 100, and 1000 h; woody, herbaceous).

Management submodel

Four actor groups were represented in our model: federal, tribal, corporate (i.e., private industrial), and family (i.e., nonindustrial private; Fig. 1). A fifth actor group representing homeowners who can treat their homesites to reduce fire hazard is also possible (Olsen et al. 2017) but was not included in the analysis described here because those decisions do not affect fire behavior in the model. The effects of homeowner decisions on fire risk will be examined in subsequent work. Oregon State lands, which consist of relatively young forests, were not managed in our scenarios, but succession and wildfire could occur there. Actors can modify forest vegetation by commercial timber harvests, tree thinning for fuels reduction, mechanical surface-fuel treatments, and prescribed fire, all of which can alter forest structure and fuel models (Appendix 4).

Management decisions for family forest owners were based on econometric models derived from surveys collected in the study area (Appendix 5). The decisions of family forest owners to implement fuels treatments are influenced by stand density, experience of wildfire near property, and presence of a structure on the property. The specific type of fuels treatment (e.g., thinning, mowing and grinding, prescribed burning) is determined from a probabilistic distribution of fuels treatments developed from rates identified from surveys of family owners within the study area.

For large landowners (federal, tribal, corporate), decisions were made based on a timber volume or treatment area target. The targets were based on interviews with public and private landowners (Charnley et al. 2017; Kline et al. *unpublished manuscript*). The target approach allows for implementation of actions (e.g., different types of fuels treatments or different types of harvests) that may be subject to a budget constraint or an implementation target. For example, federal managers have a fixed target for timber harvest volume, regardless of whether it comes from salvage logging after wildfire or planned timber harvests. When volume from a salvage harvest after a wildfire is available to federal managers, that salvage volume may be used to meet annual timber targets instead of planned timber harvests. The target approach has four components: (1) the “target” (either timber volume or area treated), (2) “constraints” that determine where on the landscape an action can occur based on biophysical or management criteria, (3) “preferences” that determine which IDUs have the highest likelihood for action during a given year, and (4) an “expand” function that spreads actions from an initial IDU to build logical treatment units that meet historical unit size distributions and constraints (Appendix 6). Examples of constraints include rules that disallow mechanical fuels treatment in Wilderness and designated roadless areas, areas with low canopy cover, or IDUs that had prior treatment within the last 14 years. Examples of preferences include giving more weight to treatment of IDUs in ponderosa pine vegetation types (where federal managers prioritize fuel treatments because of greater probability of fire than in other vegetation types) and near the WUI, and giving less weight to treatment of IDUs in moist mixed-conifer types or with lower basal area. IDUs with low preference scores for an action may still be selected if they meet the constraints and are adjacent to an IDU with a higher preference score. See Appendix 6 for details of targets, constraints, and preferences used in the scenarios.

Evaluative metrics

We developed several evaluative metrics that describe landscape fire characteristics and ecosystem services, including merchantable wood, carbon storage, and other landscape outputs during each time step of the model (Tables 1 and 2). Some of these metrics (e.g., stand structure, fire occurrence, and management activity) act as landscape feedbacks. For example, fire can affect the pattern and amount of timber removal and fuel treatments by actors, and vice versa. Initial and simulated conditions for these metrics are linked to the vegetation states, with some provision for historical effects (e.g., in the case of dead wood and some wildlife species whose habitat is dependent on time since wildfire; Appendix 7 and 8). Evaluative metrics associated with live forest structure (e.g., live-tree basal area, wood volume, carbon, etc.) were estimated with regression models built from forest inventory data for each combination of PVT group (groups of similar PVTs) and vegetation class (Appendix 9). Most

Table 1. Characteristics of evaluative metrics and potential influence on model components.

Evaluative model	Description and units	Method of calculation	Influence in model
Wood production	Volume (m^3/ha) of merchantable timber (diameter > 25 cm)	Regression models from inventory plots applied to structure classes	Total volume produced is the target for large landowner groups and influences pattern and rate of management
Carbon	Mass of live and dead aboveground carbon (Mg)	Regression models from inventory plots applied to structure classes	None: output only
Dwelling density	Number of structures in the wildland-urban interface	From population model calibrated from SILVIS[†]	Defines the wildland-urban interface; influences location of fuel treatments
Fire experience	Number of structures within 1 km of fire events	Fire submodel output and development layer	Influences firewise
Fire occurrence and size	Area of fire at different fire severities (ha)	From fire submodel (dynamic component)	Influences likelihood of family forest fuel treatments and firewise; affects forest structure composition
Fire potential (hazard)	Area of potential fire burning at high severity (ha)	From fire submodel, static (Flammap) component	None: output only
Forest structure, resilient vegetation	Area of cover-size layering and species types (ha)	From state and transition models	Influences where vegetation and fuel treatments occur and fire and actor behavior

[†]Radeloff et al. (2005).

of these combinations were represented by tens to hundreds of inventory plots, although for some, the sample size was > 2000 plots. For the three PVT group–cover-type combinations with inadequate sample sizes (< 15 plots), we used the predictive equation for a comparable cover type. Finally, the density of juniper trees (*Juniperus* spp.) and cover of bitterbrush (*Purshia tridentata*) were estimated from published data for arid lands in the region (Stebleton and Bunting 2009).

Fire-related metrics included burned area (ha), fire hazard (potential; ha) and "resilient structure" (ha; Table 1). Fire occurrence was based on simulated fire spread boundaries in the model. Hazard is potential high-severity fire based on flame-length thresholds and fire submodel outputs that replicate FlamMap (Finney 2006) "static" fire behavior calculations and were performed for weather associated with 97th percentile conditions (ERC = 60, wind azimuth = 220°, wind speed = 29 km/h). Homesites, the number of homes on an IDU, are determined by Envision's development function, which is based on a fixed ratio of population to houses, existing land-use zoning, and population projections developed by the State of Oregon. Resilient forest structure was defined for fire-frequent PVTs as the area of larger trees with open canopies (tree size ≥ 50 cm and canopy cover 10–40%; or tree size ≥ 38 cm, moderate canopy cover of 40–60%, and single canopy layer). This structure was considered resilient to fire effects and representative of the predominant historical structure of fire-frequent forests of the ponderosa pine, dry mixed, and moist mixed-conifer PVTs (Halofsky et al. 2014, Merschel et al. 2014).

Wildlife and plant habitat suitability models were developed using a combination of expert opinion and empirically derived models (Table 2). For most species, we used habitat models developed by Morzillo et al. (2014) for eastern Oregon. That approach relied on scientific literature and expert opinion to assign habitat quality scores to selected forest species based on environment (potential vegetation type) and species, cover, size, and layering of forest structure (Appendix 8 and 10). For the northern spotted owl, we developed a simple habitat suitability model based on vegetation type, canopy cover, and tree size characteristics from central Oregon northern spotted owl occurrence data (Appendix 11). For cheatgrass (*Bromus tectorum*), an invasive species, we used the habitat equations from Lovtang and Riegel (2012).

Model evaluation

Evaluating the performance of simulation models, including agent-based models, can take different forms (e.g., verification and validation) and have different objectives (Rykiel 1996). Many models only become validated over time as different users apply them and gain confidence in them. Our wildfire submodel and vegetation succession models have been tested and evaluated by Ager et al. (*unpublished manuscript*). For example, Ager et al. (*unpublished manuscript*) found that the simulated relationship of ERC and fire size and frequency captured the distribution of the historical data from 1992–2009. Barros et al. (2017) doubled and tripled the rate of management to see how that affected model behavior. They found that that at higher rates of treatment, management targets could not be met because of lack of suitable forests to treat, which makes sense ecologically given the condition of the landscape and the rules we used to identify priorities and preferences for treatment. We evaluated the integration of these models with our management submodels primarily through verification exercises. First, we verified that the integrated model was working as intended through an exhaustive series of debugging tests that examined how well volume and area targets of large landowners were being met under the current management scenario. We found that the model could meet both volume targets and area targets that were identified by managers. However, in the case of volume targets for federal owners, the area required to reach those targets was approximately 25% larger than the area that the managers indicated they harvested to meet their volume targets. This suggests that the factor we use to compute volume removed by thinning from below (20% of stand volume) was conservative. We tested the model to make sure that timber volume production from planned harvest competed with timber volume from salvage following wildfire according to the ownership-specific rules. We examined individual IDUs subject to management and fire events to make sure that transitions in vegetation and fuel model states matched those expected from model logic.

Table 2. Characteristics of habitat and conservation status of species of animals and plants used in the model. See Appendices 8, 10, and 11 for details. Expert opinion models were based on those developed for this region by Morzillo et al. (2014).

Species (model description)	Habitat	Significance
Northern spotted owl (*Strix occidentalis*) nesting and roosting habitat (Appendix 11)	Dense multilayered forests	Federally listed under *Endangered Species Act*
Pacific marten (*Martes caurina;* Appendix 8)	Older closed canopy forests with downed wood	Population is declining
Black-backed woodpecker (*Picoides arcticus;* Appendix 8)	Lodgepole pine (*Pinus contorta*) and ponderosa pine (*Pinus ponderosa*) forests with lots of dead trees, post disturbance stands	Populations are declining
White-headed woodpecker (*Picoides albolarvatus;* Appendix 8)	Open ponderosa pine forests with large trees	Population is declining
Pileated Woodpecker (*Dryocopus pileatus;* Appendix 8)	Older forests with larger dead trees	–
Northern goshawk (*Accipter gentilis*) nesting habitat (Appendix 8)	Older dense forests	Population may be declining
Western bluebird (*Siala mexicana;* Appendix 8)	Open, early successional, postfire forest; agricultural lands; juniper woodlands nest holes in dead trees or nest boxes	–
Mule deer (*Odocoileus hemionus;* Appendix 10)	Wide ranging, early successional and open forests	Socially important game species
Cheatgrass (*Bromus tectorum;* Lovtang and Riegel 2012)	Arid lands, open forests, postfire and logging environments	Invasive species

Comparison of models against independent data is considered the ultimate step in validation, but there are many reasons why this cannot be done (and is often not done) for large, complex, stochastic models (Baker and Mladenoff 1999). Hindcasting can be used, but, in our case, the historical management targets, rules, and treatment types were not the same as those being used today, and historical vegetation and fuel model layers were not available to parameterize a hindcasting model. Some people argue that validation is never possible given the variety of scenarios and extent of time periods (Rykiel 1996). For stochastic spatial models, strict spatial agreement of events or succession with real landscapes should not be expected (Urban et al. 1999, Brown et al. 2005). In these cases, it may be more realistic to compare the distributional statistics of model outputs and those from real landscapes. However, this depends on having spatially or temporally independent data (e.g., harvest unit sizes), which may not be available for a large multiownership landscape. Remote-sensing-based estimates of forest disturbance (management and fire) are available for this area (Kennedy et al. 2010); however, we are unsure how well these spectral change data can be calibrated correctly with different types of management activities (Hall 2015), especially subcanopy activities such as thinning from below, which may not result in major changes in canopy reflectance. Nevertheless, we compared the simulated size distributions of management units by owner to remote sensing for the period 2006–2012 when the model was "spun-up" from initial conditions. The size distributions of remote sensing and simulated management activity patches (thinning from below, heavy partial harvest, clear cutting) were similar for federal lands, which occupy approximately 40% of the forest lands (Appendix 12). For other owners, the sizes of the simulated patches were smaller than those recorded by remote sensing, suggesting that the rules governing management unit size for nonfederal owners need further development. The challenges of model validation with independent data mean that the findings of our study should be viewed with caution and that the focus should be on the relative differences between scenarios, which are less subject to errors in model assumptions and parameterization.

Scenarios

We developed three plausible management scenarios for 50-yr model runs based on discussions with managers, workshops with stakeholders, and information contained in planning and management documents (Table 3). We focused scenarios on changes in federal management that, in turn, would likely change the management actions of corporate owners. The fire simulation and landscape analysis applied to all landowners. Current management is what landowners are doing now. The accelerated federal management scenario ("accelerated management") reflects the desire of policy makers and stakeholders for increasing the pace and scale of treatments on federal lands to reduce high-severity fire hazard (e.g., North et al. 2012). The no federal management scenario ("no management") is plausible if funds or capacity for forest management disappear on federal and corporate lands. A no fire and no federal management scenario ("no disturbance") was used as a theoretical reference against which to evaluate the effects of fire and forest management on ecosystem services. Because our models contained probabilistic elements related to fire, vegetative dynamics, and decision-making processes, we used Envision's capability for Monte-Carlo simulation to make 15 50-yr runs for each scenario to develop probabilistic descriptions of landscape outcomes and performance metrics (all scenarios used the same 15 fire lists; see Barros et al. 2017). The no-disturbance scenario was a single run because most of the stochasticity derives from the fire submodel. Each 50-yr simulation required ~4 h of time on a 32-GB computer system running a quad core i7-6820HQ processor with a 500-GB solid state drive.

RESULTS

Fire occurrence and exposure

The mean annual proportion of the forested landscape burned with high-severity (stand replacing) fire over 50 yr (15 replications) varied from < 0.01 to 1.0%, representing an area of 100–10,000 ha (Fig. 3) across all scenarios. The median annual amount of high-severity fire for all years for fire-frequent

Table 3. Description of scenarios by actor category.

Scenario	Actor: Federal	Corporate	Tribal	Family
Current management (CM)	Current volume targets	Current volume targets	Current volume targets	Current practices for forest management
No federal management (NM)	No active management as a result of policy or budgetary or market forces	Current target for 15 yr, then no management as a result of mill closure due to lack of timber supply from federal lands	Same as CM; not affected by federal management because they have their own mill	Same as CM
Accelerated federal management	Double volume target for first 25 yr, then return to current target	Double volume target for first 25 yr, then return to current target	Same as CM	Same as CM
No fire, no federal management	No fire, same as NM	No fire, same as NM	No fire, same as CM	No fire, same as CM

environments (where most of the federal restoration is targeted) was similar for the three scenarios, although the no-management scenario had a slightly higher median (0.05%) than the other scenarios (Fig. 4A). The maximum annual area burned in any year, across all years and replications (N = 750), was highest for the no-management and lowest for the accelerated-restoration scenarios. Taking into account only the highest 10% of annual area of high-severity fire in a year, accelerated restoration had the lowest median amount (0.5%), and no management had the highest median amount (0.7%) of high-severity fire in a year (Fig. 4B).

Fig. 3. Mean annual area (%) of high-severity fire for current management, no federal treatment, and accelerated restoration scenarios over time across all forested potential vegetation types and ownerships. Broken lines indicate corresponding 95% confidence intervals; based on 15 replicates.

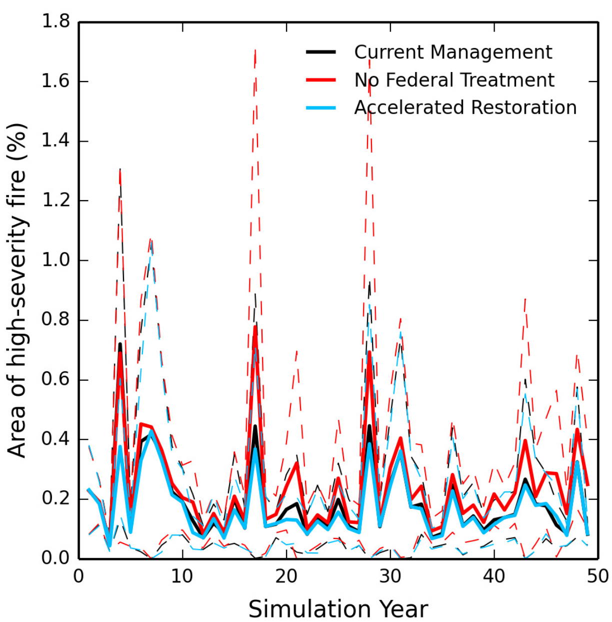
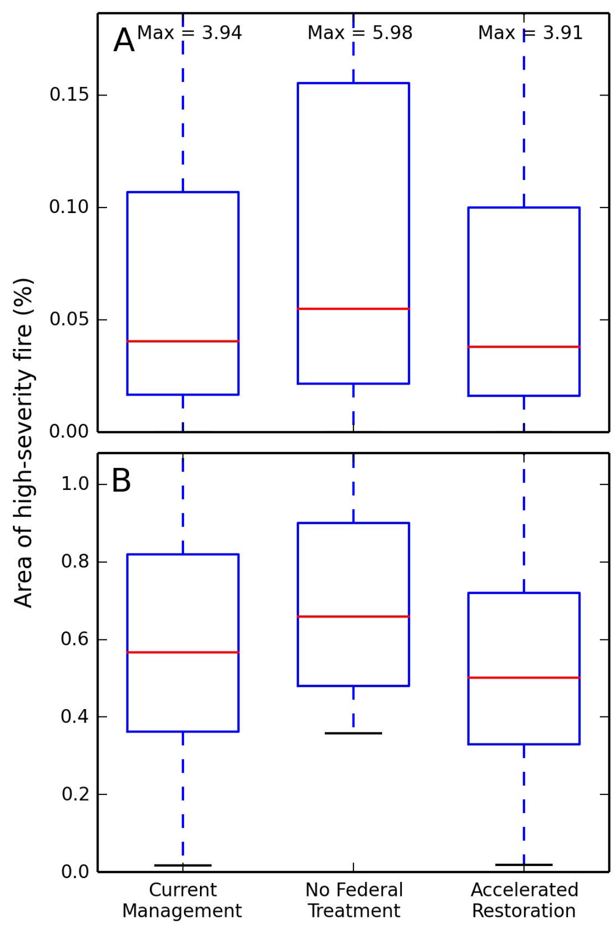
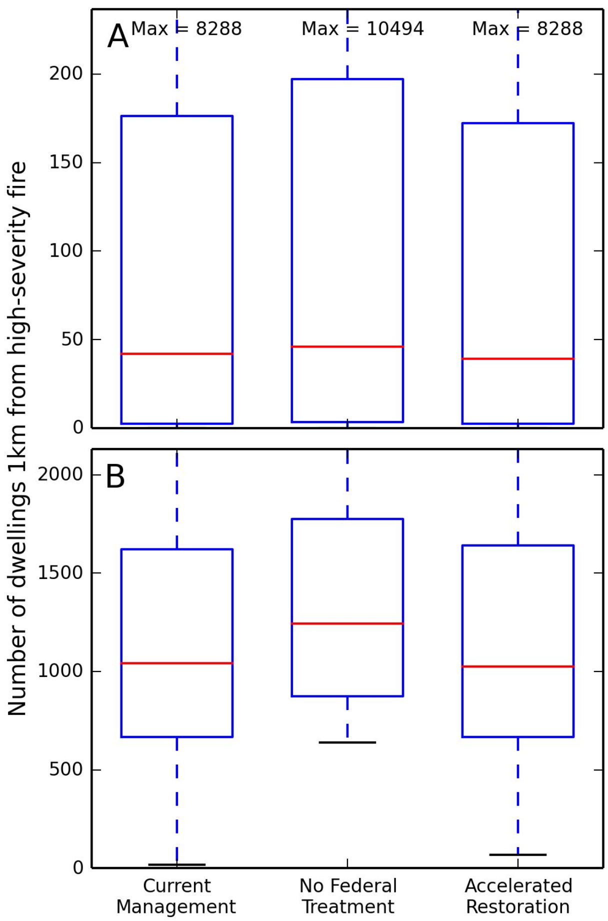


Fig. 4. Box and whisker plots of area of high-severity fire (%) for different management scenarios. Annual areal proportion of stand-replacing wildfire in all fire years for fire-prone potential vegetation types and all ownerships (A), and the top 10% of fire years (N = 75 of 750 replication years) in terms of area (B).



The median number of homes annually exposed to high severity fire (within 1 km of a fire) differed little among the three scenarios. However, the maximum number of homes exposed to a high-severity fire in any given year was largest for the no-management scenario (10,370 homes) compared to the other two scenarios, which had maximums that were approximately 20% lower (Fig. 5A). When only the top 10% of area of stand-replacing fire in a year was considered, the median annual number of homes exposed was highest for the no-management (1226 homes) and lowest for the accelerated-restoration (1065 homes) scenarios (Fig. 5B).

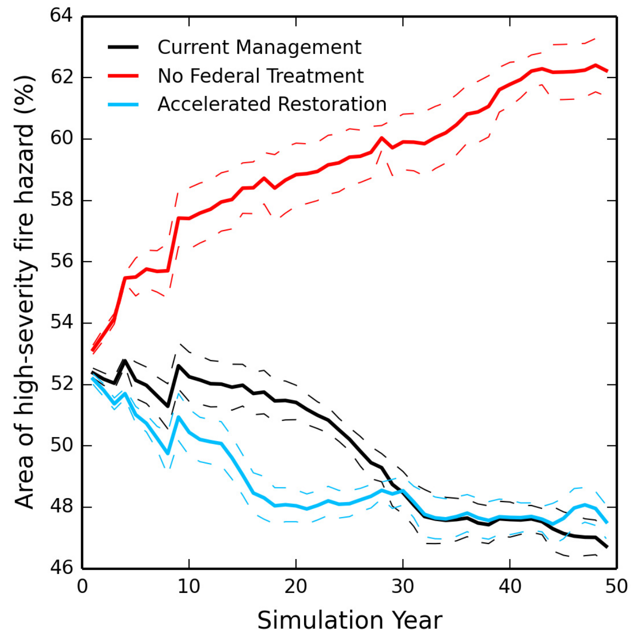
Fig. 5. Box and whisker plots of number of dwellings exposed to high-severity fire for different management scenarios. Annual number of dwellings in all fire years (A), and the top 10% of fire years (*N* = 75 of 750 replication years) in terms of area (B).



Fire hazard, wood, carbon, and forest structure

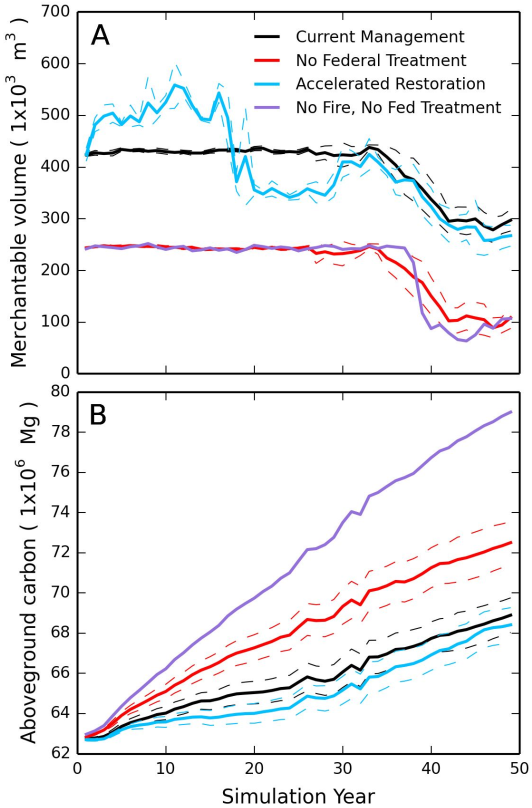
At time 0 (initial conditions), 53% of the landscape had potential for high-severity fire. Under current management, that proportion declined over the 50-yr model run to 46%, whereas it increased to 62% under the no-management scenario (Fig. 6). Treatments under the accelerated-restoration scenario initially reduced the potential for high-severity fire more than current management in the first 30 years of model runs. However, the two scenarios resulted in approximately the same level of high-severity fire potential after year 30.

Fig. 6. Mean annual area (%) of potential high-severity fire (hazard) for current management, no federal treatment, and accelerated restoration scenarios over time across all forested potential vegetation types and ownerships. Broken lines indicate corresponding 95% confidence intervals.



Under current management, harvest of merchantable wood volume was approximately 430,000 m^3 annually for ~35 years before declining (Fig. 7A). The accelerated-restoration scenario produced more wood volume in the first 15 years than current management but then produced less than current management (and less than targeted) for the remainder of the simulation, although the differences between two scenarios were not large. Of course, no management (federal with lagged effects on corporate landowners) produced less wood than either of the two scenarios with federal management. The dynamics in timber volume could be explained in part by ownership (Fig. 8). The strong decline in years 15–20 resulted from declines on federal lands and somewhat later on corporate lands (Fig. 8A and C); declines around year 40 resulted from declines on tribal lands (Fig. 8B). Family forest lands had small levels of timber production with noticeable fluctuations from year to year, especially for the no-disturbance scenario, which also produced more timber for that ownership. Without wildfire (no disturbance), the tribal lands were able to sustain target levels of timber production for a few additional years (Fig. 8B) than when wildfire was present.

Fig. 7. Mean merchantable volume (A) and aboveground carbon (B) for all owners over time for different management scenarios. Broken lines indicate corresponding 95% confidence intervals for 15 replications.



Trends in the amount of aboveground live and dead carbon differed among scenarios (Fig. 7B). The highest amounts and strongest increase occurred, not surprisingly, under the theoretical no-disturbance scenario. The next highest increase was for the no-management scenario, in which carbon increased on the landscape despite the occurrence of wildfire. Under current management and accelerated restoration, the amount of carbon initially declined and then increased nearly back to initial conditions by year 50.

The area of forest structure classes differed by scenario for all forest environments (Fig. 9). The proportion of early successional habitat increased slightly in all scenarios with fire, but declined in the absence of fire. The proportion of large and giant trees increased in all scenarios, whereas the proportion of pole and small- and medium-diameter forests declined. Presence of wildfire decreased all of the moderate and closed canopy forested vegetation classes. Although the area of large and giant forest conditions increased under all scenarios, the increase was slightly larger for the active management scenarios (current management and accelerated restoration) than the no-management scenario.

Fig. 8. Mean merchantable volume for the U.S. Forest Service (A), Warm Springs Tribe (B), corporate owners (C), and family forest owners (D) over time for different management scenarios. Broken lines indicate corresponding 95% confidence intervals for 15 replications.

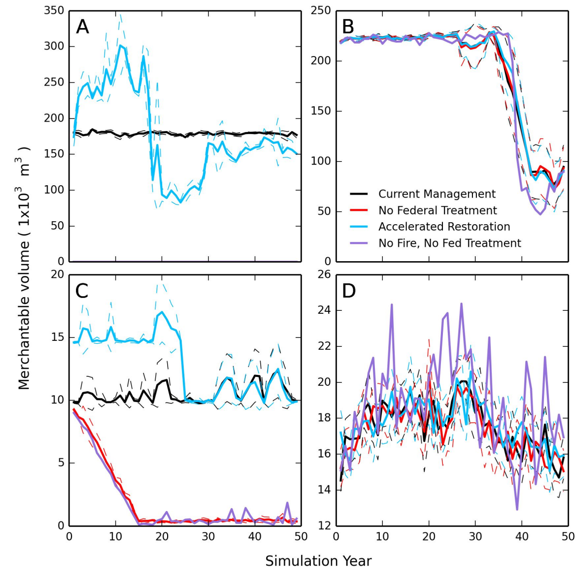
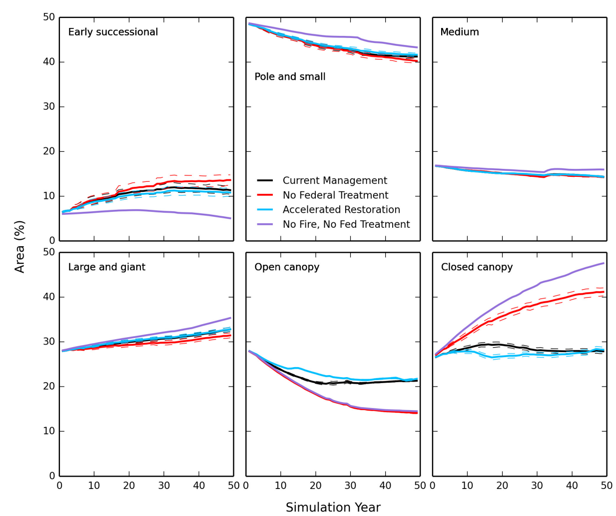
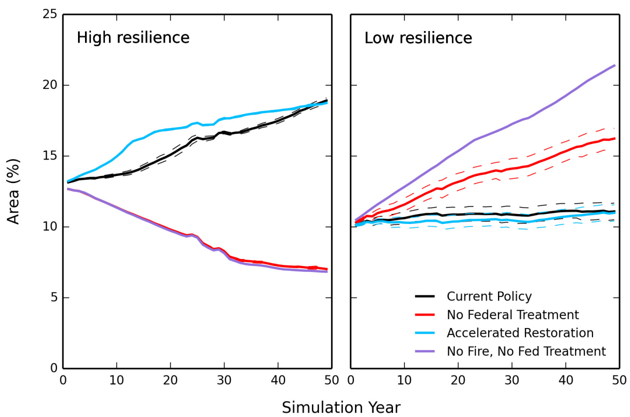


Fig. 9. Mean area of forest structural states over time for different management scenarios. Early successional = grasses, shrubs, and trees < 12 cm diameter at breast height (dbh); pole and small = trees 12–37 cm dbh; medium = trees 37–50 cm dbh; large and giant = trees > 50 cm dbh; open canopy = trees > 25 cm dbh and cover < 40%; closed canopy = trees > 12 cm dbh and canopy > 60% cover. Broken lines indicate corresponding 95% confidence intervals for 15 replications.



The amount of high-resilience, older forest structure in fire-frequent environments increased over time under current management and accelerated restoration, whereas the proportion of low-resilience, older forest structure was unchanged under those scenarios (Fig. 10). Under the no-management and no-disturbance scenarios, the proportion of resilient older forests declined by nearly one-half as a result of succession, which increased canopy cover and layering.

Fig. 10. Mean area of high- and low-resilience older forest structure for fire-prone potential vegetation types for different management scenarios. Broken lines indicate corresponding 95% confidence intervals for 15 replications.

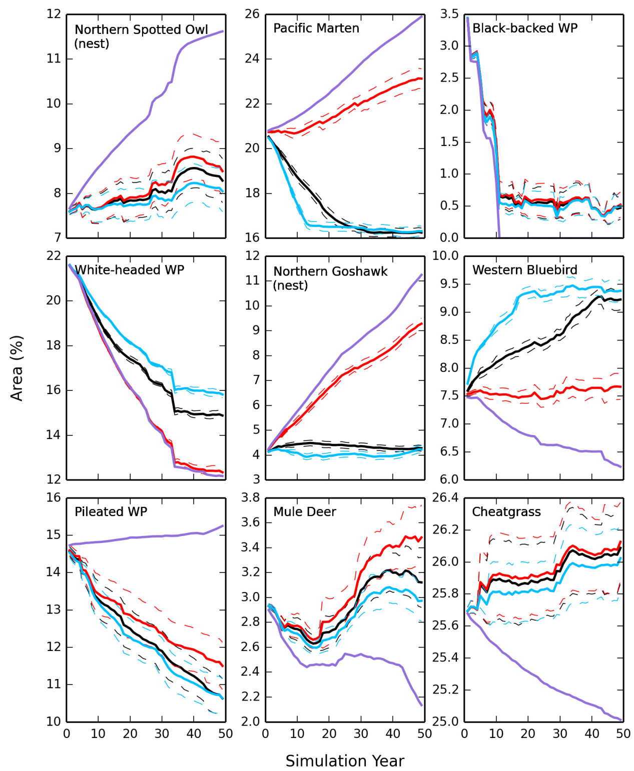


Wildlife habitat

Trends in the proportion of wildlife and plant habitat varied among species and scenarios (Fig. 11). Under current management, the proportion of the landscape providing nesting habitat for northern spotted owl and northern goshawk (*Accipiter gentilis*), and habitat for black-backed woodpecker (*Picoides arcticus*), western bluebird (*Sialia mexicana*), mule deer (*Odocoileus hemionus*), and cheatgrass increased slightly or were unchanged. The proportion of habitat for Pacific marten (*Martes caurina*) and white-headed woodpecker (*Leuconotopicus albolarvatus*) declined moderately. The general direction of trends in habitat for accelerated restoration were similar to current management for most species. Under no management, habitat increased for northern spotted owl, northern goshawk, and Pacific marten, whereas the proportion of habitat declined for the woodpeckers and remained unchanged for western bluebird and cheatgrass.

Comparing scenarios, no management resulted in more habitat than active management scenarios by the end of 50 years for northern spotted owl, Pacific marten, northern goshawk (nesting habitat), and pileated woodpecker (*Dryocopus pileatus*), species associated with dense, multistoried forests with trees > 25 cm in diameter (Fig. 11). In contrast, no management resulted in less habitat than the other scenarios for white-headed woodpecker, western bluebird, and mule deer. Compared with current management, accelerated restoration resulted in more habitat for white-headed woodpecker and western bluebird, species associated with open forests, and early successional vegetation and meadows, respectively. A comparison of the no-disturbance scenario and the scenarios with wildfire indicates that relatively large amounts of owl habitat and pileated woodpecker habitat were lost to wildfire, whereas scenarios with wildfire created some habitat for western bluebird, mule deer, and cheatgrass relative to the no-disturbance scenario.

Fig. 11. Mean area of habitat for eight species of vertebrates and one plant of interest over time for different management scenarios. Broken lines indicate corresponding 95% confidence intervals for 15 replications.



DISCUSSION

Treatment of forest fuels to reduce the potential for high-severity fire, a common goal of many landowners, may or may not be compatible with goals for forest restoration, wildlife habitat, or carbon storage (Reinhardt et al. 2008, Ager et al. 2010*b*). Our study examines how alternative landscape management scenarios could influence future fire area and severity, high-severity fire potential, wood, carbon, and wildlife habitat. By integrating forest succession, wildfire, and forest management in a spatially explicit model, we were able to reveal interactions and trade-offs that the separate submodels could not reveal. Our projections indicated that current management of federal lands by thinning and surface fuel treatments can reduce both the amount of high-severity fire, overall fire hazard (potential), and exposure of dwellings to fire, although effects were small across all fire years compared to the no-management scenario. However, when years with extreme area of fire are considered, the effects of current management and accelerated restoration were larger compared to no management on federal lands. Years with extremely high fire area would have more fire-fuel treatment encounters than in years with less fire, making higher fuel treatment scenarios more effective during those years (Rhodes and Baker 2008, Syphard et al. 2011, Barros et al. 2017). Considering only extreme fire years, the variation in amount of high-severity fire among the scenarios was quite large, and distributions of high-severity fire overlapped among the scenarios.

The relatively modest effects of current management and accelerated restoration may be a result of the small area treated. The current management scenario, which is based on volume targets, converts to approximately 6500 ha of thinning and surface fuel treatments per year on federal lands and another 1000 ha on tribal and corporate lands, which are the other two major landowners. Those rates translate to treatment rates of approximately 12% per decade for the fire-frequent forest environments and approximately 9% per decade for all forest lands, including higher elevation forest types (e.g., mountain hemlock) that have inherently longer fire return intervals and higher fire severities. Assuming the effectiveness of fuel treatments is approximately 10–20 yr, this means that at any one time, 12–24% of the fire-frequent landscape has reduced fuels from treatments. The actual proportion of low fuel conditions would be higher than this because of the presence of recent postwildfire areas and unburnable sites such as rocky soils and roads. Other studies have shown that optimized fuel treatments that cover at least 20% of the landscape will significantly reduce fire spread rates (Finney et al. 2011) and reduce risk to large, fire-resistant trees (Ager et al. 2010*b*). Given that the spatial distribution of treatments was not optimized in our simulations, it seems likely that alternative spatial designs and treating additional area would have a greater effect on the amount of high-severity fire and the amount of fire-resilient vegetation. See Barros et al. (2017) and Ager et al. (*unpublished manuscript*) for further analysis of these topics.

Federal forest treatments to reduce the potential for high-severity fire are prioritized for the WUI (as defined by federal managers) over the less human-settled parts of the landscape (Appendix 7). The federally defined WUI extends many kilometers away from homes and does not appear to place a strong spatial constraint on federal management, leading to dispersion of fuel treatments. Defining the WUI in a more restricted way (e.g., Silvis WUI; Radeloff et al. 2005) would concentrate treatments nearer to homes. Our results suggest that current management activities (based on federal WUI) reduce exposure of homes to high-severity fire (within 1 km) by almost 15% for the years with the most fire. However, exposure of homes to flames and fire brands is only one part of the risk framework for loss of homes to wildfire and may not be as important as susceptibility of the home to ignition (e.g., Calkin et al. 2014). Home ignition is a function of the live and dead fuel on and surrounding the home site as well as home building materials, especially flammability of the roof (Cohen 2000). Consequently, a more complete risk analysis should include homes' susceptibility to ignition. We did not report the results of actions by homeowners to adopt defensible space behaviors that reduce risk at the homesite scale. Olsen et al. (2017) found that almost 80% of the homes in the study area adopted some component of defensible space practices, and that these actions were more likely in locations characterized by heighted fire hazard, suggesting that a high level of risk mitigation occurs across the population of homes. Our results suggest that land management actions in this area can reduce the potential for losses.

Much of the federal restoration activity in the study area includes federal timber sales that contribute to reaching the federal harvest volume target. Our simulations suggest that efforts to increase the area of restoration (the accelerated restoration scenario) could be limited by availability of stands with suitable ecological and topographical conditions. For example, the accelerated restoration scenario, which scheduled a doubling of the volume target for the first 25 years before returning to the current management volume target level, was not able to sustain the doubling beyond 18 yr and was not able to reach the current management volume target after that given lack of treatable area. This finding suggests that efforts to increase harvesting on federal lands might not be successful in the long run without expanding the vegetation types and land allocations that can be treated, with or without harvesting. For example, we limited thinning treatments to stands dominated by trees > 25 cm diameter at breast height (dbh), canopies with > 60% cover, and multistory structure. Sensitivity analyses (not shown) indicate that accelerated restoration might be sustainable for ≥ 50 yr if treatments were allowed in less dense stands or other areas of the landscape where we assumed that treatments would not occur (see Barros et al. 2017).

Although timber production from federal lands has direct economic benefits in the jobs and business activity it generates for local communities, there are also important indirect connections between current timber production and the future capacity for businesses to do ecological restoration (Kelly and Bliss 2009). Timber from federal lands can help to maintain the forestry infrastructure and mill capacity necessary to conduct merchantable harvest-based restoration treatments (Charnley 2014). The trends we observed, however, suggest that as the densest and highest volume forests are thinned and then treated with prescribed fire, the levels of timber production will decline as management activities focus more on using prescribed fire or mechanical methods to reduce surface fuels. Barros et al. (2017) indicate that the area suitable for prescribed fire will dramatically increase under active management strategies because current area targets for prescribed fire are relatively small and fixed compared to those for thinning. Increases in prescribed fire targets may be needed to keep up with the increasing areas that have had the first installment of restoration treatments. As future timber volume may be less able to offset the costs of restoration treatments, other restoration funding mechanisms may be needed. Economics may not be the only barrier to increasing the area of prescribed fire; air quality standards and public concerns about smoke and fire escape also can occur (Charnley et al. 2015) and will require special efforts on the part of managers to build trust for this important restoration action (McCaffrey 2006). We have a smoke production model and plan to present the results in a future paper.

An eventual shortfall in harvest volume production (and area treated) was also projected for tribal lands at approximately 35 yr, when the model could not find enough stands that met the treatment criteria. This appeared to result from future lack of older stands (> 70 yr) for clearcutting, which is practiced in some forest types on tribal lands. The Envision model does not optimize harvest schedules. If the current management plan for tribal lands were put into a harvest scheduling model built to select optimally which stands to harvest while also meeting the annual timber target between now and 2050, a schedule might be found to meet the timber target in all years. Without wildfire, the volume production for tribal lands was steady and could be met for a few more years than with wildfire. The effects of wildfire on timber production have been observed (Armstrong 2004), but typically, stochastic natural disturbance agents that remove existing merchantable timber volume or shift age class distributions are not factored into forest management planning.

Carbon storage was sensitive to management scenarios. More carbon was stored in aboveground live and dead biomass under no federal management and no fire (no management and no disturbance) scenarios. Landscape-level treatments to reduce fire effects and increase restoration through thinning and surface fuel treatments reduced stored forest carbon relative to no management and no disturbance, but the relative differences were small (~5–10%) depending on year and scenario; by the end of 50 yr, the amount of stored carbon in the active management scenarios was slightly less than at the start of the simulation. Others have also found that active management in fire-prone forest landscapes can reduce carbon storage by ~5–25% (Ager et al. 2010*a,* Loudermilk et al. 2013) relative to no management depending on timing and intensity of management and assumptions about future wildfire. These results occur because treatments always reduce carbon stored in forests, and although they typically reduce carbon losses to high-severity fire at stand levels, at landscape scales many treatments do not experience fires and do not realize carbon losses associated with such fires. However, the effect of fuel treatments in reducing landscape fire spread and intensity can confer carbon sequestration benefits outside of treated areas. However, our results and those of others (Ager et al. 2010*a*) indicate that the magnitude of benefits outside of treated areas does not make up for carbon removed by harvesting and prescribed fire. Accounting for the carbon stored in wood products manufactured from timber harvested in the course of fuels treatments would increase the total carbon stored under the treatment scenarios (Bergman et al. 2014), potentially altering the carbon accounting results.

Our projections suggest that the area of larger sized trees will increase and the area of small and mid-size trees will decrease across all ownerships (though not necessarily for all individual ownerships; Charnley et al. 2017) under current management constraints and despite wildfires. This happens despite a significant area of large trees being killed by high-severity wildfire and an increase in the area of early successional forests because of wildfire and clearcutting on tribal lands. Similar trends in medium and larger diameter forest were observed in another modeling study for a landscape in this region (Halofsky et al. 2014). The net increase in mature and older forests is likely a result of ingrowth from large areas of cutover lands, timber plantations, and areas of insect outbreaks and wildfire during the 20th and early 21st centuries in ponderosa pine and dry mixed-conifer forests on public and private lands that are now maturing (Hessburg and Agee 2003). This highlights the importance of landscape legacies and age class distributions in controlling future landscape development (Wallin et al. 1994). These past land-use effects are especially important in low-productivity forest environments, where recovery from stand replacement disturbances can be slow.

Our metric for resilient older forest structure (i.e., low canopy cover forests with larger trees in fire-frequent PVTs) increased under the two active management scenarios. This metric reflects the fact that the need for forest restoration varies by environment as a function of historical fire regime and logging history (Merschel et al. 2014). In this landscape, the environments with the highest fire frequencies (and therefore potentially the greatest departures from historical regimes under fire suppression policy) are ponderosa pine, dry mixed-conifer, and moist mixed-conifer. The first two types are generally known to have fire return intervals of < 20–25 yr (Agee 1993). At present, these types have much higher densities and many fewer large fire-tolerant species such as ponderosa pine as a result of fire exclusion and logging, which both selectively removed large pine or created clearcuts that are now occupied by younger stands of pine. The history of the moist mixed-conifer type is less well understood, but recent studies in the area (Hagmann et al. 2014, Merschel et al. 2014) indicate that these environments had similar low density, large-tree structure and species composition to the dry mixed-conifer, implying a similar relatively high frequency of fire that kept grand fir and other shade-tolerant tree densities low. Baker (2012) suggests that forests in these environments were historically denser than indicated by these other studies, but his estimated historical densities are still considerably lower than current densities (Merschel et al. 2014).

Despite the increase in area of forests with highly resilient forest structure, such forests only accounted for approximately 19% of the landscape by the end of 50 yr (and less in the no-management scenarios). It is unclear what the proportion of this type of structure would have been under the historical disturbance regime. However, it probably was quite high, e.g., > 75%, given the recent historical work of Hagmann et al. (2014) and Merschel et al. (2014) and that of Baker (2015), who found that > 76% of the forests of all levels of canopy cover contained trees > 53 cm dbh in central Oregon. An earlier simulation study by Kennedy and Wimberly (2009) estimated that under historical regimes, 35% of all forest types on the Deschutes River, Oregon was covered by old forest structure, of which approximately 25% was in closed canopy conditions. The relatively low estimate of old-forest structure by Kennedy and Wimberly (2009) may result from their use of a relatively high diameter threshold (53 cm rather than 50 cm) and their assumption that historical fires had more stand replacement (high severity) patches in them than recent historical analysis indicate. If we assume that > 75% of the frequent-fire environments had large and giant trees (> 50 cm) with any canopy cover, then our analysis suggests that 50 yr and current practices will not be enough to get back to that level; we estimated that large and giant trees, regardless of canopy cover and layering (both resilient and nonresilient vegetation), increased from 28 to 32%. Without any human or natural disturbance on federal lands (no disturbance), this class is projected to compose approximately 35% of the landscape at 50 yr. The results indicate that given the management history, current age and size distributions (~48% of the area has tree size < 37 cm), relatively low site productivity, and diversity of management goals, it will take much longer than 50 yr to recover a larger portion of the original forest structure.

The management scenarios affected wildlife habitat in different ways. Habitat of species associated with relatively dense, multilayered, older forests (e.g., northern spotted owl, Pacific marten, and pileated woodpecker) was reduced by treatments to decrease stand density. For example, we found that nesting habitat for the northern spotted owl was less under the active management scenarios compared with no management. However, wildfire removed many times more owl habitat than was lost through management.

Of the species associated with dense, multilayered forests, the northern spotted owl is of particular importance because it is listed under the U.S. *Endangered Species Act* and is often used as a surrogate for threatened old-growth forest ecosystems. We emphasize the northern spotted owl here because it is both an ecological and social issue that drives federal forest management and reflects changing social values related to timber vs. biodiversity values of forests (Lee 2009). The primacy of conserving northern spotted owl habitat in federal forest management goals means that other social and ecological values (e.g., thinning to support local timber-based economies or managing for more open, fire-resilient, older forests) are constrained by concerns over providing habitat for the owl.

Only a few other modeling studies have explored questions related to owl habitat, management, and fire. Ager et al. (2007) found that fuel treatments would reduce expected loss of northern spotted owl habitat when the treatment area reached at least 20% of the landscape. The reduction in expected loss of owl habitat in that study went from approximately 2.4 to 1.3% between 0% treated and 20% of landscape treated. Ager et al.'s (2007) analysis did not allow treatment in areas that were defined as owl habitat and did not assume that succession or stand development would occur (static vegetation). The relatively lower amount of owl habitat in our study under the active management scenarios compared with no management may occur because of thinning in younger forests that reduced the potential for development of owl habitat in the future. Thus, thinning, although it was not allowed in existing habitat, reduced recruitment of future owl nesting habitat in addition to what was lost to wildfire. Wildfire was the dominant cause of habitat loss, although habitat increased under all scenarios, suggesting that it may be possible to both increase restoration and increase habitat for northern spotted owl in this landscape. Roloff et al. (2005) modeled active management and no management in fire-prone landscapes in southwestern Oregon and found that active management in owl foraging areas reduced owl habitat compared with no management (only losses to wildfire). However, in a second analysis, Roloff et al. (2012) found that active management "was more favorable to spotted owl conservation...than no management." They used FlamMap to estimate crown fire potential and assumed that if 50% of the owl territory had crown fire potential, then all of the territory would be lost to a fire. This assumption may overestimate the loss of habitat to fire. Odion et al. (2014) also found that thinning treatments in fire-prone landscapes reduced owl habitat more than did wildfire.

These studies, along with ours, suggest that the question of how to sustain northern spotted owl habitat in fire-prone landscapes is complex and needs further evaluation (Lehmkuhl et al. 2015). While stand-replacing fire has been observed to reduce owl occupancy (Clark et al. 2013), patchy fires may not have detrimental effects on northern spotted owl as long as patterns are heterogeneous and adequate amounts of nesting and roosting habitat remain. It is clear that some fuel treatment designs intended to reduce loss of owl habitat to high-severity fire will result in reduced owl habitat compared to a no-treatment option. However, several key questions remain unanswered, including: How do the rates and patterns of fuel treatment affect high-severity fire in landscapes with different initial conditions of forest structure and age? How do the amounts and landscape patterns of fuel treatments inside and outside existing and potential owl habitat affect dynamics of owl habitat, owl prey, and owl populations? And how do different landscape management strategies affect owl habitat outcomes under different future fire scenarios?

The results from other species also demonstrate the variability in effects of treatment and wildfire on species with different habitat needs. Habitat for the white-headed woodpecker declined under all scenarios, though the decline was lowest for the accelerated restoration scenario. The habitat for this species is in relatively open (< 40% canopy cover) ponderosa pine forests; however, our thinning prescription typically did not produce this low level of canopy cover because it focused on stands with high canopy cover (> 60%) and reduced it to medium canopy cover (40 to 60%). Changing the thinning prescription to promote open conditions would probably produce more habitat for this species.

Like all modeling studies, the results of our study are a product of the assumptions and limitations of the models used. Our fire submodel has been evaluated, and simulations show reasonable correspondence to historical frequencies and spatial patterns (Barros et al. 2017; Ager et al. *unpublished manuscript*). However, an area of uncertainty is the relative amounts of different fire severities, which needs further evaluation. We did not evaluate a climate change scenario. Halofsky et al. (2014) and Case, Kerns, Kim, et al. (*unpublished manuscript*) found that projected changes in area of forested PVTs in central Oregon under climate change scenarios do not differ much from current conditions until at least 40–60 years from present, so some of our 50-yr findings might not be that different for climate change scenarios. However, increasing frequencies of fire may come much sooner than 50 yr under climate change and could alter our findings and conclusions. For example, our finding that treatments are more effective in high-fire years (see also Barros et al. 2017) suggests that with increasing fire under climate change, management actions could be more effective, although the opposite could be the case for severe weather events that may cause fuel treatments to be less effective (Fernandes and Botelho 2003). In addition, using different scenarios in terms of stand treatments, landscape allocation, and rate, and using different habitat models could produce different results. We also did not report on how treatments on one ownership affect fire behavior and habitat on other ownerships (Ager et al. 2014), which is an important question for policies such as the National Cohesive Wildland Fire Management Strategy (Wildland Fire Leadership Council 2014) that seek to coordinate fire and fuels management across multiownership landscapes. We plan to report the cross-ownership effects of fire and fuels management in a future paper focused on all-lands management and landscape-level planning.

The structure of this agent-based model enabled us to explore some of the interactions between social and ecological components of this fire-prone system, but we have not fully exploited its capabilities. For example, we learned that efforts to reduce the occurrence of high-severity fire, which affects both social and ecological values, show the greatest effectiveness in years with the most fire. This indicates that for restoration actions to be most effective at landscape scales, the number of encounters between managed areas and fires must increase, either through more fire, more management, or both. We also learned that other management goals (e.g., wilderness provision, roadless areas designation, habitat conservation for northern spotted owl) could constrain the area available for thinning and restoration and may limit the potential to reach restoration goals for the entire landscape that has been affected by past management practices and fire exclusion. Although agents in this model do not "learn" in the sense of changing their management goals or rules as a result of feedbacks from the environment, their management actions do respond to how the landscape changes from the cumulative effects of their management, vegetation succession, and wildfire. For example, federal managers may not be able to reach their treatment and timber production goals if wildfire occurs in stands that are suitable for treatment, or if the cumulative effects of thinning and wildfire reduce the area of forest that is suitable for timber harvest. The model also indicates that trade-offs will occur among fire, timber, carbon storage, and wildlife habitat. More thinning will reduce fire occurrence and increase timber production and the areas for white-headed woodpeckers and other species favoring more open forests, but will also reduce habitat for northern spotted owl and carbon sequestration. How these potential trade-offs can be dealt with in management and policy is a question that federal managers are wrestling with, but they lack analytical frameworks and tools that can help reveal the spatial and temporal patterns and scales of the interactions. We plan to use the model and its results with stakeholder groups in collaborative landscape projects in the study area to determine if and how stakeholders can learn from our model and if this process changes the nature of the discussions and debates around forest landscape restoration.

We have also not yet fully exploited the capabilities of this model to examine social-ecological interactions. For example, the model could be used to examine more thoroughly how management and fire on one ownership affect ecological and social outcomes on adjacent ownerships. Such cross-boundary effects are a major concern among some private landowners, who view federal forests that abut or surround their lands as the major source of fire risk (Charnley et al. 2017). The model also could be used to focus on homeowners and family forest owners to examine how changing forest structure and fire occurrence influences their behaviors. In the current analysis, the dynamics of these agents remained unresolved given the broad focus on the entire landscape dominated by large landowners.

Few other landscape models have the range of capabilities that Envision does to represent wildfire, succession, multiowner forest management, and homeowner fire mitigation across large landscapes. Many landscape fire models exist, but few have the potential to represent human decision making in great detail. The closest example may be Landis (Scheller et al. 2007), which has many of the same capabilities as Envision, although with somewhat different submodel processes, especially for succession and forest management. Envision has multiple ways to represent agent-based behavior, include policies that guide agents based on value-to-action rules and potential for learning, and target-based approaches to decisions. We used both approaches in this effort, e.g., policies for family forest owners and homeowners and a target (subject to constraints and preferences) approach similar to that used in Landis.

The agent-based model we have developed fits within the broad set of agent-based model applications. Central features of agent-based models include large numbers of "active objects" that interact with their environment and with each other (Borshchev and Filippov 2004). Although the objects are typically people or households, they may be animals, business units, vehicles, or even spatial units (Box 2002). In our model, people occur in nested spatial structures from large ownership blocks to smaller individual landowner parcels. They interact with their environment through vegetation manipulations based on global goals and rules. They interact with each other largely through how management on their lands might affect fire spread and occurrence on other ownerships. In reality, they also interact with each other through social networks (Fischer and Jasny 2017) and indirectly through timber production as it might affect timber mill capacity and timber markets; these other relationships are not currently in the model.

The agents in our landscape are relatively few and the system we studied is relatively slow and noninteracting compared to many systems modeled with agent-based models (e.g., cities or agricultural landscapes). For example, our landscape has a low number of human agents, least in terms of the dominant area of the landscape (e.g., 80% is controlled by six agents). Also, large landowners have historically shifted behaviors slowly because of institutional factors (Steen-Adams, Charnley, and Adams *unpublished manuscript*). Another distinctive feature of this landscape is the slowness of change and infrequency of wildfire and management events. Vegetation can stay in some states for decades without change, and frequency of wildfire and management have low probabilities at an IDU level (e.g., 0.05 annual probability for some kinds of management to 0.003 for occurrence of wildfire). The real complexity and heterogeneity of this system lies in the interactions of hundreds of thousands of spatial units of vegetation, fire, managed actions of a handful of human agents, and time lags that occur over decades to centuries. The scale, elements, and interactions of our model seem appropriate to this system given that there are great expectations and concerns about how individual vegetation treatments scale up to affect behavior of fire, restoration, and outputs of ecosystems services across multiownership landscapes.

CONCLUSIONS

Using a spatial agent-based model, we were able to examine interactions between human and natural systems across spatial and temporal scales in a fire-prone landscape. We gained several insights that would have been very difficult to achieve without this type of model. Overall, our study reveals that alternative approaches to vegetation management can affect fire area, fire outcomes, exposure of homes to fire, wood production, carbon storage, vegetation conditions, and wildlife habitat. More specifically, we found that current practices can reduce fire severity compared to no management, but the magnitude of fire effects is very small for average fire years. Management to reduce fuel loads appears to have greatest effects in extreme fire years, i.e., years with large areas burned by fire. We found that current timber targets and restoration programs may be at the limit of what is sustainable under the stand structure and land allocation constraints we assumed. Reducing the area of high-severity fire and creating more resilient forest structures through current and accelerated restoration programs will result in trade-offs for carbon and wildlife habitat for some species, including the northern spotted owl, a species of critical concern in the region. Finally, our study demonstrates the importance of legacies of past disturbances, expressed in current forest structure and age, on the pattern and dynamics of future forest characteristics. Ultimately, managers and the public will need to decide what the most socially, economically, and ecologically viable strategies for landscape-scale management are in this and other fire-prone landscapes. We hope the model and our initial application can contribute to that social process and provide a way for stakeholders to understand better the landscape-scale and longer term implications of forest management decisions.

Responses to this article can be read online at:
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Appendix 1

Forest structure conditions across the landscape at beginning and end of the 50 year simulation.

Table A1.1 Percent of study area in vegetation structure (cover, tree size and layers (single or multiple) used in state and transition models at year 0. S stands for single story and M for multi-story.

Percent Cover class and layers (S, M)	**Tree Size (cm)** Grass/ Shrub	Seedling/ Sapling <12	Pole 12-25	Small 25-37	Medium 37-50	Large 50-75	Giant >75	Totals
<10	3.29	0.05	0.03	0.14	0.30	0.52	0.00	4.33
10-40 S	1.15	1.99	6.94	14.37	5.84	4.75	1.39	36.42
10-40 M	NA	NA	NA	NA	NA	1.69	0.40	2.09
40-60 S	0.00	0.00	5.95	8.96	5.81	1.11	0.05	21.88
40-60 M	NA	NA	NA	NA	NA	3.74	0.44	4.18
>60 S	0.00	0.00	4.75	7.59	4.95	0.04	0.01	17.35
>60 M	NA	NA	NA	NA	NA	11.30	2.45	13.75
Totals	4.43	2.05	17.67	31.06	19.90	23.15	4.74	

Table A1.2. Mean percent of study area in vegetation structure (cover, tree size and layers (single or multi)) used in state and transition models at year 50. Values in parentheses are lower and upper 95th percentile confidence intervals from 15 replications.

Cover class and layers (S,M)	Tree Size (cm) Grass/ Shrub	Seedling/ Sapling	Pole 12-25	Small 25-37	Medium 37-50	Large 50-75	Giant >75	Totals
<10	3.15 (2.82, 3.47)	1.01 (0.85, 1.17)	0.00 (0.00, 0.00)	0.02 (0.02, 0.03)	0.20 (0.19, 0.21)	0.29 (0.24, 0.34)	0.01 (0.00, 0.02)	4.68
10-40 S	2.10 (1.73, 2.46)	5.30 (4.97, 5.13)	5.05 (4.97, 5.13)	10.71 (10.49, 10.92)	5.21 (5.18, 5.24)	4.70 (4.64, 4.76)	0.57 (0.56, 0.57)	33.62
10-40 M	NA	NA	NA	NA	NA	0.16 (0.16, 0.17)	0.02 (0.02, 0.03)	0.19
40-60 S	0.00 (0.00, 0.00)	0.02 (0.00, 0.02)	4.08 (4.02, 4.14)	9.99 (9.80, 10.18)	5.88 (5.81, 5.95)	7.74 (7.59, 7.90)	0.26 (0.24, 0.28)	27.98
40-60 M	NA	NA	NA	NA	NA	1.38 (1.36, 1.40)	0.03 (0.03, 0.03)	1.41

>60 S	0.01 (0.00, 0.01)	0.00 (0.00, 0.00)	4.23 (3.97, 4.48)	7.05 (6.99, 7.11)	3.09 (2.99, 3.18)	0.56 (0.53, 0.59)	0.09 (0.09, 0.09)	15.02
>60 M	NA	NA	NA	NA	NA	10.69 (10.45, 10.94)	6.41 (6.19, 6.63)	17.10
Totals	5.25	6.33	13.36	27.77	14.38	25.52	7.39	

Appendix 2

Area and names of potential vegetation types in study area.

Table 2.1. Percent of study area of potential vegetation (PVT) type groups. Groups combine 39 individual PVTs. Fire-frequent types used in landscape analysis are shaded.

PVT Type	Area (ha)	Percent
Arid	115980	9.26
Moist,High Elevation, other	186616	14.89
Lodgepole	93516	7.46
Moist Mixed Con	157296	12.55
Dry Mixed Con	304383	24.29
Ponderosa Pine	157491	12.57
Juniper	139271	11.12
Not Modeled	98353	7.85
Total	1252906	100.00

Table 2.2. Names and description of forested PVTs and classification into PVT management groups

VDDT Modeling Region	PVT description	PVT Management Group
Oregon Blue Mountains	Grand fir - cool, moist	Moist mixed conifer
Oregon Blue Mountains	Subalpine fir - cold, dry	Moist, high elevation, other
Oregon Blue Mountains	Subalpine woodland	Moist, high elevation, other
Oregon Blue Mountains	Ponderosa pine - dry, with juniper	Ponderosa pine
Oregon Blue Mountains	Ponderosa pine - xeric	Ponderosa pine
Oregon Blue Mountains	Mountain hemlock - cold, dry	Moist, high elevation, other
Oregon Blue Mountains	Mixed conifer - cold, dry	Dry mixed conifer
Southeast Oregon	Mixed conifer - cold, dry	Dry mixed conifer
Southeast Oregon	Mixed conifer - dry (pumice soils)	Dry mixed conifer
Southeast Oregon	Ponderosa pine - dry (residual soils)	Ponderosa pine
Southeast Oregon	Ponderosa pine - xeric	Ponderosa pine
Oregon East Cascades	Western hemlock - wet	Moist, high elevation, other
Oregon East Cascades	Western hemlock - intermediate	Moist, high elevation, other
Oregon East Cascades	Western hemlock - cold	Moist, high elevation, other
Oregon East Cascades	Pacific silver fir - warm	Moist, high elevation, other
Oregon East Cascades	Pacific silver fir - intermediate	Moist, high elevation, other
Oregon East Cascades	Mountain hemlock - intermediate	Moist, high elevation, other
Oregon East Cascades	Mixed conifer - moist	Moist mixed conifer
Oregon East Cascades	Oregon white oak / Ponderosa pine	Ponderosa pine

Oregon East Cascades	Subalpine parkland	Moist, high elevation, other
Oregon East Cascades	Shasta red fir - dry	Moist, high elevation, other
Oregon East Cascades	Mixed conifer - dry (pumice soils)	Dry mixed conifer
Oregon East Cascades	Lodgepole pine - wet	Lodgepole
Oregon East Cascades	Lodgepole pine - dry	Lodgepole
Oregon East Cascades	Ponderosa pine - dry (residual soils)	Ponderosa pine
Oregon East Cascades	Mixed conifer - dry	Dry mixed conifer
Oregon East Cascades	Mixed conifer - cold, dry	Dry mixed conifer
Oregon East Cascades	Mountain hemlock	Moist, high elevation, other
Oregon East Cascades	Ponderosa pine - xeric	Ponderosa pine
Oregon East Cascades	Ponderosa pine - Lodgepole pine	Dry mixed conifer
Southwest Oregon	Subalpine parkland	Moist, high elevation, other
Southwest Oregon	Mountain hemlock - cold, dry	Moist, high elevation, other
Southwest Oregon	Shasta red fir - moist	Moist, high elevation, other
Southwest Oregon	White fir - cool	Moist mixed conifer
Southwest Oregon	White fir - intermediate	Dry mixed conifer
Southwest Oregon	Douglas-fir - moist	Dry mixed conifer
Southwest Oregon	Douglas-fir - dry	Dry mixed conifer
Southwest Oregon	Oregon white oak	Moist, high elevation, other
Southwest Oregon	Ponderosa pine - dry, with juniper	Ponderosa pine

Appendix 3

Envision Model Overview, Design Concepts, and Details (ODD)

1. Purpose

The model has at least two purposes: 1) to advance scientific understanding of the dynamics and interactions of forest management, fire, and vegetation across landscapes characterized by multiple owners; and 2) contribute to management and collaborative restoration of fire-prone landscapes by serving as a tool for managers and stakeholders to evaluate ecological and social outcomes of different management, policy and climate scenarios.

2. Entities, state variables, and scales

The spatial entities are individual decision units (IDU) that have a mean size of 3.15 ha and range from 0.06 to 8.5 ha. They are defined by the intersection of vegetation type, topography and ownership. The study area used in this paper contains 397,041 IDUs. Vegetation is classified into structure classes based on cover classes (%) (4), tree size classes (cm) (7), and number of canopy layers (single or multiple) (2), and time since last disturbance in years Six main classes of forest owner (federal, state, corporate, tribal, family and homeowner) are recognized with potential to subdivide within those main groups (e.g. forest districts or individual corporate owners). IDUs are also characterized in terms of: topography, land management zones, fuel models, potential vegetation zones, housing density, and distance to roads. The model is run at annual time steps for 50 years.

3. Process overview and scheduling

Within a single year the order of processes and state variable change is: 1) vegetation succession; 2) identify possible areas for treatment given constraints and preferences; 3) implement management actions to meet targets or other satisfy equations (family forest owners) management actions; 4) ignite and spread fires; 5) change vegetation and fuel models.

4. Design concepts

The model is based on existing theories models of fire behavior and spread, forest and fuel succession, and empirically-based knowledge of forest management goals, objectives and silvicultural effects, and human development. For the most part the submodels, fire, vegetation, management and development are well developed and established in various forms. However, few models have put all of these submodels together in a single framework (but see Landis, Scheller et. al. 2007). The model also has capability to evaluate climate change effects on fire and how it might in turn affect vegetation dynamics. The model is especially designed to explore landscape-scale interactions of four processes: 1) wildfire occurrence, spread and severity, 2) succession in vegetation structure and composition and fuels, 3) forest management treatment type, pattern and rate; and 4) increases in housing density in forest environments. While vegetation succession is modeled using relatively simple state and transition models which limits evaluation of fine-scale vegetation processes (e.g. dispersal, regeneration, competition, and changing interactions of biotic processes and climate), the vegetation model includes hundreds of states, thousands of possible pathways and probabilistic transitions for a diverse set of forest environments and community types. The model can produce emergent behavior that is difficult to predict over time and space from general knowledge of rates and patterns of fire, succession, and vegetation management across ownerships. Given the fundamental state variables, metrics of timber volume, carbon, biomass and wildlife habitat can be calculated and evaluated. The model is parameterized for a large existing landscape based on spatial models of current vegetation and fuel conditions, topography and knowledge of landowner management objectives and vegetation treatment approaches. It uses many of the component models that federal managers currently use individually but not together in an integrated framework. Consequently, the model has great potential for real-world applications, in addition to its capabilities to evaluate current scientific questions of how fire, vegetation and management interactions scale-up from stand to landscape levels.

Emergence

The landscape-scale pattern and dynamics of fire (size, severity, and area), vegetation states and vegetation treatments emerge from the stand or patch-level dynamics and management rules that affect almost 400,000 spatial units covering multiple ownerships over a 50-year time horizon. State variables can be used to calculate additional landscape-scale effects of fire-succession-management interactions on fire occurrence, fire exposure, smoke, timber volume production, carbon, and wildlife habitat. Large landowner objectives are focused on achieving ownership-scale timber volume or area treatment targets under constraints and preferences for certain vegetation types or management zones. In some cases fire and landowners "compete" for timber volume. For example, if wildfires kill merchantable trees some landowners will be forced to harvest those trees within a year or two and reduce timber harvest and fuel treatments by equivalent amounts in unburned areas. This rule acts as a budget constraint on forest management. The landscape scale effects of these objectives and rules on outputs including fire occurrence and severity, carbon, wildlife habitat and other metrics are not easily predictable, especially with large wildfires occurring stochastically in response to climate variation and dynamics in vegetation structure and composition. For example, managers may not be able to reach their volume or area targets over 50 years if fire and high rates of cutting have reduced available volumes or suitable acres.

Adaptation

Major landowner agents have targets (volume or area treated goals) and general rules (constraints on actions, and preferences within constraints) that guide location and timing of management actions; agents shift location and area of activities based on highest volume and suitability of vegetation structure according to constraints and preferences. Past management actions or fire effects, growth and succession in vegetation or changes in wildlife habitat can alter location and amount of management actions. Family forest owners can adapt (increase fuel treatments) if fire has occurred recently in surrounding lands or if vegetation becomes denser and they perceive increased fire hazard.

Objectives

For large landowners the objectives are framed in terms of targets of volume production or area treated. IDU's are screened by constraints that eliminate IDUs from treatment consideration based on volume, forest age, time since last treatment, land allocation, vegetation type and other characteristics. IDUs that are not eliminated by constraints, are scored based on characteristics such as timber volume, vegetation type, proximity to other IDUs with similar volumes, and wildlife habitat. The aggregate scores are then used to determine the probability that an IDU will be selected for treatment during a year. For family forest owners, objectives are determined by empirical equations that set the probability of forest management (timber removal or fuel reduction treatment) in an IDU based on conditions in the IDU, history of occurrence of wildfire in nearby areas and perception of fire hazard in IDUs surrounding the family forest IDU.

Sensing

Family forest owners harvest and reduce fuels based on perception of forest fire hazard in the surrounding landscape and based on past occurrence of wildfire in areas around their IDU.

Interaction

Interactions among landowners and IDUs are indirect and mediated by fire spread. For example, if management on one ownership affects fire occurrence and spread it may alter how fire spreads and burns on adjacent ownerships. Of course, fire itself interacts spatially with vegetation and conditions of IDUs. IDUs surrounded by vegetation that is resistant to spread of fire, will burn less frequently than those that are contiguous with IDUs have high fuel loads.

Stochasticity

Fire ignition and weather (spread and severity potential) are stochastic. Factors driving fire ignition probabilities and weather not modeled. Some successional transitions are probabilistic; selection of IDUs for management actions is random given equal constraints and preference scores.

Observation

Data collected for testing, understanding and analyzing model results are termed evaluative models. The list of these is quite long and includes measures of fire occurrence, severity, potential and exposure, wood volume, biomass, smoke, housing density, carbon, and habitat scores for several species of wildlife.

5. Initialization

The landscape conditions including vegetation structure and composition, fuel models, history of disturbance are initialized for 2012. The initial conditions were characterized from satellite imagery and forest inventory plots and other GIS layers. It is important to have a realistic representation of the initial state of the landscapes since it will be used by managers and stakeholders to evaluate alternative strategies for managing this area.

6. Input data

Time series of weather influence fire behavior. Annual volume and treatment area targets are preset based on interviews with land owners.

7. Submodels

Three major submodels operate in Envision: 1) fire; 2) vegetation succession; and 3) management. A fourth submodel population operates to populate people and homes in IDUs. The fire submodel is based on Flammap and is described in detail in Ager et al. unpublished manuscript. The vegetation succession model is based on a state and transition model of vegetation structure and composition classes and fuel models. The vegetation submodel is described in Spies et al. this issue. The management submodel uses empirically generated rules to schedule vegetation management activities according to the constraints and preferences of the different owners. Those models are described in the main body of this paper and in the appendices. The development submodel uses projected rates of increase in human population and semi-randomly populates IDUs according to distance from cities and state of Oregon landuse planning zones.

Literature cited:

Scheller, R. M., J. B. Domingo, B. R. Sturtevant, J. S. Williams, A. Rudy, A., E. J. Gustafson, and D. J. Mladenoff. 2007. Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. *Ecological Modelling* 201(3):409-419.

Appendix 4

Effect of fire severity and management actions on forest structure and fuel models.

Table A4.1. Effect of fire severity and management on average tree size, canopy cover, layering, and fuels in state-transition vegetation classes. QMD = quadratic mean diameter.

Fire severity / management activity	Effect of disturbance / management activity			
	Size (QMD)	Canopy cover	Number of canopy layers	Fuels
Surface fire (includes prescribed fire)	No change	No change	Reduces multi-layered states to single layer for some vegetation states	Reduces surface fuels; transitions to fuel model 181 or 182 (low load compact litter)
Mixed-severity fire	No change	Decreases cover by one or two classes (e.g., high to moderate, moderate to low, moderate to open)	Reduces multi-layered states to single layer	Reduces surface fuels; post-fire fuel model depends on pre-fire state
Stand-replacing fire	Trees are killed; transition to grass-forb or shrub vegetation state	Decreases tree cover to none or low	No canopy layers remain	Reduces surface fuels; transition to fuel model 181 (low load compact conifer litter)
Mowing and grinding	No change	No change	No change	Eliminates shrub layers and increases surface fuel; transition to custom model for masticated fuel beds
Pre-commercial thinning	No change	Decreases high cover states to low or moderate cover	Generally no change	Increases surface fuels; transitions to fuel model 185 (high load conifer litter)
Thin from below	No change	Decreases high cover states to moderate cover	Generally reduces multi-layered states to single layer	Increases surface fuels; transitions to fuel model 185 (high load conifer litter)

Partial harvest	Primarily no change	Generally decreases cover by one class in high and moderate cover states	Generally reduces multi-layered states to single layer	Increases surface fuels; transitions to fuel model 185 (high load conifer litter)
Partial harvest – heavy	Reduces size by one class (e.g., large to medium)	Decreases cover by one or two classes (e.g., high to moderate, moderate to low, moderate to open)	Reduces multi-layered states to single layer	Increases surface fuels; transitions to fuel model 185 (high load conifer litter)
Regeneration harvest	Trees are removed; transitions to grass-forb or shrub state	Decreases tree cover to none or low	No canopy layers remain	Increases surface fuels; transitions to fuel model 185 (high load conifer litter)
Post-fire salvage of dead trees	No effect	No effect	No Effect	Increases surface fuels; transitions to fuel model 185 (high load conifer litter)

Appendix 5

Management by family forest actors

Family forest actors manage the landscape with commercial harvest and fuels treatment. The operation of our model is based on analysis of data obtained from a survey of family forest landowners within our study area completed for this project (see Kline et al. this issue).

Commerical timber harvest by family forest actors takes is completed with partial harvest that removes 75% of the stand volume. Partial harvest on family forest lands can be used in stands of lodgepole pine, moist and dry mixed conifer forest, and ponderosa pine with average stand dbh of at least 25 cm. The likelihood of a family forest IDU to have harvest is predicted for each timestep of the model with the following equation:

$$\Pr(\mathrm{HARVEST}) = \frac{e^{x}}{1 + e^{x}}$$

where:

$x = -4.5525 + (0.1061 * BA)$ and

BA = basal area (square meters per hectare) at start of period.

Individual parcels meeting the ecological contraints for partial harvest shown above, and with a predicted likelihood greater than a randomly generated number between 0 and 1 computed in each timestep, do partial harvest.

Family forest actors do fuels treatments using three approaches: thinning from below, mowing and grinding of surface fuels, and prescribed burning of surface fuels.

Thinning from below is restricted to ponderosa pine, dry mixed-conifer, moist mixed-conifer, or lodgepole pine stands. Thinning from below removes 20% of the stand volume and can occur only in stands with mean diameters at breast height (dbh) of more than 25 cm and multistory, closed canopies (>60% cover). Stands may not have been disturbed within the last 14 years.

Mowing and grinding treatments can only happen in forest stands with fuel models that are high load dry climate shrubs, very high load climate shrubs or very high load dry climate timber-shrub (Scott and Burgan 2005). At least nine years must have passed since the last stand disturbance, including mowing and grinding treatments.

The likelihood of a family forest actor to undertake any fuels treatment is predicted for each timestep of the model for each family forest IDU with the following equation:

$$\Pr(\mathrm{TREATMENT}) = \frac{e^{x}}{1 + e^{x}}$$

where:

$x = -1.1116 + (0.00044 * TPH) + (0.5487 * FIRE\_5) + (1.4101 * STRUCTURE)$

and:

TPH = average trees per hectare on parcel

FIRE_5 = 1 if wildfire occurred within 10 km within past 5 years; 0 otherwise.
STRUCTURE = 1 if there is a residential structure on the parcel; 0 otherwise.

IDUs with a predicted likelihood of fuels treatment greater than a randomly generated number between 0 and 1 computed in each timestep undergo a fuels treatment. The specific fuels treatment action is selected probabilistically based on observed pattern of fuels treatment found in responses to our survey:

Thinning from below	48%
Mowing and grinding	44%
Prescribed burning	8%

Scott, J.H. and R.E. Burgan 2005. *Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model*. Gen. Tech. Rep. RMRS-GTR-153. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 72 p.

Appendix 6

Management constraints and preferences for large landowner actor groups.

Federal forests

The primary commercial harvest is thinning from below which is restricted to ponderosa pine, dry mixed-conifer, moist mixed-conifer, or lodgepole pine stands. Thinning from below removes 20% of the stand volume and can occur only in stands with mean diameters at breast height (dbh) of more than 25 cm and multistory, closed canopies (>60% cover). Stands may not have been thinned within the previous 14 years. Stands that are within U.S. Congressionally-designated Wilderness areas, classified by the USFS as unsuitable for commercial timber production, on slopes of 30% or more, in nesting habitat for the federally-protected northern spotted owl, or that recently experienced a stand-replacing fire may not undergo thinning from below. The size of thinning from below treatment units is assumed to be normally distributed around a mean size of 50 ha.

Salvage harvesting is possible on stands that meet the characteristics required for thinning from below described in the preceding paragraph and removes 50% of remaining standing sawtimber volume. Salvage logging is only possible in years 1 through 3 after stand-replacing fire. The size of salvage harvests units is assumed to be normally distributed around a mean size of 27 ha.

Prescribed fire may be used in stands of dry mixed conifer and ponderosa pine with mean dbh of more than 25 cm. Stands must have single-story, closed (>60% cover) canopies. Prescribed fire may not be used in stands located within U.S. Congressionally-designated Wilderness areas, on lands classified by the USFS as unsuitable for commercial timber production, or in nesting habitat for the federally-protected northern spotted owl. At least nine years must pass between prescribed fire treatments within the same stand. The size of prescribed fire treatment units is assumed to be 40 ha.

Surface treatments are mowing and grinding activities and can only happen in forest stands with fuel models that are high load dry climate shrubs, very high load climate shrubs or very high load dry climate timber-shrub (Scott and Burgan 2005). Stands that are within U.S. Congressionally-designated Wilderness areas, classified by the USFS as unsuitable for commercial timber production, on slopes of 30% or more, or in nesting habitat for the federally-protected northern spotted owl may not undergo surface treatments. At least nine years must have passed since the last stand disturbance, including mowing and grinding treatments. The size of mowing and grinding treatment units is assumed to be 40 ha.

Preference weights used to rank eligible IDUs for thinning from below, salvage harvest, prescribed fire and surface treatments are shown in Table A3.

Tribal lands

Commercial harvest on tribal lands is done using a combination of thinning from below with a culminating clearcut. Thinning from below removes 20% of the stand volume and is restricted to stands outside of nesting habitat for the federally-protected northern spotted owl where dominant tree species are lodgepole pine (age>70 years), mountain hemlock (age>70 years), moist mixed conifers (age> 40 years), dry mixed conifer (age>40 years), western hemlock (age>60 years), western white pine (age>60 years), pacific silver fir/Douglas-fir (age>60 years), western larch/lodgepole pine (age> 60 years) and alpine/high elevation vegetation (age>70 years). The size of thinning from below treatment units is assumed to be 30 ha.

Clearcutting removes 100% of standing volume and is restricted to stands outside of nesting habitat for the federally-protected northern spotted owl, more than 30 meters from streams, and where the last harvest was more than 19 years prior. The dominant tree species in the stand must be lodgpole or mountain hemlock that is more than 130 years old, moist or dry-mixed conifer stands more than 70 years old, western white pine, pacific silver fir/Douglas-fir, western hemlock more than 90 years old, or high-elevation species stands greater than 130 years old. The size of clearcutting treatment units is assumed to be 20 ha.

Salvage harvesting that removes 50% of remaining standing sawtimber volume is possible in stands of moist or dry-mixed conifer or ponderosa pine on slopes of less than 30 percent and outside the conditional use zone and outside of nesting habitat for the federally-protected northern spotted owl. Salvage logging is possible in periods immediately after the fire and years 1 and 2 post fire. There is no limit to the size of salvage harvests, but total harvested volume in any single year must be less than or equal to the timber volume target for the year.

Prescribed fire may be used in any stand of ponderosa pine, Douglas-fir or dry mixed conifers outside of habitat for the federally-protected northern spotted owl. The size of prescribed fire treatment units is assumed to be 81 ha.

Preference weights used to rank eligible IDUs for thinning from below, clearcutting, salvage harvesting, and prescribed fire are shown in Table A3.

Private corporate forest

Commercial harvest on private corporate lands within the study area is done using partial harvest that removes 75% of the stand volume. Partial harvest on corporate land can be used in stands of any forest type with average stand dbh of at least 25 cm that had not been harvested in the previous 19 years.

Salvage harvesting that removes 50% of remaining standing sawtimber volume is possible in stands of commercial timber species on slopes of less than 30 percent. Salvage logging is possible in immediately after the fire and years 1, 2, and 3 post fire.

Preference weights used to rank eligible IDUs for thinning from below and salvage harvest are shown in Table A3.

Table A6.1. Preferences and weights used in Envision for for management treatments of IDUs by large land owners.

Owner	Treatment	Preference characteristic	Preference weight
Federal	Thinning from below	Ponderosa pine stands	1,100
		Dry mixed-conifer stands	1,000
		Lodgepole stands	900
		Basal area > 20.67 square meters/ha	500
		Stands with medium or high canopy closure	500
		Stands within the wildland urban interface	500
		Dry mixed-conifer or ponderosa pine stands with high potential for high-severity fire	400
		Dry mixed-conifer or ponderosa pine stands with high potential for moderate-severity fire	300
		Moist mixed-conifer stands	-20
		Within area designated as potential habitat for northern spotted owl	-100
	Salvage harvest	Within 366 meters of a road	3
		Within area designated as potential habitat for northern spotted owl	-3
	Prescribed fire	Thinning from below happened within the last four years	3
		Ponderosa pine stands with single-layered, low closure canopies	2
		Dry mixed-conifer stands with single-layered, low closure canopies	1
		Dry mixed-conifer or ponderosa pine stands with high potential for moderate-severity fire	1
		Fuel model is high-load dry climate shrub, very high load dry climate shrub, very high load dry climate timber-shrub, moderate load dry climate shrub	-3
		Within area designated as potential habitat for northern spotted owl	-3
		Stands within the wildland urban interface	-5
	Surface fuel treatment	Stands within the wildland urban interface	5
		Within 400 meters of a major road	2
		Prior prescribed fire or wildfire was 20 or more years ago	1

		Fuel model is high-load dry climate shrub, very high load dry climate shrub, very high load dry climate timber-shrub, moderate load dry climate shrub	1
		Fuel model is moderate load dry climate shrub	0.5
		Within area designated as potential habitat for northern spotted owl	-3
Tribal	Thinning from below and clearcut	Within Beaver or Upper Warm Springs planning area	3
		Within Badger, Mill Creek, or Shitike planning area	1
		Slope is less than 30%	2
		Distance to major road is less than 600 meters	1
		Within 30 meters of a stream	-2
		Northern spotted owl foraging habitat	-3
	Salvage harvest	Grand fir species type	3
		Distance to major road is less than 600 meters	2
		Within 30 meters of a stream	-3
		Northern spotted owl foraging habitat	-3
	Prescribed fire	Ponderosa pine or Douglas-fir stands	3
		Fuel model is high-load dry climate shrub, very high load dry climate shrub, very high load dry climate timber-shrub, moderate load dry climate shrub	3
		Less than five years since prior disturbance	2
		Mixed-conifer stands	2
		7 to 10 years after fuel treatment	1
		Northern spotted owl foraging habitat	-3
		Within 30 meters of a stream	-3
Forest industry	Partial harvest	Basal area greater than 23 square meters/ha	10
		Slope less than 30%	5
	Salvage harvest	Distance to road is less than 366 m	3

Appendix 7

Dead wood biomass calculation

Dead wood following fire was calculated based on regression equations for assigning biomass to the structure classes. Pre-fire dead wood was assumed to be consumed by the fire. First the amount of dead wood created was estimated from the severity class. High severity fire, moderate severity fire and low severity fire killed 90%, 50% and 10% of the prefire biomass, respectively. The amount of consumption by fire of prefire volume for high, moderate and low severity was 0.08, 0.07 and 0.03 respectively (Campbell et al. 2007). The amount of fire-killed wood was then decayed according to the following:

Equation 5.1 $Y_t = Y_0 e^{-kt}$

where Yt is the amount (mass or volume) of wood at time t and Y_0 is the amount of dead wood at time 0, immediately after the disturbance and k is the decay constant that reflects a combination of fragmentation and mineralization processes for decay of snags and down logs. Snags and down logs were lumped into one class of dead wood. K = 0.05 based on a rough estimate from Table 3 in Harmon et al. 1986.

Thus the estimate of dead biomass (Y) at time t following fire would be

Equation 5.2 $Y_t = LF*LB*e^{-kt}$, where LB = live biomass before fire.

At some point in the future (e.g. 20 years) the estimated dead biomass at a future point in time will be mainly a function of dead wood produced in the new post fire stand. This estimate would come from the look-up table as described above. The transition from the modeled dead wood to the dead wood from the structure class lookup table for an IDU was accomplished by using the lookup table value when the modeled amount was less than the lookup table amount.

Campbell, J., D. Donato, D. Azuma, and B. Law. 2007. Pyrogenic carbon emission from a large wildfire in Oregon, United States. Journal of Geophysical Research: Biogeosciences (2005–2012) 112 (G4).

Harmon, M.E., Franklin, J.F., Swanson, F.J., Sollins, P., Gregory, S.V., Lattin, J.D., Anderson, N.H., Cline, S.P., Aumen, N.G., Sedell, J.R., Lienkaemper, G.W., Cromack, K., and Cummins, K.W. 1986. Ecology of coarse woody debris in temperate ecosystems. Adv. Ecol. Res. **15**: 133–302.

Appendix 8

Description of wildlife habitat models developed by Morzillo et. al. 2014.

Summary:

First, habitat structure in an IDU is evaluated and scored as habitat (1) or not habitat (0) based on canopy cover, tree size, layering and tree species composition (cover type). Second, the physical environment of an IDU is evaluated and scored (1-3) based on PVT. The final score is the product of the habitat structure score and the PVT score. Scores of 3 were considered habitat.

Details:

The following are lookup tables for the different species. Mapping is based on a combination of following variables:

- Canopy Cover, Canopy Layering and Size – 1/0 entries (1 = habitat; 0 = not habitat)
- COVERTYPE – 1/0 entries (1 = habitat; 0 = not habitat)
- PVT – 3/2/1 entries (3 = good; 2 = fair; 1 = poor)

Table A8.1 Scoring rules based on PVT and stand structure scores

PVT Score	Score based on stand characteristics	
	1	0
3	3	0
2	2	0
1	1	0

For all species other than mule deer, the binomial (1/0) stand characteristic score is defined as:
    1 = habitat
    0 = not habitat
For each species, only those stand characteristics that have a value of “1” (VEGCLASS (Size =1, Canopy Cover =1 and Canopy Layering = 1) AND COVERTYPE = 1) are assigned a PVT score. For each species, those stand characteristics that have a value of “0” are not assigned a PVT value because they are non-habitat for that species based on the binomial score.

Areas considered habitat in the modeling and analysis had PVT scores of ‘3’ (except for Black-backed Woodpecker which had scores of 2 or 3) based on presence of suitable structure and PVT.

Table A8.2. Canopy Cover Lookup Table**.** PM=Pacific Marten; BBWO Black-backed Woodpecker; NOGO = Northern Goshawk; PIWO = Pileated Woodpecker; WEBL = Western Bluebird; WHWO = White-headed Woodpecker .

Canopy Cover	PM	BBWO	NOGO	PIWO	WEBL	WHWO
None		*			1	
Low		1			1	1
Medium	1	1		1		
High	1		1	1		
Post-Disturb		1			1	1

Table A8.3. Scores for species canopy layering

Canopy Layering	AM	BBWO	NOGO	PIWO	WEBL	WHWO
None		*			1	
Single		1			1	1
Multi	1		1	1		1

Table A8.4. Scores for species by stem size

Size	AM	BBWO	NOGO	PIWO	WEBL	WHWO
Barren						
Development						
Meadow	1				1	
Shrub		*			1	
Seedling/Sapling		*			1	
Pole		1			1	1
Small Tree	1	1		1	1	1
Medium Tree	1	1	1	1	1	1
Large Tee	1	1	1	1	1	1
Giant Tree	1	1	1	1		1

* For Black-backed woodpecker, open, single layer and shrub seedling/sapling conditions are scored as '1' if area has experienced a fire within 10 years and pre-fire conditions had forest vegetation with size > Pole.

Table A8.5. Scores for species by cover type

	AM	BBWO	NOGO	PIWO	WEBL	WHWO
SubAlp parkland	1	1				
Asp_Willow			1			
Oak					1	
OakPine	1	1	1	1	1	1
DougFir	1	1	1	1	1	1
DougFir Mix						
DFWF	1	1	1	1	1	1

GfirEspruce	1	1	1	1	1	1
SFmix	1		1	1	1	
LPPWlarch	1	1	1	1		
Western Hemlock						
GrandFir	1	1	1	1	1	1
White Fir	1	1		1		1
RedFir	1	1	1	1		1
RFWF	1	1	1	1		1
EspruceSAfir	1	1	1			
MtnHem	1	1				
Lodgepole	1	1	1			
LPWUI	1	1				
MixPine	1	1	1	1	1	1
Ponderosa Pine	1	1	1		1	1
PP/LP	1	1	1			1
WhitePine	1					
Jeffrey Pine						
Western Juniper						

Table A8.6 Scores for species by PVT

Region	PVT	AM	BBWO	NOGO	PIWO	WEBL	WHWO
Oregon Blue Mountains	Idaho fescue - Prairie junegrass		1	1	1	1	1
Oregon Blue Mountains	Bluebunch wheatgrass - Sandberg bluegrass		1	1	1	1	1
Oregon Blue Mountains	Low sage - Mesic, no juniper		1	1	1	1	1
Oregon Blue Mountains	Low sage - Mesic, with juniper		1	1	1	2	1
Oregon Blue Mountains	Mountain big sagebrush - With juniper		1	1	1	2	1
Oregon Blue Mountains	Bitterbrush - With juniper		1	1	1	2	1

Oregon Blue Mountains	Rigid sage		1	1	1	1	1
Oregon Blue Mountains	Wyoming big sagebrush - With juniper		1	1	1	2	1
Oregon Blue Mountains	Western juniper woodland		1	1	1	3	1
Oregon Blue Mountains	Wyoming big sagebrush - No juniper		1	1	1	1	1
Oregon Blue Mountains	Subalpine fir - cold, dry	2	2	1	1	1	1
Oregon Blue Mountains	Grand fir - cool, moist	2	3	3	3	3	2
Oregon Blue Mountains	Ponderosa pine - dry, with juniper	2	2	3	3	3	3
Oregon Blue Mountains	Mountain hemlock - cold, dry	3	3	3	1	1	1
Oregon Blue Mountains	Mixed conifer - cold, dry	3	3	3	1	2	1
Oregon Blue Mountains	Subalpine woodland	2	2	1	3	1	1
Oregon Blue Mountains	Ponderosa pine - xeric	2	3	3	3	3	3
Oregon Southeast	Low sage - Mesic, no juniper			1		1	
Oregon Southeast	Low sage - Mesic, with juniper			1		2	
Oregon Southeast	Mountain big sagebrush - With juniper			1		2	
Oregon Southeast	Mountain mahogany			1		1	

Oregon Southeast	Bitterbrush - With juniper			1		2	
Oregon Southeast	Rigid sage			1		1	
Oregon Southeast	Salt desert shrub - Lowland			1		1	
Oregon Southeast	Wyoming big sagebrush - With juniper			1		2	
Oregon Southeast	Western juniper woodland			1		2	
Oregon Southeast	Wyoming big sagebrush - No juniper			1		1	
Oregon Southeast	Mixed conifer - cold, dry			3		2	
Oregon Southeast	Mixed conifer - dry (pumice soils)			3		2	
Oregon Southeast	Ponderosa pine - dry (residual soils)			3		3	
Oregon Southeast	Ponderosa pine - xeric			3		3	
Oregon Eastern Cascades	Idaho fescue - Prairie junegrass	1	1	1	1	1	1
Oregon Eastern Cascades	Bluebunch wheatgrass - Sandberg bluegrass	1	1	1	1	1	1
Oregon Eastern Cascades	Low sage - Mesic, no juniper	1	1	1	1	1	1
Oregon Eastern Cascades	Low sage - Mesic, with juniper	1	1	1	1	1	1
Oregon Eastern Cascades	Mountain big sagebrush - With juniper	1	1	1	1	2	1
Oregon Eastern	Bitterbrush - With juniper	1	1	1	1	2	1

Cascades	Rigid sage	1	1	1	1	1	1
Oregon Eastern Cascades	Wyoming big sagebrush - With juniper	1	1	1	1	1	1
Oregon Eastern Cascades	Western juniper woodland	1	1	1	1	2	1
Oregon Eastern Cascades	Wyoming big sagebrush - No juniper	1	1	1	1	1	1
Oregon Eastern Cascades	Idaho fescue - Prairie junegrass	1	1	1	1	1	1
Oregon Eastern Cascades	Bluebunch wheatgrass - Sandberg bluegrass	1	1	1	1	2	1
Oregon Eastern Cascades	Low sage - Mesic, no juniper	1	1	1	1	2	1
Oregon Eastern Cascades	Low sage - Mesic, with juniper	1	1	1	1	1	1
Oregon Eastern Cascades	Subalpine parkland	1	2	1	1	1	1
Oregon Eastern Cascades	Lodgepole pine - dry	2	3	3	1	1	2
Oregon Eastern Cascades	Lodgepole pine - wet	3	3	3	1	1	2
Oregon Eastern Cascades	Mixed conifer - dry	3	3	3	3	2	3
Oregon Eastern Cascades	Mountain hemlock	3	3	3	1	1	1
Oregon Eastern Cascades	Mountain hemlock - intermediate	3	3	3	1	1	1
Oregon Eastern Cascades	Mixed conifer - moist	2	3	3	3	2	3

Oregon Eastern Cascades	Mixed conifer - dry (pumice soils)	3	3	3	3	2	3
Oregon Eastern Cascades	Mixed conifer - cold, dry	3	3	3	3	2	3
Oregon Eastern Cascades	Oregon white oak / Ponderosa pine	1	3	2	2	2	2
Oregon Eastern Cascades	Ponderosa pine - dry (residual soils)	2	3	3	2	3	3
Oregon Eastern Cascades	Ponderosa pine - Lodgepole pine	3	3	3	2	2	3
Oregon Eastern Cascades	Shasta red fir - dry	3	1	3	3	1	1
Oregon Eastern Cascades	Pacific silver fir - intermediate	3	1	3	3	3	1
Oregon Eastern Cascades	Pacific silver fir - warm	3	1	3	3	3	1
Oregon Eastern Cascades	Western hemlock - cold	3	1	3	3	3	1
Oregon Eastern Cascades	Western hemlock - intermediate	3	1	3	3	3	1
Oregon Eastern Cascades	Western hemlock - wet	3	1	3	3	3	1

Oregon Eastern Cascades	Ponderosa pine - xeric	3	1	3	3	3	1
Oregon Southwest	Subalpine parkland	1	2	1	1	1	1
Oregon Southwest	White fir - cool	3	3	2	3	1	2
Oregon Southwest	Douglas-fir - dry	3	2	3	3	3	3
Oregon Southwest	Douglas-fir - moist	3	2	3	3	3	3
Oregon Southwest	White fir - intermediate	3	3	2	3	1	2
Oregon Southwest	Mountain hemlock - cold, dry	3	3	3	1	1	1
Oregon Southwest	Ponderosa pine - dry, with juniper	2	3	3	2	3	1
Oregon Southwest	Shasta red fir - moist	3	1	3	3	1	2
Oregon Southwest	Oregon white oak	1	1	1	1	1	1

Morzillo, A. T., Comeleo, P., Csuti, B., & Lee, S. Application of State-and-Transition Models to Evaluate Wildlife Habitat. 2014. Pages 129-145 in Halosfky, J.E, M.K. Creutzburg, and M.A. Hemstrom Eds. *Integrating Social, Economic, and Ecological Values Across Large Landscapes*, Portland OR, USDA Forest Service Pacific Northwest Research Station, PNW GTR-896. 206 p.

Appendix 9

Predicting basal area, volume and biomass from state and transition model age and structure attributes.

The data rollup process (see methods) appeared to be effective in assigning individual forest inventory plots (along with their forest structure data) to each vegetation state. However, we found that when states transitioned to other states (through succession, fire, partial harvest, etc.), the quantitative difference in forest structure (e.g., volume) between the pre-transition state (one inventory plot) and post-transition state (a different inventory plot) did not always make sense. For instance, a partial harvest would be expected to generate positive timber volume, but in some cases the post-transition volume was greater than the pre-transition volume, resulting in a negative harvest volume. To address this problem and all the plot-to-plot variability, we instead predicted forest structure attributes from regressions developed with data from the entire suite of 25,000-plus inventory plots in the study area. The plots were stratified by 41 combinations of PVT groups (similar PVTs) and dominant tree species (Table A6). Basal area, tree density (trees/ha), volume and biomass were regressed on forest characteristics described by the state and transition models: stand age, quadratic mean diameter, canopy cover, and number of canopy layers. We used proc glmselect (SAS Institute) with the lasso option for selecting the best models. The values assigned to each structure stage were calculated by multiplying the regression coefficients by the numeric equivalent of the size and canopy cover class midpoints for that structure stage. Age values for each structure stage were based on means from the inventory plots. The predictive equations met our objective of generating an expected trajectory of forest structure attributes across structure stages, that is, from small to large tree sizes, open to high canopy cover, and single- to multi-layered canopies. R-square values in the predictive equations ranged from 0.24 to 0.99, with median r-squares ranging from 0.66 to 0.88. The regression approach was not used for dead biomass due to poor model fit. Instead, we used the values from the rollup process for dead biomass.

Table A7. Adjusted r-squared values from best models of forest structure attributes regressed on stand age, quadratic mean diameter, canopy cover, and number of canopy layers. Attributes: sample size (N), total basal area (BA, m^2/ha), bole volume (VPH, m^3/ha), bole volume of trees 2.54-25 cm dbh (VPH3-25, m^3/ha), number of trees (TPH, trees/ha), number of trees $\geq$ 50 cm dbh (TPH50, trees/ha), and total biomass (Bio, Mg/ha).

PVT group	Cover type	N	BA	VPH	VPH3-25	TPH	TPH50	Bio
Mixed conifer – dry	Douglas-fir	371	0.89	0.90	0.70	0.73	0.65	0.90
	Douglas-fir/white fir	508	0.87	0.86	0.67	0.70	0.69	0.86
	ponderosa pine	1135	0.89	0.87	0.70	0.77	0.57	0.87
Mixed conifer – dry, pumice	ponderosa pine	1302	0.87	0.86	0.69	0.76	0.60	0.86
	white fir	533	0.85	0.85	0.67	0.72	0.71	0.85
Mixed conifer – cold, dry	Douglas-fir/white fir	36	0.87	*	*	0.69	0.73	*
	lodgepole pine	1356	0.87	0.85	0.69	0.79	0.58	0.85
	ponderosa pine	30	0.80	0.93	0.72	0.75	0.62	0.93
	white fir	629	0.87	0.86	0.66	0.65	0.68	0.86

Mixed conifer – cool, moist	Douglas-fir	439	0.87	0.89	0.66	0.72	0.43	0.89
	grand fir/Engelmann spruce	12	0.88	0.83	0.86	0.87	0.24	0.83
	ponderosa pine	1302	0.88	0.86	0.70	0.78	0.58	0.86
	red fir	63	0.97	0.96	0.84	0.86	0.85	0.96
	red fir/white fir	530	0.84	0.86	0.56	0.63	0.71	0.86
	western larch/lodgepole pine	39	0.79	0.81	0.55	0.81	*	0.81
	white fir	1049	0.88	0.88	0.63	0.63	0.69	0.88
White fir	Douglas-fir	426	0.86	0.84	0.62	0.65	0.69	0.84
	Douglas-fir/white fir	357	0.92	0.92	0.64	0.72	0.68	0.92
Ponderosa pine – dry	juniper	235	0.81	0.80	0.46	0.65	0.31	0.80
	ponderosa pine	2482	0.89	0.88	0.66	0.72	0.64	0.88
Ponderosa pine – xeric	juniper	409	0.82	0.78	0.52	0.69	0.55	0.78
	ponderosa pine	2528	0.90	0.89	0.69	0.74	0.63	0.89
Ponderosa - lodgepole	lodgepole pine	326	0.79	0.77	0.55	0.78	0.52	0.77
	ponderosa pine	771	0.89	0.90	0.69	0.76	0.69	0.90
	ponderosa pine/lodgepole pine	89	0.90	0.47	0.63	0.67	*	0.47
Lodgepole pine – dry	lodgepole pine	1347	0.89	0.90	0.63	0.69	0.71	0.90
Lodgepole pine – wet	lodgepole pine	984	0.86	0.88	0.43	0.71	0.71	0.88
Oak – Pine	oak-pine	352	0.91	0.92	0.70	0.74	0.68	0.92
	Oregon white oak	278	0.89	0.89	0.73	0.74	0.63	0.89
Western hemlock	Douglas-fir	921	0.89	0.89	0.62	0.67	0.73	0.89
	silver fir/Douglas-fir	700	0.91	0.91	0.62	0.67	0.75	0.91
Mountain hemlock	Engelmann spruce/subalpine fir	5	0.76	*	0.99	0.73	0.97	*
	grand fir	9	0.79	0.74	0.73	0.89	*	*
	lodgepole pine	711	0.87	0.86	0.69	0.77	0.57	0.86
	lodgepole pine/western larch	18	0.89	0.69	*	0.93	*	0.69
	mixed pine	338	0.77	0.77	0.59	0.74	0.61	0.77
	mountain hemlock	1665	0.89	0.88	0.63	0.62	0.68	0.88
	red fir	724	0.90	0.89	0.62	0.63	0.71	0.89
	western white pine	2	*	*	*	*	*	*
Subalpine parkland	subalpine parkland	630	0.88	0.89	0.59	*	0.74	0.89
	whitebark pine	15	0.65	0.87	0.70	0.59	0.88	0.87

* *Equation was substituted from another comparable cover type due to poor model fit.*

Appendix 10

Habitat model for the Mule Deer

Mule Deer Modeling Zones:

- Oregon East Cascades =
- Oregon West Cascades = N/A
- Blue Mountains

Purshia tridentata shrub layer cover:

- Given in %

For all modeling zones:

First, PVTs are used to classify habitat into three general types: good (3), fair (2), and poor (1). Then, within each of those three types, each observational unit of habitat is given a landscape score based on plant species and structure.

PVT type = 1, 2,

↓

Landscape Score = Foraging + Hiding + Thermal Habitat Score

NOTE: PVT types not listed as 1, 2, or 3 OR size class Barren, Developed, or Agriculture are designated as Not Capable and given a foraging, hiding, thermal and landscape score of -1.

The Landscape score is the addition of the following 3 scores:

- Foraging habitat score (range 5-20)
- Hiding habitat score (range 2-10)
- Thermal habitat score (range 0-11)

Table A10.1 Description of how the Landscape score and PVT are combined

	Sum of foraging, hiding, and thermal based on stand characteristics		
PVT score	41-31	30-19	18-7
3	9	6	3
2	8	5	2
1	7	4	1

Habitat ranking of 9-1 in matrix is based on PVT versus stand characteristics scores. Rank of 9 is the highest, indicated by a PVT value of “3” that corresponds with the highest 30% of stand characteristics scores. Rank of 1 is the lowest, indicated by a PVT value of “1” that corresponds with the lowest 30% of stand characteristics scores. Within each category of stand characteristics (columns), higher PVT scores correspond to higher rankings.

Table A 10.2. Habitat model for mule deer: scoring system for foraging habitat. (Note: QMD is quadratic mean diameter.)

Vegetation characteristic	Class	Score
Cover type	Development	0
	Agriculture	0
	Bare ground	0
Size class	Remnant	1
	Barren	0
	Development (low, medium and high density residential)	3
	Meadow	4
	Shrub	4
	Seedling/sapling	4
	Pole (QMD = 12.5-25 cm)	2
	Small (QMD = 25-38 cm)	1
	Medium (QMD = 38-51 cm)	1
	Large (QMD = 51-76 cm)	1
	Giant (QMD > 76 cm)	1
Canopy cover	None (0-10%)	10
	Low (10-40%)	6
	Medium (40-60%)	2
	High (> 60%)	1
	Post-disturbance	0
Canopy layers	None	1
	Single	1
	Multi	0
Cover of bitterbrush (*Purshia tridentata*)	0-10%	2
	>10%	4

Table A10.3. Habitat model for mule deer: scoring system for hiding habitat. (Note: QMD is quadratic mean diameter.)

Vegetation characteristic	**Class**	**Score**
Cover type	Ponderosa pine, lodgepole pine, Douglas-fir,	1
	Oregon white oak, western juniper	1
Size class	Remnant	0
	Barren	0
	Development (low, medium and high density residential)	1
	Meadow	3
	Shrub	3
	Seedling/sapling	3

	Pole (QMD* = 12.5-25 cm)	3
	Small (QMD = 25-38 cm)	3
	Medium (QMD = 38-51 cm)	3
	Large (QMD = 51-76 cm)	2
	Giant (QMD > 76 cm)	2
Canopy cover	None (0-10%)	0
	Low (10-40%)	2
	Medium (40-60%)	4
	High (> 60%)	4
	Post-disturbance	0
Canopy layers	None	0
	Single	1
	Multi	1

Table A10.4. Habitat model for mule deer: scoring system for thermal habitat.

Vegetation characteristic	**Class**	**Score**
Cover type	Ponderosa pine, lodgepole pine, Douglas-fir,	1
	Oregon white oak, western juniper	1
Size class	Remnant	0
	Barren	0
	Development (low, medium and high density residential)	1
	Meadow	0
	Shrub	0
	Seedling/sapling	0
	Pole (QMD* = 12.5-25 cm)	1
	Small (QMD = 25-38 cm)	1
	Medium (QMD = 38-51 cm)	1
	Large (QMD = 51-76 cm)	2
	Giant (QMD > 76 cm)	2
Canopy cover	None (0-10%)	0
	Low (10-40%)	2
	Medium (40-60%)	4
	High (> 60%)	6
	Post-disturbance	0
Canopy layers	None	0
	Single	1
	Multi	2

*If the grid cell is a 90 meter pixel, then no averaging is attempted since the 90 meter pixel contains the whole female daily home range which is the 9-cells with an 8-cell neighborhood.

Table A10.5 Mule Deer PVT Lookup table

Region	PVT	PVT code	Score
17	1	OBM_gfk	1
17	3	OBM_gpp	1
17	5	OBM_sln	1
17	6	OBM_slw	2
17	7	OBM_smb	2
17	10	OBM_spt	3
17	11	OBM_srs	1
17	14	OBM_swb	2
17	15	OBM_swj	3
17	16	OBM_swn	1
7	6	OBM_fcd	1
7	5	OBM_fcm	3
7	12	OBM_fdp	3
7	16	OBM_fmh	2
7	16	OBM_fmz	2
7	7	OBM_fsw	1
7	13	OBM_fxp	2
18	3	OSE_sln	1
18	4	OSE_slw	2
18	5	OSE_smb	2
18	6	OSE_smm	3
18	8	OSE_spt	3
18	9	OSE_srs	1
18	10	OSE_ssd	1
18	12	OSE_swb	2
18	13	OSE_swj	3
18	14	OSE_swn	1
19	1	OEC_gfk	1
19	2	OEC_gfv	2
19	3	OEC_gpp	1
19	5	OEC_sln	1
19	6	OEC_slw	2
19	7	OEC_smb	2
19	8	OEC_smm	3
19	9	OEC_sms	3
19	10	OEC_spt	3
19	11	OEC_srs	1

19	12	OEC_ssd	1
19	14	OEC_swb	2
19	15	OEC_swj	3
19	16	OEC_swn	1
9	9	OEC_fal	1
9	13	OEC_fld	2
9	12	OEC_flw	2
9	16	OEC_fmd	3
9	18	OEC_fmh	2
9	6	OEC_fmi	2
9	7	OEC_fmm	2
9	11	OEC_fmx	3
9	17	OEC_fmz	3
9	8	OEC_fop	3
9	15	OEC_fpd	3
9	20	OEC_fpl	3
9	10	OEC_frf	3
9	5	OEC_fsi	3
9	4	OEC_fsw	3
9	3	OEC_fwc	3
9	2	OEC_fwi	3
9	1	OEC_fww	3
9	19	OEC_fxp	3
11	1	OSW_fal	1
11	5	OSW_fcw	2
11	13	OSW_fdd	3
11	12	OSW_fdm	3
11	6	OSW_fiw	2
11	2	OSW_fmh	2
11	22	OSW_fpd	3
11	3	OSW_frm	3
11	17	OSW_fwo	3

Appendix 11

Habitat model for the northern spotted owl (*Strix occidentalis*)

The model was built in two steps: First, an understanding of habitat relationships was developed based on empirical data from the study area. Second a habitat suitability model was developed based on the understanding of habitat relationships from the statistical model.

We obtained owl site and use data from 35 northern spotted owl sites on the Deschutes National Forest from Ray Davis (USDA Forest Service, Region 6 Old Forests and Spotted Owls Monitoring Lead). We used a combination of logistic regression and selection ratio analyses (Manly et al. 2002) to compare circular areas around the nest sites to the surrounding landscape at three scales: the nest stand (100 ha), the core home range area (500 ha), and the annual home range (2000 ha). Habitat analysis was conducted using year 2000 GNN vegetation data (pre B&B fire). The owl sites were also all pre-2003 sites for consistency with the vegetation data. We evaluated a suite of biologically plausible mixed-effects logistic regression models for each scale using an information theoretic approach (Burnham and Anderson 2010, Singleton 2013). We then investigated the predicted resource selection values from those models and identified thresholds representing areas used less than, equal to, or greater than available across the analysis landscape. Finally, we quantified the range of covariate values found within each resource selection class and identified classification thresholds for each covariate that best distinguished between the classes. The "Good" habitat class represents habitat conditions found to be used more than available across the three scales of analysis, and is generally consistent with spotted owl "nesting / roosting" habitat (Courtney et al. 2004). The "Moderate" habitat class represents habitat conditions generally found to be used in proportion to available, and is more consistent with "foraging" habitat. The "Poor" habitat class represents habitat conditions used less than available and was considered to be "non-habitat".

We then used the habitat relationships from the empirical analysis to build a habitat suitability model that could be used with our state and transition model structure classes:

Habitat Classes:

0 = Non-Habitat
1 = Moderate Habitat (foraging)
2 = Good Habitat (nesting)

Table A8.1. Habitat quality scores for mixed conifer types: Douglas-fir, Douglas-fir-White fir, white fir, grand fir, and red fir/white fir.

		Canopy Cover		
Stem Size		Low (Open)	Medium	High (Closed)
	Sapling	0	0	0
	Pole	0	0	0
	Small	0	1	1
	Medium	0	1	2
	Large	0	1	2

	Very Large (Giant)	0	1	2

For Cover Type Group 2 (Mixed Ponderosa pine)

		Canopy Cover		
Stem Size		Low (Open)	Medium	High (Closed)
	Sapling	0	0	0
	Pole	0	0	0
	Small	0	0	0
	Medium	0	0	1
	Large	0	0	1
	Very Large (Giant)	0	0	1

For Cover Type Group 3 (Mountain Hemlock)*

		Canopy Cover		
Stem Size		Low (Open)	Medium	High (Closed)
	Sapling	0	0	0
	Pole	0	0	0
	Small	0	1	1
	Medium	0	1	1
	Large	0	1	1
	Very Large (Giant)	0	1	1

*Only for CT_MH areas < 1800 m elevation and < 1km from Good (2) habitat

Literature Cited:

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Courtney,S.P., Blakesley,J.A., Bigley,R.E., Cody,M.L., Dumbacher,J.P., Fleischer,R.C., Franklin,A.B., Franklin,J.F., Gutierrez,R.J., Marzluff,J.M. and Sztukowski,L. 2004. Scientific evaluation of the status of the Northern Spotted Owl. Sustainable Ecosystems Institute, Portland OR.

Manly, B.F., L.L. McDonald, D.L. Thomas, T.L. McDonald, W.P. Erickson. 2002. Resource Selection by Animals: Statistical design and analysis for field studies. Second Edition. Kluwer Academic Publishers. Dordrecht, The Netherlands.

Appendix 12

Comparison of simulated size distributions of forest cutting units (thinning, partial harvest, clear cutting) with observed unit sizes estimated from Landsat imagery for the period 2006-2010. The Envision model was run for four years on vegetation data that represented conditions as of 2006.