

Analyzing fine-scale spatiotemporal drivers of wildfire in a forest landscape model

Alan A. Ager^{a,*}, Ana M.G. Barros^b, Michelle A. Day^c, Haiganoush K. Preisler^d, Thomas A. Spies^e, John Bolte^f

^a USDA Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory, 5775 US Highway 10W, Missoula, MT, 59808, USA

^b Oregon State University, College of Forestry, Forest Ecosystems & Society, 321 Richardson Hall, Corvallis, OR, 97331, USA

^c Oregon State University, College of Forestry, Forest Engineering, Resources & Management, 280 Peavey Hall, Corvallis, OR, 97331, USA

^d USDA Forest Service, Pacific Southwest Research Station, 800 Buchanan Street, Albany, CA, 94710, USA

^e USDA Forest Service, Pacific Northwest Research Station, 3200 SW Jefferson Way, Corvallis, OR, 97331, USA

^f Oregon State University, Department of Biological Engineering, Corvallis, OR, 97331, USA

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ABSTRACT

We developed and applied a wildfire simulation package in the Envision agent-based landscape modelling system. The wildfire package combines statistical modelling of fire occurrence with a high-resolution, mechanistic wildfire spread model that can capture fine scale effects of fire feedbacks and fuel management, and replicate restoration strategies at scales that are meaningful to forest managers. We applied the model to a landscape covering 1.2 million ha of fire prone area in central Oregon, USA where wildland fires are increasingly impacting conservation, amenity values and developed areas. We conducted simulations to examine the effect of human versus natural ignitions on future fire regimes under current restoration programs, and whether contemporary fire regimes observed in the past 20 years are likely to change as result of fire feedbacks and management activities. The ignition prediction model revealed non-linear effects of location and time of year, and distinct spatiotemporal patterns for human versus natural ignitions. Fire rotation interval among replicate simulations varied from 78 to 170 years and changed little over the 50-yr simulation, suggesting a stable but highly variable and uncertain future fire regime. Interestingly, the potential for fire-on-fire feedbacks was higher for human versus natural ignitions due to human ignition hotspots within the study area. We compare the methods and findings with other forest landscape simulation model (FLSM) studies and discuss future application of FLSMs to address emerging wildfire management and policy issues on fire frequent forests in the western US.

1. Introduction

In the western US, large-scale forest management efforts are being implemented on public lands to restore forest resiliency to wildfire in fire-dependent forests and reduce fire risk to socioecological values. The work is aimed at counteracting the effects of a century of fire suppression originally intended to reduce wildfire risk (Calkin et al., 2014; North et al., 2015). The unforeseen and unintended consequences of these past fire suppression policies have been amplified by climate change (Westerling, 2016), urban expansion (Theobald and Romme, 2007), and poor perception of risk from highly uncertain wildfire events, leading to a system that has been termed a “socioecological” pathology (Fischer et al., 2016). One tool that can help understand the long-term effectiveness of these policies are forest landscape simulation

models (FLSMs) that simulate forest management under a background of stochastic wildfire over time. These models can help test a wide range of policy questions about how landscapes respond to forest management activities under a stochastic background of large fire events that often mask long-term landscape change. For instance, does variability in bioregional and landscape scale climatic drivers of wildfire overwhelm the potential effects of fire-on-fire feedbacks under elevated burning rates predicted by climate change models (McKenzie and Littell, 2017)?

There are few FLSMs that can simulate detailed forest fuels and restoration management programs under a background of stochastic, large (e.g., > 10⁴ ha) fire (Loudermilk et al., 2014; Scheller and Mladenoff, 2004, 2007; Syphard et al., 2011), and even fewer available to researchers with the ability to incorporate human decision making

* Corresponding author.

E-mail address: aager@fs.fed.us (A.A. Ager).

related to forests and fire. For example, modelling landscape trajectories in response to widespread federal forest restoration policies in the western US (Stephens et al., 2016) requires the simulation of spatially explicit, stand-scale simulation of fuel treatments that include multi-year sequences of mechanical thinning, surface fuels mastication, piling, and prescribed fire. Silvicultural prescriptions aimed at reducing fire severity must be modelled to consider the structure, species, biophysical setting, and fire ecology of individual stands (Cochran et al., 1994; Haugo et al., 2015; O'Hara et al., 2010). Stand treatments within restoration planning areas must then be coordinated in terms of treatment density, dimensions, and spatial arrangement (Finney, 2001, Fig. 5) to achieve specific ecological and fire management objectives (Collins et al., 2010; Finney, 2001; Stevens et al., 2016). Equally important is the accurate representation of post treatment fuels since the landscape effect of fuel treatments on large fire spread is strongly influenced by the ratio of pre to post treatment spread rates (see Finney (2001), Fig. 9). Forest dynamics in treated and burned areas are modelled to replicate recovery of fuels after treatment under specific ecological conditions (Prichard et al., 2010; Safford et al., 2012; USDA Forest Service, 2014) to capture the temporal dynamics of fire-on-treatment interactions (Barnett et al., 2016) and fire-on-fire feedbacks (Prichard et al., 2017).

The complexity of FLSMs is amplified on typical western US landscapes that are mosaics of different forest types and public, private, and private industrial ownerships, each having respective operational and economic constraints, and motivations to manage forests and fuels towards particular ecological and socioeconomic goals (Charnley et al., 2015). Analyzing how landowner behavior affects landscape change requires incorporating agent behavior and preferences for the adoption of specific policies (Kline et al., 2017; Spies et al., 2014). Agent-based landscape simulation models are relatively new for scenario planning on landscapes that are subjected to frequent ecological disturbances (e.g., floods, wildfire, windstorms, insect outbreaks, (Loehman et al., 2017; Scheller et al., 2017)) and where multiple agents (e.g., land managers representing different ownerships, homeowners, and stakeholders) who may not own land but influence decision making by landowners exist. In such cases, agent-based models (ABMs) can provide a way to understand agent behavior, policy feedbacks and unexpected impacts over long time periods (Bone et al., 2014; Hulse et al., 2016; Spies et al., 2014).

Compared to modelling forest management activities and landowner (agent) behavior, incorporating stochastic disturbance has its own set of challenges, and in the case of wildfire includes: (1) plausible future spatiotemporal patterns of human (agent) versus natural ignitions (Parisien et al., 2016); (2) modelling fire spread through heterogeneous fuel beds (Finney et al., 2011); and (3) representing fire severity and fire effects on forest vegetation (Reinhardt et al., 1997). Large fires (e.g., 20,000 to > 100,000 ha) in the western US are relatively rare events that account for most of the area burned and have limited historical precedence within a typical study area (e.g., 10,000–100,000 ha), making model calibration difficult. Human ignitions, which are important drivers of fire in some but not all areas (Balch et al., 2017; Parisien et al., 2016) are highly non-random and correlated with anthropogenic variables. In ABM frameworks, actor groups that drive wildfire ignitions in specific locations and seasons also respond to wildfire impacts over time with policies to manage landscape fuels.

In this paper we describe the development and application of a wildfire modelling subsystem within the agent-based landscape modelling system, Envision (Bolte et al., 2004; Guzy et al., 2008; Hulse et al., 2009). Envision is a spatially explicit landscape modelling platform capable of simulating multiple processes of landscape change and has been applied to a range of environmental management problems including watershed management, restoration of fire adapted forests, and land use change (Barros et al., 2017; Bolte, 2010; Spies et al., 2017). We describe the design, testing and application of the wildfire

submodel on a 1.2 million ha study area. Specifically, we used Envision to simulate a 50-yr period with and without contemporary forest management activities and used the outputs to address the following questions: (1) Are fire distributions and fire severity stationary over time for human versus natural ignitions, or are there tipping points? (2) Is there evidence for potential feedbacks between human and natural ignitions, i.e., is current fire limited by past fire? (3) What are the effects of contemporary forest restoration policies on fire distributions generated from the different sources of ignitions? (4) What is the variability in annual fire activity relative to the effects of management? The methods advance the integration of wildfire simulation with agent-based landscape models, and the results show how landscape feedbacks and human drivers of wildfire can affect fire regimes and ecological conditions. We compare our work with Envision to other landscape modeling studies and highlight current trends, as well as important differences in the structuring of submodels for wildfire and forest management. The work complements related studies as part of the “Forests, People, Fire” project (Spies et al., 2014) on long-term impacts of alternative forest restoration activities and fire regimes on ecosystem services (Ager et al., 2017a; Barros et al., 2017; Spies et al., 2017).

2. Methods

2.1. Study areas

We used two nested study areas for the work reported here. The first is the 3.32 million ha “Forests, People, Fire” (FPF) project (Spies et al., 2014) located in central and south-central Oregon (Fig. 1). This larger area was used to build and calibrate the fire prediction system described below, and detailed descriptions of the forest conditions and ownership are reported elsewhere (Ager et al., 2014a). We used a smaller 1.25 million ha subarea to simulate scenarios with Envision (henceforth north study area). The land in the north study area is owned and administered by a number of entities including federal, tribal, corporate forests, family forests, and a large number of small private inholdings (homeowners). The tribal lands (Confederated Tribes of Warm Springs, 21%) occupy the northern portion of the study area, and federal lands (61%) are primarily the Deschutes National Forest (DNF). Corporate forests (6%) and family forests (4%) are intermixed with federal land. The Gilchrist State Forest accounts for 2% of the land area and homeowners cover about 7% of the study area. Management on the DNF is based on a suite of land management designations (e.g., general forest, scenic areas, recreation, wildlife, wilderness) determined by the land and resource management plan (USDA Forest Service, 1990), with ca. 46% of the area available for forest and fuel management activities.

Dominant forest types range from subalpine forest along the eastern slope of the Cascades to the west of the north study area to juniper woodlands and arid shrublands to the east (Fig. 1). In between lies a mosaic of dry and moist mixed conifer forest intermixed with lodgepole pine (*Pinus contorta*) and ponderosa pine (*Pinus ponderosa*). Dry mixed conifer forests are composed of ponderosa pine, lodgepole pine, Douglas-fir (*Pseudotsuga menziesii*) and grand and white fir (*Abies grandis* and *A. concolor*). Moist mixed conifer forests include the same species as in the dry mixed forest with associations of mountain hemlock (*Tsuga mertensiana*).

Much of the lower elevation forested area has dense understories as a result of fire suppression, although federal managers have thinned and underburned some of these to promote fire resiliency (Appendix A, Fig. A1 in supplemental material), and partial harvest during the 20th century removed many of large fire resistant ponderosa pine and Douglas-fir (Merschel et al., 2014). The mean number of ignitions per year was 372 (1992–2013), and the mean area burned was 1423 ha. The area was affected by large fires (> 10,000 ha) in the last two decades including the B&B complex fire in 2003 (36,733 ha) and Sunnyside Turnoff in 2013 (21,448 ha).

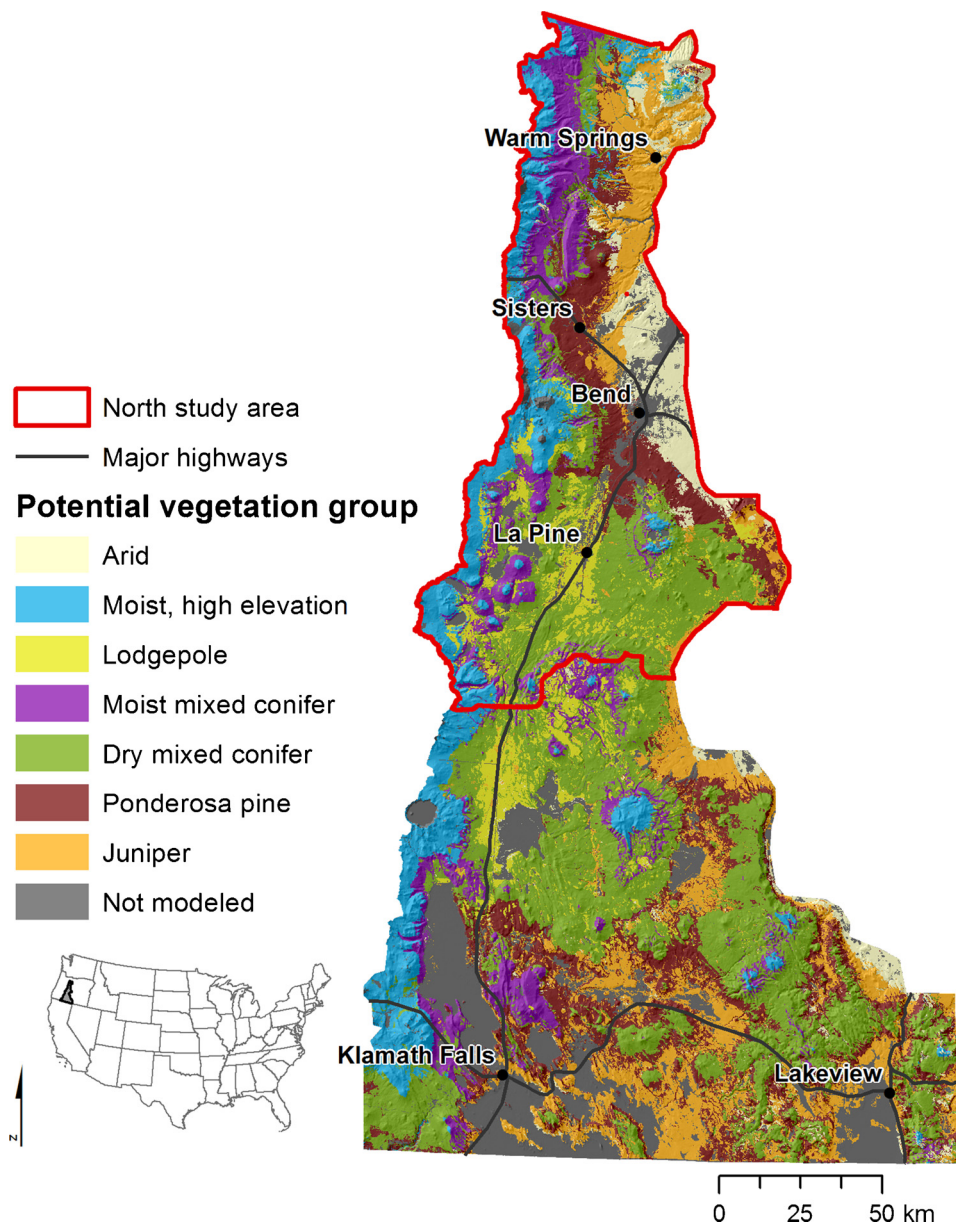


Fig. 1. Map of the study area used for the fire model development (modified from Ager et al. (2017b)), and north study area used for simulations with potential vegetation groups adopted from Halofsky et al. (2014a).

2.2. Envision overview

Envision (Guzy et al., 2008; Hulse et al., 2009, 2016) is a landscape modelling platform that consists of a core spatial landscape and policy system with a plug-in architecture allowing the incorporation of physical and biological disturbances and human activities on a spatially explicit landscape over time (Appendix A, Fig. A2 in supplemental material). The modelling platform consists of five main components: (1) a spatial framework for representing landscape features as polygons, points, and grids; (2) an agent-based modelling system to simulate the decision-makers and their adoption of different policies; (3) a policy scenario building system that specifies policies with landscape activities; (4) a plug-in architecture to incorporate autonomous process models (submodels); and (5) evaluation models that track and report landscape production metrics. The interface also provides a number of tools for visualizing spatial inputs and outputs.

Envision landscapes were represented by individual decision units (IDU), polygons attributed with a vegetation state, fuels, and

management activities (Spies et al., 2017). Envision submodels were created to model landscape change over time as affected by wildfire, vegetation succession, and forest management activities (Appendix A, Fig. A2 in supplemental material). The latter is implemented via a preference system specific to each policy scenario that allocates management activities on the landscape. The Envision configuration for the FPF project included five submodels: vegetation dynamics, forest management, wildfire and wildfire effects, and population growth (Spies et al., 2017). The latter model is described elsewhere and was not invoked in the present study. The remaining models are briefly described below with a focus on the wildfire and wildfire effects submodels. Additional details are available in Appendix A in the supplementary material and in related papers that used the modelling system (Ager et al., 2017c; Charnley et al., 2017; Spies et al., 2017).

2.3. Vegetation dynamics

Vegetation dynamics were simulated with a state-and-transition

Table 1

Vegclass structural stage attributes used for 127 unique cover type combinations (e.g., Douglas-fir/white-fir, trembling aspen/willow). Each vegclass includes a combination of tree size, canopy cover and layering.

Structural Stage Attribute	Class
Size (dbh)	Barren
	Meadow
	Shrubs
	Seedling/sapling
	Pole (0.13–0.25 m)
	Small tree (0.25–0.38 m)
	Medium tree (0.38–0.51 m)
	Large tree (0.51–0.76 m)
Canopy cover	Giant tree (> 0.76 m)
	Low (open, 10–40%)
	Medium (40–60%)
	High (closed, > 60%)
Layering	Post-disturbance
	None
	Single
	Multi

simulation model (STSM) adopted from Halofsky et al. (2014a). The model classified the landscape into a discrete set of vegetation states (hereafter vegclass) with each vegclass having a probabilistic and deterministic pathway that describes the vegetation trajectory over time in response to succession and disturbance (wildfire and/or forest management). A vegclass is characterized by a dominant and codominant tree species, average tree size, forest canopy cover percentage, and canopy layering category (Table 1). Table A1 (Appendix A in supplementary material) shows the ecological stratification of the landscape and potential vegetation management groups. Vegclasses are transient and define the state of an IDU at a given point in time. When one or more characteristics of the vegclass change, a state transition is triggered and the IDU is attributed a new vegclass which is passed along to the next simulation time step. State transitions, which can be deterministic or probabilistic, were developed using the Vegetation Dynamics Development Tool (VDDT) and adopted from Halofsky et al. (2014a). Vegclass attributes at the initial condition (year one in simulation) were based on 2006 satellite imagery and inventory plots using the gradient nearest neighborhood (GNN) method (Ohmann et al., 2011) and updated to reflect vegetation growth and large historical fires recorded in the Monitoring Trends in Burn Severity dataset (MTBS, MTBS Data Access, 2017) for 2006 to 2012, and forest management (see below and see Spies et al. (2017) for more details).

2.4. Forest management

Forest management was modelled by allocating treatments on the landscape based on user-defined allocation rules that are specific to treatment actions and the ownerships in the study area, however only federal land management was modelled in this study. Management unit-specific wood volume or area treatment targets are used to constrain treatment activity. Allocation rules include stand characteristics that preclude management, hectares treated per year and mean patch size of treated areas. Management options included various types of commercial and non-commercial harvesting, prescribed fire, and mowing and grinding simulated on federal lands. In the current simulations we specifically modelled two scenarios: (1) a no management scenario (NOMAN), and (2) a “current management” scenario (CMAN) that treated a total of 8500 ha year⁻¹ with treatment types allocated as 50% mechanical thinning, 30% mowing and grinding and 20% prescribed fire. The current management scenario represents a treatment rate of 0.7% of the study area per year.

2.5. Wildfire

Wildfire was simulated within Envision via a wildfire simulation submodel (Fig. 2) using the minimum travel time (MTT) fire spread algorithm (Finney, 2002) and associated crown fire models as implemented in FlamMap (Finney, 2006) and distributed in the USFS Fire Behavior Library (Brittain, 2018). The code library contains all the input and output functionality of the FlamMap5 program. The MTT algorithm models two-dimensional fire growth under constant weather by Huygens’ principle where the growth and behavior of the fire edge are modelled as a vector or wave front (Knight and Coleman, 1993). The MTT algorithm has been extensively applied in both the research and management environments (Miller and Ager, 2013; Noonan-Wright et al., 2011) and is embedded in a number of wildfire decision support systems used in the US and elsewhere (Kalabokidis et al., 2016; Oliveira et al., 2016; Salis et al., 2016; Wells, 2009).

The wildfire submodel is called each simulation year by Envision, initiating a sequence of modelling steps (Fig. 2). In sequence, the submodel first reads simulation run parameters from an XML file including file paths and related information. The submodel then reads and translates the vegclass from the IDU polygons to the five fuels variables and three topography variables (aspect, slope, elevation), and writes a binary raster (90 x 90 m) input file for FlamMap. Fuel variables are the fuel model (Scott and Burgan, 2005) that describes surface fuels and four variables measuring canopy fuels: canopy bulk density, canopy cover, canopy base height and total stand height. Canopy fuels were determined by simulating representative stands for each vegclass through the Forest Vegetation Simulator-Fire and Fuels Extension (FVS-FFE, Dixon, 2002) and recording the mean value. Surface fuel models for the portion of the study area in the DNF were assigned to each IDU based on the majority representation in the Forest’s fuel model layer. Outside the Forest we used the LANDFIRE 2008 rapid refresh FBFM40 layer (LANDFIRE, 2013). Both the LANDFIRE and DNF fuel layers have been extensively used for fire simulation as part of forest project planning. Surface and canopy fuels were modelled dynamically according to the state transitions associated with each vegclass. In addition to the baseline fuel models, each vegclass had one or more fuel-model variants to accommodate changes in fuels that were not accompanied by changes in the vegclass (Appendix A, Table A3 in supplementary material). The baseline fuel model was assigned to variant 1 and additional variants were invoked when an IDU was disturbed by fire or management, but the corresponding vegclass did not change. The type of disturbance dictated which variant was selected (Appendix A, Table A3 in supplementary material) by Envision. The variant remained in place until the Time-in-Variant (TIV) limit was reached, or the vegclass transitioned to a new class as a result of a deterministic or probabilistic transition.

2.5.1. Spatiotemporal fire prediction model

We used empirically-derived relationships between energy release component (ERC) and historical fire attributes to predict daily fire occurrence and fire size (Finney et al., 2011; Preisler and Ager, 2013; Preisler et al., 2004). The statistical model was developed using historical ignition data (1992–2009) for the entire FPF study area from the spatial wildfire database of the US (Short, 2014). There were 11,618 ignitions in the study area between 1992 and 2009, 6379 were natural, and 5239 were human-caused. Daily ERC data were downloaded from the RAWS USA Climate Archive for 25 remote stations (Appendix A, Table A2 and Fig. A3 in supplementary material) in the study area from 1961 to 2011 depending on the station (Western Regional Climate Center, 2014). Variability among the stations was relatively low and hence ERC values were averaged by day of ignition. We developed independent statistical models for fire occurrence versus fire size as described individually below. The predictions used as input to Envision are obtained by performing random draws from the corresponding estimated distributions.

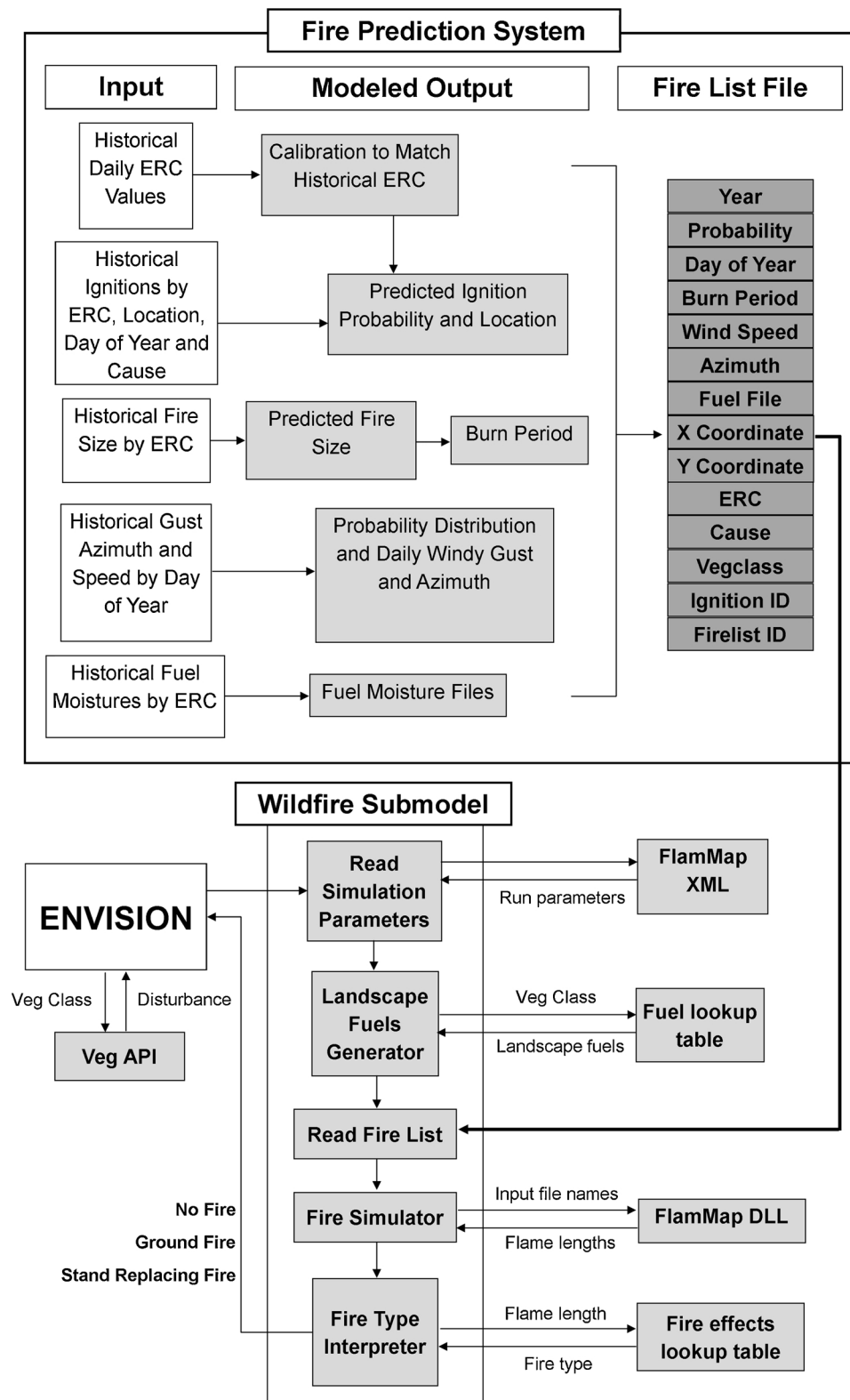


Fig. 2. Diagram showing the major components of the wildfire submodel in Envision. Top flow chart shows the components of the spatiotemporal fire prediction system including input variables and resulting fields in the firelist file that are read into Envision. Bottom shows the wildfire submodel that uses the FlamMap fire spread algorithms to simulate each fire event in the firelist file. See [Appendix A](#), Fig. A2 in supplementary material for schematics of the entire Envision model.

2.5.2. Predicting fire occurrence

Plots of the historical fire occurrence data in the study area for the period 1992–2009 indicated differences in both spatial and temporal patterns of ignitions, and substantial differences between ignition types (see [Figs. 3 and 4](#) in [Ager et al. \(2017b\)](#) and [Fig. 3](#)). Consequently, we

estimated separate probability models for lightning and human caused fires, with spatial location, day-of-year and ERC as explanatory variables. In other words, the probability models are spatially (km^2) and temporally (day-of-year) explicit. We followed previous statistical modelling of wildfires and fire danger rating systems used in the US

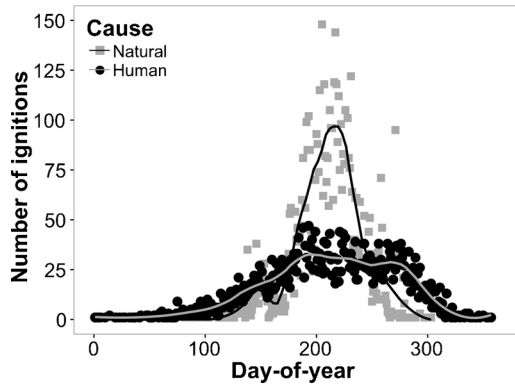


Fig. 3. Seasonal patterns of wildfire ignitions by ignition cause, human versus natural (lightning), in the study area during 1992–2009 from Short (2014). Figure modified from Ager et al. (2017b).

(Bradshaw et al., 1983) that used ERC as a predictor (Finney et al., 2011). The spatially explicit statistical models follow those in Preisler et al. (2004) and Preisler et al. (2009). The specifics of the model were:

$$\text{logit}(p_1) \sim \alpha_{10} + \log(1/\pi) + g_{11}(\text{ERC}) + g_{12}(\text{long, lat}) + g_{13}(\text{day.of.year}) + \tau \quad (1)$$

$$\text{logit}(p_2) \sim \alpha_{20} + \log(1/\pi) + g_{21}(\text{ERC}) + g_{22}(\text{long, lat}) + g_{23}(\text{day.of.year}) \quad (2)$$

where p_1 and p_2 are the probability of lightning and human caused ignitions respectively. The functions, g , are non-parametric smooth spline functions (Wood, 2006) included in the model to account for the effect of ERC and the potentially non-linear seasonal and spatial patterns seen in the ignition data (see also Preisler et al., 2009). Because we observed outliers (large number of ignitions) in some years due to large lightning events, and because none of the explanatory variables used in the model account for these lightning episodes, we included a random year effect, τ , in the model to simulate episodic lightning ignitions (Brillinger et al., 2006). The term, $\log(1/\pi)$, is an offset added to the intercept α , with π equal to the sampling proportion of the $\text{km} \times \text{km} \times \text{day}$ voxels with no ignition (Brillinger, 2003). Sampling of the voxels with no ignition was done to create a manageable data size. The total number of voxels in the study area over the 18 year study period was over 800 million. To find voxels that lacked ignitions we used a 500 m grid of the study area and randomly selected three sets of grid points for each day of the historical ignition data record (6534 days) and the mean ERC value for that day from the 25 stations was assigned to these “non-ignitions.” These were added to the ignition data to create a dataset that included both ignitions and non-ignitions. Location (lat, long) was included in the model to account for spatial drivers of ignition patterns, although these specific factors were not investigated. While climate change may lead to changes in spatial lightning patterns, and population growth may lead to increases in ignition numbers, these considerations were beyond the scope of the current study.

We used the Mixed GAM Computation Vehicle (mgcv) package (Wood, 2006) in the open source R statistical package (R Core Team, 2014) to estimate the models in Eqs. (1) and (2). The estimated probabilities of ignition were then used to simulate spatially and seasonally explicit ignitions for both lightning and human caused fires. The estimated random year effects in the model for lightning ignitions were not Gaussian. Consequently, in our simulations we generated a random year effect by sampling from the estimated empirical distribution of τ .

Next, we estimated a model for the probability of an ignition resulting in a fire > 10 ha. The model used ERC and spatial location as explanatory variables. We found no significant seasonal effect on the probability of an ignition becoming a large fire, consequently the final models did not include a day-of-year term. The specific models used

were,

$$\text{logit}(P_1) \sim \beta_{10} + \beta_{11} * \text{ERC} + h_{12}(\text{long, lat}) \quad (3)$$

$$\text{logit}(P_2) \sim \beta_{20} + \beta_{21} * \text{ERC} + h_{22}(\text{long, lat}) \quad (4)$$

where P_1 and P_2 are the probability of a lightning and human caused ignition burning an area larger than 10 ha, respectively. The functions, h , are non-parametric smooth spline functions included in the model to account for the effect of spatial location on the probability of ignitions becoming large fires. For each day and location with a simulated ignition, the estimated values of P_1 and P_2 were used to simulate a large fire occurrence. Fires > 10 ha in our historical sample included 313 fires out of 11,000.

2.5.3. Predicting fire size

The distribution of fire sizes, given an occurrence of a fire greater than 10 ha, was estimated using the log-generalized Pareto distribution with ERC as an explanatory variable (Ager et al., 2014c). Specifically, we used

$$f(u|x) = \frac{1}{\sigma(x)} \times \left[1 + \frac{\alpha(x)(u-10)}{\sigma(x)} \right]^{-1 - \frac{1}{\alpha(x)}} \quad (5)$$

where $u = \log(\text{fire size})$ for fires greater than 10 ha; $x = \text{ERC}$; and α and σ are the shape and scale parameters, respectively. We used a spline function for the relationship between the shape parameter and ERC, and a linear function for the relationship between the scale parameter and ERC.

For location and day with a simulated fire greater than 10 ha we used the estimated shape and scale parameters to simulate a fire size from the Pareto distribution in Eq. (5).

2.5.4. Generating future ERC

The daily ERC values, which drive the estimation process, were derived from historical data from the RAWs climate archive referenced above and listed in Appendix A, Table A2 in supplementary material. We used historical daily ERC values, averaged over the study area, to characterize the distribution of ERC streams. Specifically, we estimated the parameters for an autoregressive model of order one with day-of-year as an explanatory to account for the seasonal pattern noted in section 2.5.2. The equation for the model was

$$y_{ti} = \mu_i + y_{t-1,i} + s(\text{day.of.year}) + \varepsilon \quad t = 2, \dots, 365; i = 1, \dots, T \quad (6)$$

where s is a smooth spline function and ε random noise, the subscript i refers to the i^{th} simulated year out of T years. Finally, the intercept μ_i is a random intercept to account for between year variability seen in the historical ERC data. This model was used to generate streams of 365 daily ERC values for each simulated year as specified by the user. Replicate firelists are created by repeating the process creating a unique sequence of ERC values based on historical patterns.

2.5.5. Fuel moistures

Fuel moisture files are used by the FlamMap DLL to set moistures for each fuel size class (1-hr, 10-hr, 100-hr, 1000-hr) and fuel model (Scott and Burgan, 2005) as well as live herbaceous and woody components. We used the historical (1987–2011) mean fuel moisture values for each fuel size class for each value of ERC used in the simulations.

2.5.6. Winds

Winds were modelled independently from fire probabilities. We used historical records (1994–2011) to randomly sample gust wind direction based on day-of-year. To simulate ignitions under conditions when fires actively spread, we based wind speed values on gust data derived from Lava Butte RAWs weather data but restricted to days in the historical record where fires occurred that exceeded 500 ha. A gust

speed probability distribution was generated from these records and used to sample gust speed for each ignition.

2.5.7. Burn periods

The MTT fire spread algorithm uses inputs on time rather than size of fire (Finney, 2002) thus to obtain the fire size predicted by the fire prediction system it was necessary to translate fire size (ha) to burn period (minutes), and subsequent adjustments if the desired fire size was not achieved. In other words, it was necessary to guarantee that the simulated fire perimeters were materialized in any specific landscape and burning conditions with fire size and spatial distributions that reflect the predicted firelist.

We created a fire-size burn period distribution with an MTT version encapsulated in FConstMTT (a command line version of Flammap, Finney (2002)), by simulating multiple sets of 100 random ignition points with burn periods ranging from 30 min to 8000 min. Wind speed, azimuth and ERC were fixed at 18 mph, 220 degrees and 60, respectively. The simulated fire sizes and corresponding burn periods were used to estimate a second-order polynomial linear regression model using fire size as predictor and burn period as dependent variable (Appendix A, Fig. A4 in supplementary material). The model was applied to obtain an initial burn period for each predicted fire size on the firelist (Table 2).

2.5.8. Creating firelists

We developed the fire prediction system in R (R Core Team, 2014) that reads synthetic future ERC streams (section 2.5.4) and predicts daily fire occurrence (section 2.5.2), location and size (section 2.5.3). The prediction system writes a text file with lists of ignitions (firelist) and associated predicted fire weather parameters (wind speed and azimuth, section 2.5.6), burn probability (section 2.5.2), burn period (section 2.5.7), fire cause (lightning or human) and fuel moisture conditions (section 2.5.5) for each day a fire occurs in each simulation year (Table 2). The firelists are generated for a user-specified simulation period and number of replicates. The fire prediction system was executed before an Envision simulation. The fire prediction system was designed to run in parallel on 8 processors and was batch run on a six-core 3.50 GHz Intel Xenon CPU with 128 GB of RAM for 30 replicates of 50 years each (section 2.7). For a given batch run to generate five firelists predicting 50 years each took under 25 min. We assessed the statistical model by comparing the distribution of random draws from the estimated probability models with the empirical distributions of the observed data, both data sets plotted against ERC.

Table 2
Firelist output variables from the spatiotemporal ignition prediction model.

Variable	Description
Yr	Fire year
prob	Probability of ignition (always 1)
Julian	Day-of-year (1–365)
burnper	Burn period (min)
WindSpeed	Wind gust speed (mph)
azimuth	Wind gust direction (0–360°)
FMfile	Fuel moisture filename
IgnitionX	X coordinate of ignition
IgnitionY	Y coordinate of ignition
Original_Size	Fire size (ha)
ERC	Energy Release Component
Cause	Fire cause (1 = lightning; 2 = human)
vegclass	Vegetation class (0 = arid, 1 = alpine/high elevation, 2 = lodgepole, 3 = moist mixed conifer, 4 = dry mixed conifer, 5 = ponderosa pine, 6 = areas with juniper, 99 = wetlands and other vegetation)
ignitionID	unique fire ID
listID	unique fire ID including firelist #, fire year and day-of-year

2.5.9. Burn period adjustments

To determine whether the predicted fire size would materialize under variable sets of ignition location, fuel and weather conditions we ran a set of firelists with Envision. To control for the potential effect of vegetation succession, wildfire and management in simulated fire size we forced all ignitions to occur in the same year (simulation year = 1). We observed two issues with fires simulated with Envision, the first being that when ignitions landed in non-burnable or fuel-limited areas the predicted fire size was not reached. To correct this first problem we determined that if the simulated fire size in Envision was smaller than the predicted fire size by a factor of 0.2, the ignition location (X, Y) was randomly sampled within a radius of 5 km, up to a maximum of five times. The X and Y coordinates of the simulated fire size that came closest to the predicted fire size replaced the original fire location. A second problem was observed whereby fire sizes were overestimated in Envision – usually as a consequence of ignitions landing on fast burning fuels coupled with sampled weather conditions well above the average conditions. In these cases, if the fire size was more than 1.5 times the predicted fire size, the original burn period (BP) was reduced proportionally to the difference between the predicted and simulated fire sizes as follows:

$$NewBP = Original\ BP / 0.5 \left(\frac{Simulated}{Predicted} \right) \quad (7)$$

The resulting predicted versus simulated fire size was then plotted and examined for outliers.

2.6. Fire effects

Fire effects were implemented on each burned IDU using flame length generated by the wildfire submodel. A fire effects lookup table was used to translate flame lengths into severity classes that include low-intensity fires (mortality ≤ 20%), mixed severity fires (20% < mortality ≤ 80%) and stand-replacing fire (mortality > 80%). Flame length thresholds used to classify fire severity were obtained using FVS-FFE simulations on representative tree lists for each vegclass. In this process the fire and fuels extension to FVS (Reinhardt and Crookston, 2003) was used to simulate fires of varying flame lengths for each representative tree list, and the flame length thresholds that generated the abovementioned stand mortality thresholds were determined, similar to the approach used previously to build loss functions for mortality to old growth (Ager et al., 2010).

Within Envision these flame length thresholds are cross-referenced with flame lengths from fire perimeters generated by the wildfire submodel to determine wildfire effects on each IDU. Low severity fires do not trigger changes in vegclass but reduce surface fuel accumulation (fuel model). Stand-replacing fires will kill the majority of trees and return the IDU to a post-disturbance state. Depending on the IDU pre-fire conditions mixed-severity fires can alter surface fuel (i.e., fuel model) or can trigger a state transition if changes occur to canopy cover and/or number of canopy layers. Comparisons of initial fire severity outputs (Barros et al., 2017; Spies et al., 2017) with fire severity data from the MTBS project suggested that Envision overestimated the proportion of stand-replacing fire in forested areas. Thus, we increased the upper flame length thresholds of mixed severity fire, above which fire severity was classified as stand-replacing. This adjustment corrected the proportion of stand replacing fire simulated by Envision to levels comparable with historical fire severity according to MTBS severity maps (Eidenshink et al., 2007). Severity classes were also used to compute other fire-related metrics, e.g., smoke production, timber volume losses.

2.7. Envision execution

Envision runs on an annual time step in the following simplified sequence: vegetation succession, wildfire submodel, forest management

submodel and evaluative models (see Spies et al. (2017) for a detailed description of evaluative models in Envision). After each module runs, the relevant IDU information is updated and carried over to the next module and/or time step. This precludes, for example, thinning from below to happen in a stand that experienced stand-replacing fire, even though salvage logging can occur. The wildfire submodel reads the firelist generated from the fire prediction system (section 2.5.8) along with fire weather conditions for each fire. Each fire is simulated sequentially, but fires are not allowed to overlap within the year. Fire perimeters are written as a shapefile and a grid of flame lengths is recorded both annually and daily. The flame length grid for each perimeter is overlaid with the IDU polygons and the mean flame length is calculated and used to affect state changes in vegetation as described in the fire effects section 2.6. The wildfire submodel also generates a grid of flame lengths similar to that generated by a static FlamMap simulation (Ager et al., 2011) using predefined fuel moisture and fire weather conditions.

2.8. Simulation experiments

We performed 30 replicates where each replicate simulation used a different firelist (section 2.5.8) covering 50 years of ignitions generated by the fire prediction system. We used the simulation output to describe the performance of the fire prediction system and the simulated fires within Envision. This included examination of: (1) statistically generated ERC versus historical, and (2) fire size distributions of historical, predicted and simulated datasets. Evidence for fire feedbacks was obtained by analyzing intersections among simulated fire perimeters within the previous ten years. We chose a ten-year timespan based on previous analyses that showed fires did not affect current fire growth if they were older than 10 years (Ager et al., 2017a). For the remaining questions we analyzed simulation outputs for area burned and severity by year for the 30 replicates. For a given scenario, a 50-yr Envision run takes 3 h to run on a six-core 3.50 GHz Intel Xenon CPU with 128GB of RAM. Envision is available for download at <http://envision.bioe.orst.edu/> and submodels described here are available by request to the author.

3. Results

3.1. Historical ignition patterns

We previously described aspects of the historical fire regime in the study area (Ager et al., 2017b) and include additional description here to provide the context for simulation experiments (below). Several aspects of the fire regime including the spatial patterns of ignitions provided important details that affected our design and calibration of the Envision fire simulation submodel. The mean annual historical area burned (1992–2009) for the FPF study area was 14,997 ha, or 0.48% per year, with 645 ignitions per year, and a mean fire size of 22 ha (median = 12 ha). Historical mean fire size from human ignitions was 26 ha (median = 6 ha) compared to 22 ha for fires caused by natural ignitions (median = 6 ha). Excluding fires that were less than 10 ha, mean fire size for human versus natural ignitions was 620 versus 1741 ha (median = 268 vs 371), respectively. Temporal ignition patterns were distinctly different for human versus lightning ignitions within the study area (Fig. 3), with the latter showing strong peaks during the summer compared to the former. Human ignitions occurred throughout the period of natural ignitions but were more frequent in the spring and fall, effectively extending the fire season by about three months and generating fires under low ERC relative to lightning ignitions. The episodic pattern of lightning ignitions results from regional convective activity associated with cold fronts that intersect high pressure systems that develop over the Pacific Northwest during mid-summer. Spatial patterns of ignitions were also distinctly different between human and lightning categories (Fig. 4). Human ignitions were

strongly clustered around developed areas, and to a lesser extent in popular recreation sites (e.g., Deschutes River, Fig. 4B). Two of the largest developed areas, Warm Springs and Bend (Fig. 4D) had the highest density of human ignitions. Lightning ignitions had the highest densities in the south-central and southeast portion of the study area.

3.2. Fire forecasting model validation

Both daily ignition frequency and the resulting fire size were positively and non-linearly related to ERC. ERC streams generated by the model (Eq. 6) captured daily and yearly variability and seasonal trends (Fig. 6), with forecasted values generally remaining within the maximum and minimum observed data. Fire size distributions generated by the statistical model (Eq. 5) showed a similar pattern and distribution as the historical data (Fig. 5A, B). Additionally, we compared the forecasted wildfire size generated from the statistical prediction model with the outputs from the Envision run to validate the fire prediction system (see 2.5.9 for details). We used the contemporary management scenario (CMAN) for this comparison, and the results showed that fire sizes generated from random draws from the empirical distributions were closely related to fire sizes simulated within Envision runs (Fig. 7). Observed outliers were caused by a number of factors including ignitions that occurred with a combination of fire spread conditions that include fuel models with slower spread rate, low windspeed and low ERC.

3.3. Simulation experiment

The 50-yr Envision simulation experiment using contemporary forest management (CMAN) revealed substantial among replicate ($n = 30$) and inter-annual (50 years) variability, similarly to the historical fire data (Fig. 8). The mean proportion of area burned per year was similar between historical and simulated fires and equaled 0.86% and 0.84% of the study area, respectively. The pooled among year coefficient of variation (CV) across all replicates for area burned per year was 153%, indicating that the magnitude of variation among years was about three times larger than the mean annual area burned. Fire rotation interval (number of years required to burn the entire study area) varied among the 30 replicates from 78 to 170 years. The comparison between fire size distributions for predicted (statistical model) and simulated (for 3 out of 30 Envision replicates) (Fig. 9) showed good correspondence. When compared to the fire size obtained with Envision, the 1st and 3rd quartiles and mean and median fire size matched well over the datasets. Mean fire size across all replicates from human ignitions was 601 ha (median = 27 ha) compared to 1047 ha for fires caused by natural ignitions (median = 34 ha). Simulated replicates showed on average higher median values (Fig. 9) and larger extreme values than the predicted dataset. This was mostly due to over-estimation in simulated datasets of the number of fires between fire size classes of 1×10^3 ha and 1×10^6 ha. We also examined the occurrence of extreme fire years with burn areas above the 10-yr moving average. On average in each 50-yr simulation there were 17 (min-max; 12–21 years) and 15 (min-max; 11–19 years) very large extreme years (Fig. 10).

To examine the effect of ignition type on area burned over time we analyzed area burned by cause for the CMAN scenario (Fig. 11). Although the mean annual area burned over the simulation did not vary substantially between the two ignition types, temporal trends showed decadal periods where human ignitions burned up to about 0.3% more (37,500 ha) on an annual basis compared to natural ignitions. For instance, in simulation year 20, natural ignitions resulted in about 0.8% (100,000 ha) of the study area burning compared to about 0.3% human caused fires. Spatial differences in burned area between the ignition types were apparent from the simulation outputs, with the effects of human ignitions especially pronounced along the northeast end of the study area where there were ignition hotspots around developed areas

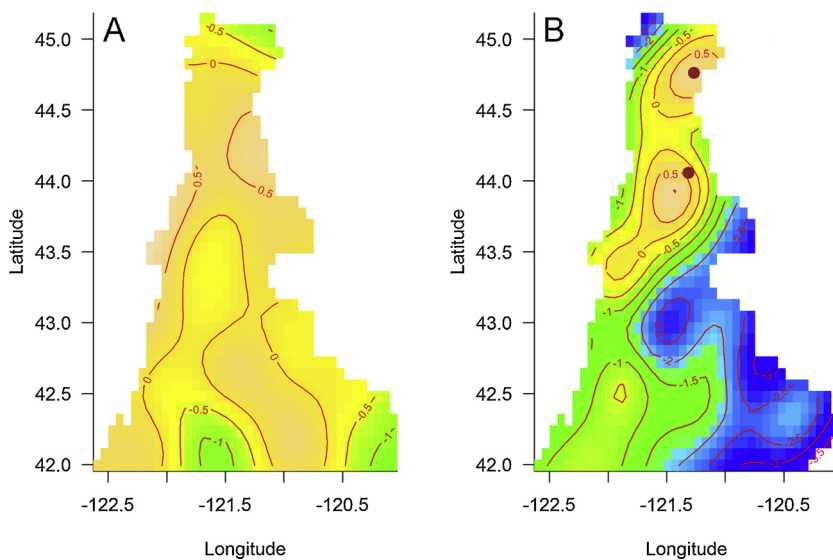


Fig. 4. Estimated effect of spatial location on probability of (A) natural versus (B) human caused ignitions. Contours show the log-odds of an ignition relative to the average log-odds level which is set to zero. The highest values (> 0.5) surround Warm Springs and Bend (dark red dots in panel B). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

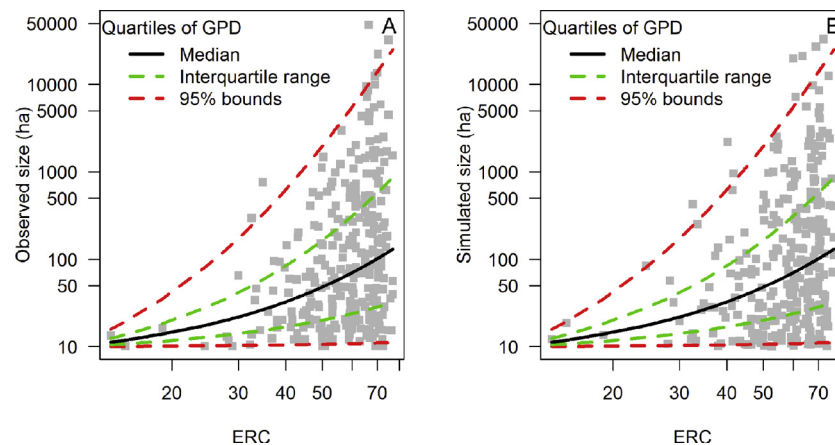


Fig. 5. Relationship between energy release component (ERC) and fire size and frequency from the study area based on the A) observed historical ignition data and B) data predicted by the statistical models. GPD = generalized Pareto distribution.

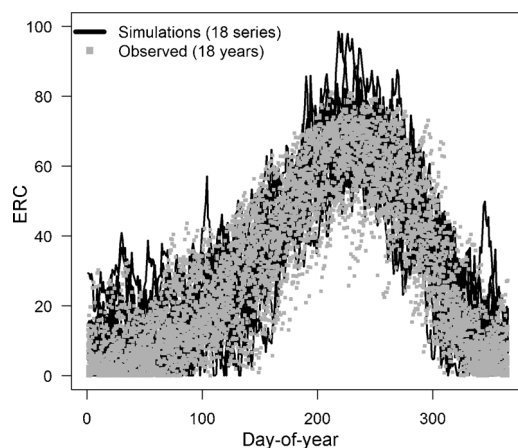


Fig. 6. Goodness-of-fit of the autoregressive model for forecasting energy release component (ERC) from empirical data (gray dots) as used by the fire prediction system to create synthetic ERC streams (black lines) used in simulations.

and recreation sites (Fig. 12). In general, there was an east-west and north-south gradient of area burned from natural ignitions that resulted from the combined effects of ignition probability and spread rates of vegetation and fuels in the different locations (Fig. 12).

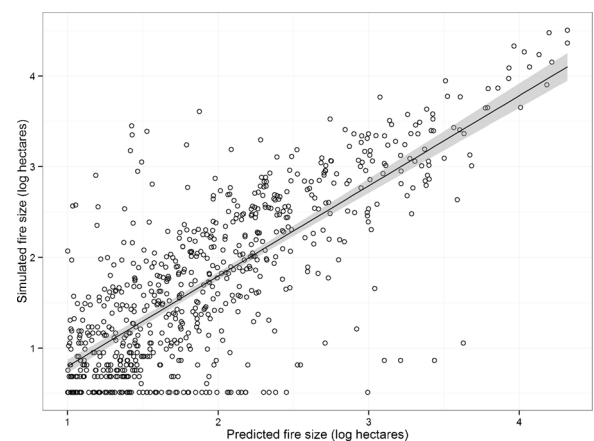


Fig. 7. Comparison of fire sizes generated by the fire prediction system and the size simulated during the burn period calibration process in Envision as described in the Section 2.5.9.

Most area burned in the simulations resulted from mixed severity fire, followed by high severity (Fig. 13) which is in agreement with recent empirical fire severity reported for the study area by Reilly et al. (2017). The different classes of fire severity (surface, mixed severity, stand replacing) did not have substantial trends over time for the CMAN

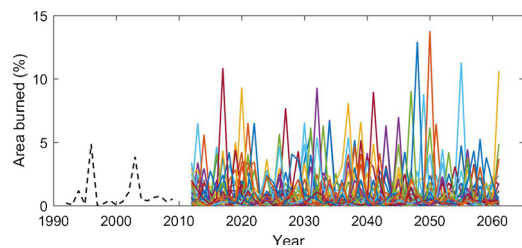


Fig. 8. Variability in the percentage of study area burned per year among five (out of 30) replicate Envision simulations under contemporary forest management (CMAN) scenario over 50 years. Dashed lines show the percentage of area burned annually based on historical data (1992–2009).

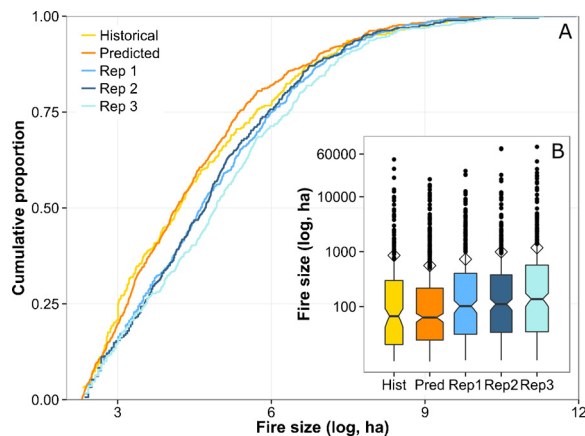


Fig. 9. (A) Cumulative proportion of fires in the study area by fire size, and (B) fire size distribution for historical ignition data (Hist, 1992–2009) from Short (2014), one sample predicted by the fire ignition prediction system (Pred) and three sample Envision runs from the contemporary management scenario (Rep 1 – Rep 3). Boxplots in panel B show the 25%, 50% and 75% quantiles of fire size observations as the lower, middle and upper hinges, respectively. Diamonds in panel B indicate average fire size and dots represent outlier points defined as observations beyond the end of the whiskers.

scenario (Fig. 13B) or the NOMAN scenario (Fig. 13A, although more area burned overall under NOMAN). There was a slight downward trend in the area burned by mixed severity and corresponding upward trend in surface fire severity, especially in the last decade of the simulation, although inter-annual variability masked the trends. Changes in vegetation and fuels from succession and management activities were not sufficient to dramatically change trends in area burned within the study area (Fig. 13). The potential fire behavior as measured by flame length and spread rate exhibited upward trends for the landscape (NOMAN) as a whole as determined from FlamMap simulations (Appendix A, Figs. A5–A6 in supplemental material).

Under the modelled contemporary rates of burning, the potential for fire feedbacks to self-regulate wildfire spread within our simulations was not large based on the frequency with which fires intersected previous fire footprints (Fig. 14). For instance, the rate of intersection among fires that burned within a ten-year time window (average life-span of fuel treatment, Prichard et al., 2017) was estimated at between 2–4% at any given year, per year, and did not change between the NOMAN and CMAN scenarios (Fig. 14). Given that there are about 14 fires per year on average, an intersection of two fires would be expected about every other year. The relationship between fire size and intersection frequency showed that both small and large fires had a high propensity to intersect – the latter because they spread farther over the landscape, and former because their ignitions are spatially clustered in ignition hotspots (Fig. 15) but lack the fuels to spread. Thus the hotspots for human ignitions increased the potential for landscape feedbacks compared to natural ignitions, which are more dispersed.

4. Discussion

Our simulation experiments complement related research (Ager et al., 2017a; Barros et al., 2017, 2018; Charnley et al., 2017; Spies et al., 2017) as part of the “Forest, People, Fire” (FPF) project (Spies et al., 2014), although a number of modifications and improvements to the Envision model were made since these earlier analyses. The results of the current study suggested that future burned area is not limited by available fuels even with fuel reduction as part of forest restoration management programs (Noss et al., 2006; Stephens et al., 2016; USDA Forest Service, 2015), and that current climate regimes are not sufficient to generate “megafire” tipping points (Adams, 2013) that dramatically alter the forest landscape. This result is similar to other modelling studies in the western US (Loudermilk et al., 2014; Scheller and Mladenoff, 2007; Stevens et al., 2016; Syphard et al., 2011) where a wide range of simulated management scenarios did not dramatically alter rates of burning. However, restoration management combined with contemporary levels of wildfire did result in ecologically important reductions in fire intensity and severity, a finding also consistent with empirical and simulation studies on the effect of fuels modification on fire behavior (Kalies and Yocom Kent, 2016). The predicted reduction in severity and intensity, but not spread rate (burned area), can be traced to the differences in the recovery rate of the respective fire regime components. Specifically, recovery rates for fire spread are relatively short (5–20 years), compared to fire frequency (30–100 years) (Prichard et al., 2017), thus allowing the effects of management to dissipate on the landscape before the next fire typically arrives. Nevertheless, the ecological changes we observed in the simulation lend support to restoration policies that call for thinning and burning to improve fire resiliency on federal forests in the western US (Stephens et al., 2016), and indicate the rate of treatment needs to be sufficiently high to maintain reduced fuel levels on a large enough part of the landscape or in key places.

Our analysis of variability among years and replicates for future wildfire scenarios depicted a high uncertainty of large wildfire events. Fire rotation interval among plausible future scenarios varied among replicate simulations from 78 to 170 years meaning that there was a twofold difference in the average rate of burning (area per year), highlighting the uncertainty of fire as a driver of future landscape change even without considering potential amplification of fire regimes from climate change. Extreme fire years (Hulse et al., 2016) were considered as those that exceeded a 10-yr moving average and were observed in 15 out of 50 years in the simulation. Previous FLSM studies rarely report fire event level details regarding variation in size, frequency, and severity, or describe unusual extreme fire events that are important from a policy perspective since these fires can change attitudes towards fire and public policy. Our most extreme fire event burned 11.4% of our study area. A few studies do report variation in fire size. Syphard et al. (2011) reported mean fire size by elevation class for a 50-yr simulation in the Sierra Mountains, the maximum simulated fire being 36,237 ha (1.7% of the study area). Loudermilk et al. (2014) report a maximum mean fire size of 652 ha among five replicates over a 100-year simulation for a 85,000 ha fire prone study area (0.8%) in California. High variability in fire size (e.g., years with little fire) slows the development of robust risk governance systems that can adapt to changing fire regimes with legislation and local policies that govern development in fire-prone areas (Steelman, 2016). One reason we get extremely large fires in Envision compared to some other models is that fire sizes are drawn from statistical distributions rather than Monte Carlo simulation of historical events or pre-determined fire regimes (Syphard et al., 2011). Our model captures potentially rare but plausible fire events as predicted in time series analyses of ERC streams and captures inter-annual variability in weather (Abatzoglou and Williams, 2016). This bottom-up fire model improves the ability to model major events that drive landscape change and helps incorporate the stochastic and unpredictable nature of landscapes and populations (Scheller et al.,

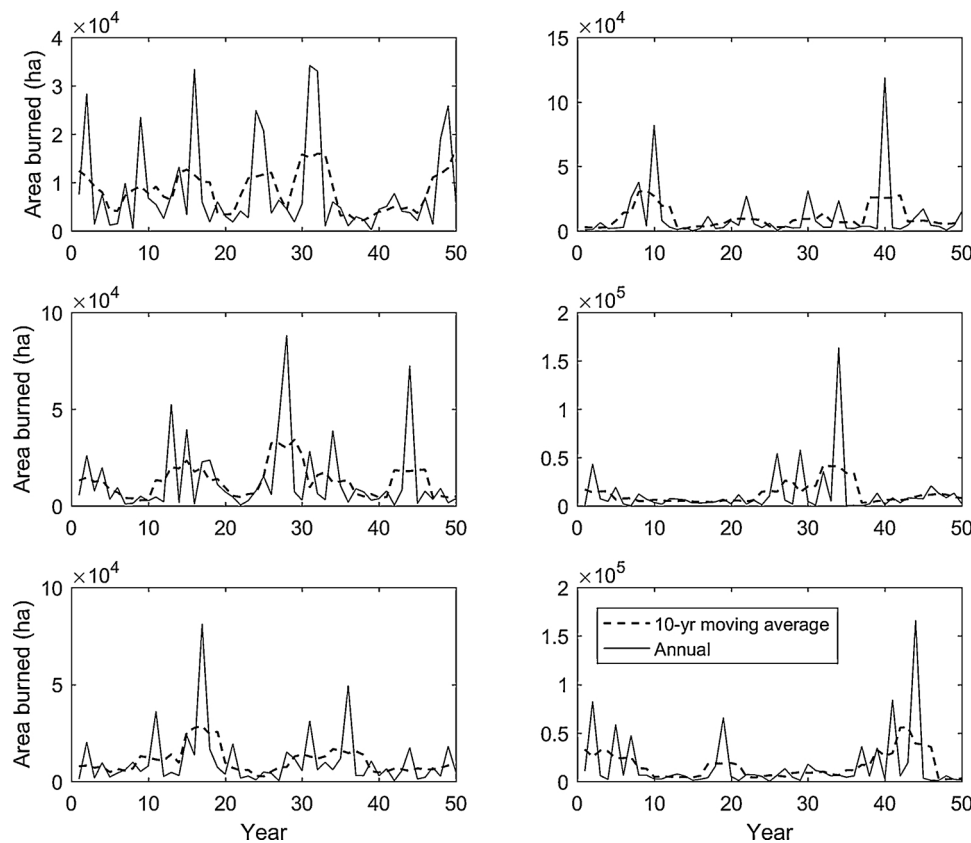


Fig. 10. Frequency of extreme fires (Hulse et al., 2016) with area burned above the 10-yr moving average for a sample of six replicate simulations. Dotted line is the 10-yr moving average and the solid line is the actual area burned in the year.

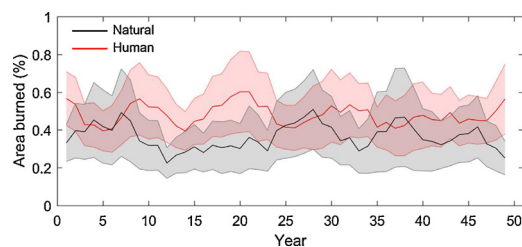


Fig. 11. Area burned by human versus natural ignitions for the contemporary forest management (CMAN) scenario. Data are average values over the 30 replicate simulations with corresponding standard error bands. Area burned is represented as a percentage of the study area.

2011).

In our study, we found that the potential for fire feedbacks as estimated from encounter rates between fire events was dependent on both fire size and ignition type. Both small and large fires had high encounter rates, a finding that suggests other factors besides area burned (Price et al., 2015) influence fire-on-fire events. Modelling how fire feedbacks interact with fuel management at the patch or event scale is key to understanding how fire can be leveraged to meet ecological restoration objectives in US federal land management agencies (Barros et al., 2018; North et al., 2015). Self-regulating wildfire results from interactions between ignition events and fuel beds that modulate burned area and severity. Ignitions within prior fire footprints can fail to spread or spread at a lower rate and intensity (Krawchuk et al., 2006; Prichard et al., 2010; Safford et al., 2009), or ignited fires can burn into previously burned areas and go out. Understanding these mechanisms and the dynamics of fire-on-fire and fire-on-treatment interactions is key to addressing the current fire deficit with policies that allow more natural ignitions to burn on low-risk landscapes (North et al., 2012). Prior

studies on the self-regulating properties of wildfire are almost exclusively based on empirical data and are limited to either single events or relatively small samples of historical fires (Barnett et al., 2016; Collins et al., 2009; Coop et al., 2014; Holsinger et al., 2016; Parks et al., 2015, 2016; Price et al., 2015). In contrast to empirical studies with available data, forest simulation models can provide detailed outputs that can be mined to study these interactions on large populations of fire-on fire interactions over many fire rotations and replicate simulations.

As in our previous work (Ager et al., 2014c; Preisler and Ager, 2013) we used empirically-derived relationships between energy release component (ERC) and historical fire attributes to predict daily fire occurrence, location, and fire size. However, we improved the spatio-temporal resolution of the fire prediction model compared to other fire simulation (Finney et al., 2011) and forest landscape simulation studies by using a generalized additive model (GAM) that included non-linear effects of location and time of year. A wide range of statistical techniques have been used to estimate fire ignition probability from empirical data including random forest analysis (Oliveira et al., 2012), kernel density interpolations (de la Riva et al., 2004; Koutsias et al., 2004), maximum entropy (MaxEnt) estimation (Parisien et al., 2012), and logistic regression (del Hoyo et al., 2011; Lozano et al., 2007; Martell et al., 1987; Padilla and Vega-García, 2011). GAM applies nonparametric splines to fit a wide range of functional forms compared to parametric functions, allowing us to model non-linear relationships between the log-odds of fire occurrence and explanatory variables within a logistic model (Brillinger et al., 2006; Preisler et al., 2004). The method is particularly useful for accounting for non-linear interactions between ignition location and day-of-year observed in complex spatiotemporal patterns of lightning and human ignitions. We note that our use of ERC as a driver assumed a stationary fire-climate response which is appropriate for most of the northwestern US where the biomass of

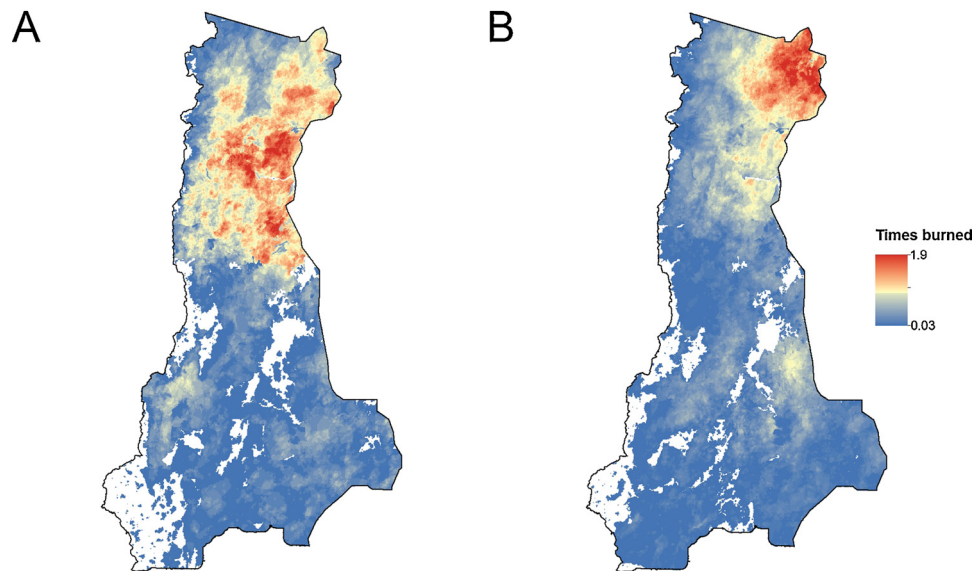


Fig. 12. Number of times a 90-m pixel burned in the north study area in a 50-yr simulation from fire ignited by natural (A) or human (B) ignitions for the contemporary forest management (CMAN) scenario.

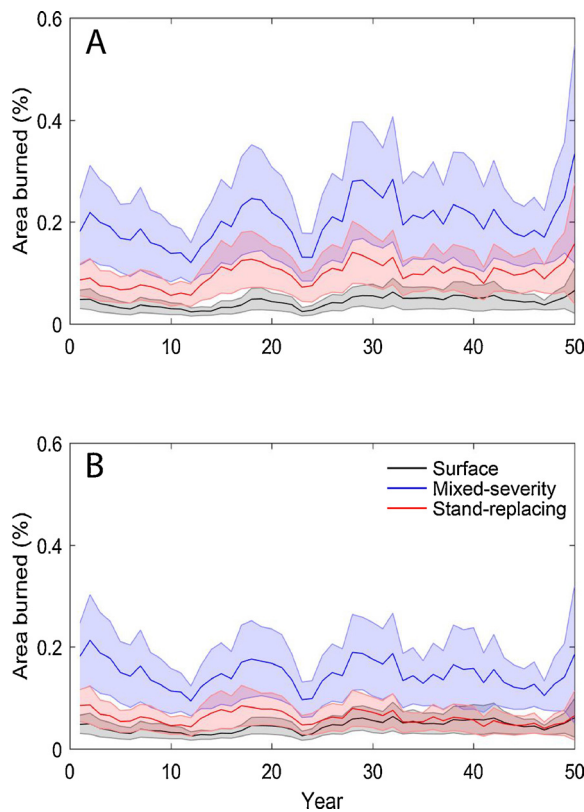


Fig. 13. Fire severity by severity class through in a 50-yr simulation and corresponding standard error bands for the 30 replicate Envision simulations for (A) the no management scenario (NOMAN) and (B) the contemporary management (CMAN) scenario.

fuels is generally not limiting (McKenzie and Littell, 2017) but fuel moisture limits fire activity (Littell et al., 2009). We acknowledge that in other regions, where fuels are driven by short-term climate drivers, our modelling approach is not appropriate (McKenzie and Littell, 2017). We also note that our predicted fire activity does not account for potential future increases in ERC from climate change (Abatzoglou and Williams, 2016; Abatzoglou and Brown, 2012; Littell et al., 2009)

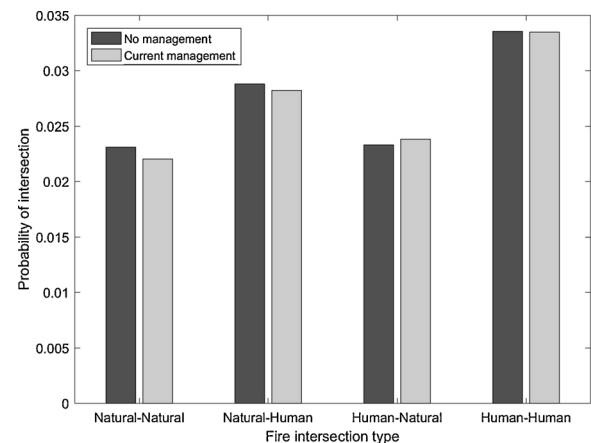


Fig. 14. Intersections between fire perimeters by ignition source within a 10 year time span of antecedent fire. For instance, Natural-Human data show the probability a fire ignited by lightning intersecting the footprint of a human-ignited fire within 10 years for contemporary forest management (CMAN) and no management (NOMAN) scenarios.

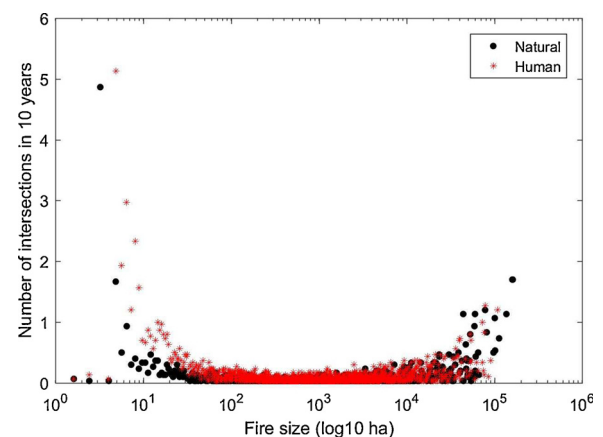


Fig. 15. Effect of fire size on the number of intersections with fires that burned within the past 10 years for the contemporary forest management (CMAN) scenario by ignition cause.

which is the subject of our future work.

Concurrent application of the Envision model as part of the broader FPF study (Spies et al., 2014) revealed a number of additional findings. Barros et al. (2017) examined a range of alternative fuel management scenarios and found that relative to a no management scenario, area burned and the likelihood of very large fires was reduced under all management scenarios, though differences on average were rather small. The authors also found that despite the reduction in area burned when the forest was managed, there was no decreasing trend in area burned through a 50-yr period. Spies et al. (2017) analyzed the impact of different restoration scenarios on fire behavior, wood production, carbon, and measures of biodiversity, and resilient vegetation and found that fuel treatments could have significant effects on landscape conditions over time. Ager et al. (2017a) estimated reduction in area burned from fire feedbacks for a range of fire rotation intervals. Both short-term negative and long-term positive feedbacks were observed.

Our studies as part of the FPF project add to prior FLSM studies which have focused on tradeoffs among multiple, competing, ecological and management objectives under dynamic disturbances (e.g., Scheller et al., 2011). Barros et al. (2018) found that the addition of one simulated wildfire per year under favorable weather conditions in low-risk areas and over the course of 50 years increased forest resilience in fire-adapted forest types but there were tradeoffs, including potential reduction in wildlife habitat, and increases in smoke and area burned in fire-sensitive forest types. Other studies have examined tradeoffs between treatment rate and intensity, and long-term versus short-term risks (Ager et al., 2017a; Halofsky et al., 2014b; Scheller et al., 2007; Spies et al., 2017; Syphard et al., 2011). For instance, Syphard et al. (2011) found that area treated had a larger effect than intensity of treatment, and treatments were most effective where wildfire likelihood was the highest—thus treatment location was more important than treatment type. Risk tradeoffs or “competing risks” from fuel management programs, i.e., the relative effects of short-term negative impacts to ecological values (critical habitat, carbon) versus long-term benefits from reduced future wildfire impacts, have been examined in a number of studies that incorporated wildfire into simulations (Loudermilk et al., 2014; Scheller et al., 2011; Syphard et al., 2011), and others factoring it as an exogenous process (Collins et al., 2011; Roloff et al., 2005). Spies et al. (2017) found in the central Oregon Cascades that management reduced spotted owl habitat despite also reducing wildfire severity. This occurred in part because treatments kept younger non-habitat forests from becoming owl habitat and replacing owl habitats lost to wildfire. By contrast, Syphard et al. (2011) found more biomass and large trees survived wildfire post fuels treatment in the southern Sierra Nevada Mountains. Small biomass was removed that protected large trees where biomass was accumulated and treatments conferred ecological benefit by preserving large trees. Scheller et al. (2011) also studied risk tradeoffs in fisher (*Martes pennanti*) habitat in the Sierra Nevada Mountains and found that direct negative effects on habitat were less than indirect positive effects over the long run. In general, these and other studies have found that management activities that cause short-term loss of habitat or other ecosystem services have longer-term positive impacts from reduced fire extent and or severity and thus suggest long-term benefits outweigh short-term adverse impacts of management.

Another contribution to the FLSM literature is our partitioning of human and natural ignitions as separate disturbance processes. Many models do not consider potential agent influences as sources of ignitions, which is necessary to model ecological change driven by natural influences versus human-caused ignitions (Balch et al., 2017; Parisien et al., 2016; Syphard and Keeley, 2015). Fires from human ignitions are not permitted to be managed for ecological benefit and thus policy simulations to explore fire feedbacks that let fires burn due to changes in suppression policies need to consider the ignition source (Barros et al., 2018). Expansion of the WUI is predicted to double by year 2030 (Theobald and Romme, 2007) thus both human activity in the

wildlands that cause ignitions and susceptible structures will both increase. Our results indicate that both the timing and location of the two ignition types differ substantially in the study area, both contributing nearly equally to area burned but with different spatial patterns and feedbacks. Studies of human versus natural ignitions have illustrated regional and continental-wide patterns, and the role of human ignitions lengthening the fire season (Balch et al., 2017; Campos-Ruiz et al., 2018; Parisien et al., 2016) and the differential impacts to structures (Collins et al., 2016), but not their effect on fire regimes over time. In our study area the slightly smaller fires from human ignitions could be related to both the timing and location of the two sources of ignitions relative to roads and suppression resources. Human ignitions were relatively more frequent in the spring and fall and thus extended the fire season compared to natural ignitions alone (Balch et al., 2017). Over the long run, ecological effects of the two ignition sources could change successional trajectories if they ignite in different seasons and the fires have different effects on vegetation. Studies that have investigated climate-wildfire drivers have not distinguished between human and lightning and the relationships are likely different in ignition-limited systems (McKenzie and Littell, 2017). The integration of ignition-specific wildfire occurrence models adds functionality that is needed to model agent behavior as both progenitors of fire and actors that respond to it. For instance, policy adoption for regulations on forest activities (hunting, recreation) and wildfire risk education (Butry et al., 2010; Prestemon and Butry, 2010; Prestemon et al., 2010) would be connected to locations and seasons with ignition hotspots. By contrast, policy adoption for fuel management with protection objectives would focus on areas with high lightning ignition, escape potential and risk. Policies that seek to expand area burned by natural ignitions to restore fire regimes would emphasize areas of frequent ignitions and low risk fires. Agent-based simulations can then be used to identify synergies between fuel management policies, ignition prevention programs, and fires managed for restoration to broadly address human versus natural fires in a coupled human and natural systems framework.

Our study contributes to scientific progress in ecological modelling in several areas including fire feedbacks (Prichard et al., 2017), the role of human versus natural ignitions as drivers of landscape change (Balch et al., 2017; Hulse et al., 2016; Parisien et al., 2016) and fine-scale statistical modelling of fire ignitions (Preisler et al., 2004). Moreover, we coupled two foundational simulation frameworks – the fire behavior models built on the USFS Fire Behavior Libraries (Brittain, 2018) and Envision (Bolte, 2018). The Fire Behavior code library encapsulates core fire modelling components used in continental scale wildfire research for strategic and tactical planning by researchers and practitioners in the US and elsewhere (Ager et al., 2014b; Alcasena et al., 2017; Andrews, 2007; Brittain, 2018; Finney et al., 2011; Gill et al., 1987; Kalabokidis et al., 2015; Noonan-Wright et al., 2011; Oliveira et al., 2016; Rollins, 2009; Salis et al., 2014). The integration into a FLSM can simulate management, disturbance, succession, and ecological impacts with agents that are “aware” of landscape conditions and respond to them within particular policy or goal domains. Policies include dynamic and spatially explicit restoration activities (thinning, mastication, underburning) applied at densities according to specific landscape priorities over time. Other FLSM platforms have to varying degrees represented both human-management policies and biophysical processes (Conlisk et al., 2015; Finney et al., 2007; Loudermilk et al., 2014; Millington et al., 2009; Scheller et al., 2011). However, management policies are typically “hardwired” over time to different degrees in these models while ignoring agent-landscape and landscape-fire feedbacks, a gap that is most significant on mixed owner landscapes where risk governance is fragmented and biophysical and social risk systems interact to drive public wildfire policy implementation (Charnley et al., 2017; Steelman, 2016). In our study, the location and rate of treatments were dynamically allocated in response to landscape conditions at annual time steps. Treatments were not, however, receptive to agent feedbacks since we assumed static agent behavior in

this particular study (see Spies et al., 2017).

Many challenges remain, particularly in the representation of agent behavior and translating social science in the models (e.g., a better understanding of how fire outcomes affect attitudes and forest management policy at landscape and ownership scales (Charnley et al., 2017; Kline et al., 2017)). It is possible that many existing models operate at spatiotemporal scales that mask the patch dynamics of forest succession, disturbance and management that ultimately drive landscape change (Keane et al., 2015)—for example, seed dispersal and establishment in post-fire environments. Challenges also exist to develop diverse research teams required to integrate social and biophysical science into agent based-FLSMs (Kline et al., 2017; Shindler et al., 2017). Our future work is leveraging Envision to understand the interacting effects of climate change, fuel treatment and increased wildfire on future habitat for protected wildlife species. These experiments will also allow the comparative assessment of leverage (Price et al., 2015) from synergies between wildfire versus fuel management to reduce ecological impacts of large, severe fire, thus addressing current fire policy debates in the western US over the management of wildfires to reduce the fire deficit and improve ecological use of wildfires as fuel treatments (North et al., 2015). Statistical downscaling of climate change scenarios and ERC streams (Abatzoglou and Brown, 2012) makes it possible to simulate the effects of climate change on fire activity within Envision. Since large fire activity is driven by sequences of high ERC rather than average conditions (Finney et al., 2009) we expect a more robust estimation of future wildfires compared to modelling efforts that use average fire regimes predicted by global circulation model data. Our modelling platform sets the stage for simulating future climate impacts on fire (Abatzoglou and Kolden, 2013) and how agent behavior can improve adaptation to future fire regimes.

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Appendix A. Supplementary material

Details on Envision submodels and the fire prediction system.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.ecolmodel.2018.06.018>.

References

- Abatzoglou, J.T., Brown, T.J., 2012. A comparison of statistical downscaling methods suited for wildfire applications. *Int. J. Climatol.* 32, 772–780.
- Abatzoglou, J.T., Kolden, C.A., 2013. Relationships between climate and macroscale area burned in the western United States. *Int. J. Wildland Fire* 22, 1003–1020.
- Abatzoglou, J., Williams, A.P., 2016. Impacts of anthropogenic climate change on wildfire across western US forests. *Proc. Natl. Acad. Sci.* 113 114770–114775.
- Adams, M.A., 2013. Mega-fires, tipping points and ecosystem services: managing forests and woodlands in an uncertain future. *For. Ecol. Manag.* 294, 250–261.
- Ager, A.A., Vaillant, N.M., Finney, M.A., 2010. A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. *For. Ecol. Manag.* 259, 1556–1570.
- Ager, A.A., Vaillant, N.M., Finney, M.A., 2011. Integrating fire behavior models and geospatial analysis for wildland fire risk assessment and fuel management planning. *J. Combust.* 572452, 19.
- Ager, A.A., Day, M.A., Finney, M.A., Vance-Borland, K., Vaillant, N.M., 2014a. Analyzing

- the transmission of wildfire exposure on a fire-prone landscape in Oregon, USA. *For. Ecol. Manag.* 334, 377–390.
- Ager, A.A., Day, M.A., McHugh, C.W., Short, K., Gilbertson-Day, J., Finney, M.A., Calkin, D.E., 2014b. Wildfire exposure and fuel management on western US national forests. *J. Environ. Manage.* 145, 54–70.
- Ager, A.A., Preisler, H.K., Arca, B., Spano, D., Salis, M., 2014c. Wildfire risk estimation in the Mediterranean area. *Environmetrics* 25, 384–396.
- Ager, A.A., Barros, A., Preisler, H.K., Day, M.A., Spies, T., Bailey, J., Bolte, J., 2017a. Effects of accelerated wildfire on future fire regimes and implications for the United States federal fire policy. *Ecol. Soc.* 22, 12.
- Ager, A.A., Evers, C.R., Day, M.A., Preisler, H.K., Barros, A.M., Nielsen-Pincus, M., 2017b. Network analysis of wildfire transmission and implications for risk governance. *PLoS ONE* 12, e0172867.
- Ager, A.A., Houtman, R., Seli, R., Day, M.A., Bailey, J., 2017c. Integrating large wildfire simulation and forest growth modeling for restoration planning. In: Keyser, C., Keyser, T.L. (Eds.), *Proceedings of the FVS e-Conference*. Gen. Tech. Rep. GTR-SRS-224. USDA Forest Service, Southern Research Station, Asheville, NC, pp. 129–139.
- Alcasena, F.J., Salis, M., Ager, A.A., Castell, R., Vega-Garcia, C., 2017. Assessing wildland fire risk transmission to communities in northern Spain. *Forests* 8, 27.
- Andrews, P.L., 2007. BehavePlus fire modeling system: past, present, and future. In: *Proceedings of 7th Symposium on Fire and Forest Meteorology*. American Meteorological Society, Bar Harbor, Maine. p. 13.
- Balch, J.K., Bradley, B.A., Abatzoglou, J.T., Nagy, R.C., Fusco, E.J., Mahood, A.L., 2017. Human-started wildfires expand the fire niche across the United States. *Proc. Natl. Acad. Sci.* 114, 2946–2951.
- Barnett, K., Parks, S., Miller, C., Naughton, H., 2016. Beyond fuel treatment effectiveness: characterizing interactions between fire and treatments in the US. *Forests* 7, 237.
- Barros, A., Ager, A.A., Day, M.A., Preisler, H., Spies, T., White, E., Pabst, R., Olsen, K., Platt, E., Bailey, J., Bolte, J., 2017. Spatiotemporal dynamics of simulated wildfire, forest management and forest succession in central Oregon, U.S.A. *Ecol. Soc.* 22, 24.
- Barros, A.M.G., Ager, A.A., Day, M.A., Krawchuk, M., Spies, T.A., 2018. Wildfires managed for restoration enhance ecological resilience. *Ecosphere* 9, e02161. <http://dx.doi.org/10.1002/ecs2.2161>.
- Bolte, J., 2010. *Envisioning Future Landscape Trajectories*. Powerpoint. (24 January 2017). <http://pf.forestry.oregonstate.edu/envisioning-future-landscape-trajectories-bend>.
- Bolte, J., 2018. *ENVISION: Integrated Modeling Platform*. Oregon State University, Corvallis, OR.
- Bolte, J.P., Hulse, D.W., Gregory, S.V., Smith, C., 2004. Modeling biocomplexity - actors, landscapes and alternative futures. In: Pahl-Wostl, C., Schmidt, S., Rizzoli, A.E., Jakeman, A.J. (Eds.), *Complexity and Integrated Resources Management: Transactions of the 2nd Biennial Meeting of the International Environmental Modelling and Software Society*. iEMSs, Osnabrück, Germany. pp. 1–10.
- Bone, C., Johnson, B., Nielsen-Pincus, M., Sproles, E., Bolte, J., 2014. A temporal variant-invariant validation approach for agent-based models of landscape dynamics. *Trans. GIS* 18, 161–182.
- Bradshaw, L.S., Deeming, J.E., Burgan, R.E., Cohen, J.D., 1983. *The 1978 National Fire-Danger Rating System: Technical Documentation*. USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT p. 44.
- Brillinger, D.R., 2003. Three environmental probabilistic risk problems. *Stat.Sci.* 18, 412–421.
- Brillinger, D.R., Preisler, H.K., Benoit, J., 2006. Probabilistic risk assessment for wildfires. *Environmetrics* 17, 623–633.
- Brittain, S., 2018. *Fire Behavior Applications and Libraries*. Alturas Solutions, Missoula, MT. http://sbrittain.net/fb/fb_api.htm.
- Butry, D.T., Prestemon, J.P., Abt, K.L., Sutphen, R., 2010. Economic optimisation of wildfire intervention activities. *Int. J. Wildl. Fire* 19, 659–672.
- Calkin, D.E., Cohen, J.D., Finney, M.A., Thompson, M.P., 2014. How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proc. Natl. Acad. Sci.* 111, 746–751.
- Campos-Ruiz, R., Parisien, M.-A., Flannigan, M.D., 2018. Temporal patterns of wildfire activity in areas of contrasting human influence in the Canadian boreal forest. *Forests* 9, 159. <http://dx.doi.org/10.3390/f9040159>.
- Charnley, S., Poe, M.R., Ager, A.A., Spies, T.A., Platt, E.K., Olsen, K.A., 2015. A burning problem: social dynamics of disaster risk reduction through wildfire management. *Hum. Organization* 74, 329–340.
- Charnley, S., Spies, T.A., Barros, A.M.G., White, E.M., Olsen, K.A., 2017. Diversity in forest management to reduce wildfire losses: implications for resilience. *Ecol. Soc.* 22, 22. <http://dx.doi.org/10.5751/Es-08753-220122>.
- Cochran, P.H., Geist, J.M., Clemens, D.L., Clausnitzer, R.R., Powell, D.C., 1994. *Suggested Stocking Levels for Forest Stands in Northeastern Oregon and Southeastern Washington*. Res. Note PNW-RN-513. USDA Forest Service, Pacific Northwest Research Station, Portland, OR 21 pp.
- Collins, B.M., Miller, J.D., Thode, A.E., Kelly, M., van Wagtenonk, J.W., Stephens, S.L., 2009. Interactions among wildland fires in a long-established Sierra Nevada natural fire area. *Ecosystems* 12, 114–128.
- Collins, B.M., Stephens, S.L., Moghaddas, J.J., Battles, J., 2010. Challenges and approaches in planning fuel treatments across fire-excluded forested landscapes. *J. For.* 108, 24–31.
- Collins, B.L., Stephens, S.L., Roller, G., Battles, J.J., 2011. Simulating fire and forest dynamics for a landscape fuel treatment project in the Sierra Nevada. *For. Sci.* 57, 77–88.
- Collins, K.M., Penman, T.D., Price, O.F., 2016. Some wildfire ignition causes pose more risk of destroying houses than others. *PLoS ONE* 11, e0162083. <http://dx.doi.org/10.1371/journal.pone.0162083>.
- Conlisk, E., Syphard, A.D., Franklin, J., Regan, H.M., 2015. Predicting the impact of fire

- on a vulnerable multi-species community using a dynamic vegetation model. *Ecol. Model.* 301, 27–39.
- Coop, J.D., Holsinger, L., McClernan, S., Parks, S.A., 2014. Influences of previous wildfires on change, resistance, and resilience to reburning in a montane southwestern landscape. In: Keane, R., Jolly, M., Parsons, R., Riley, K. (Eds.), *Large Wildland Fires Conference. Proc. RMRS-P-73*. USDA Forest Service, Rocky Mountain Research Station, Missoula, MT. p. 345.
- Core Team, R., 2014. *R: A Language and Environment for Statistical Computing*, 3.1, 1 ed. R Foundation for Statistical Computing, Vienna, Austria.
- de la Riva, J., Pérez-Cabello, F., Lana-Renault, N., Koutsias, N., 2004. Mapping wildfire occurrence at regional scale. *Remote Sens. Environ.* 92, 363–369.
- del Hoyo, L.V., Isabel, M.P.M., Vega, F.J.M., 2011. Logistic regression models for human-caused wildfire risk estimation: analysing the effect of the spatial accuracy in fire occurrence data. *Eur. J. For. Res.* 130, 983–996.
- Dixon, G.E., 2002. *Essential FVS: A User's Guide to the Forest Vegetation Simulator*. USDA Forest Service, Forest Management Service Center, Fort Collins, CO, pp. 226.
- Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z., Quayle, B., Howard, S., 2007. A project for monitoring trends in burn severity. *Fire Ecol.* 3, 3–21.
- Finney, M.A., 2001. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. *For. Sci.* 47, 219–228.
- Finney, M.A., 2002. Fire growth using minimum travel time methods. *Can. J. For. Res.* 32, 1420–1424.
- Finney, M.A., 2006. An overview of FlamMap fire modeling capabilities. In: Andrews, P.L., Butler, B.W. (Eds.), *Fuels Management-How to Measure Success. Proceedings RMRS-P-41*. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO, pp. 213–220.
- Finney, M.A., Seli, R.C., McHugh, C.W., Ager, A.A., Bahro, B., Agee, J.K., 2007. Simulation of long-term landscape-level fuel treatment effects on large wildfires. *Int. J. Wildl. Fire* 16, 712–727.
- Finney, M.A., Grenfell, I.C., McHugh, C.W., 2009. Modeling containment of large wildfires using generalized linear mixed model analysis. *For. Sci.* 55, 249–255.
- Finney, M.A., McHugh, C.W., Grenfell, I.C., Riley, K.L., Short, K.C., 2011. A simulation of probabilistic wildfire risk components for the continental United States. *Stoch. Env. Res. Ris.* A 25, 973–1000.
- Fischer, A.P., Spies, T.A., Steelman, T.A., Moseley, C., Johnson, B.R., Bailey, J.D., Ager, A.A., Bourgeron, P., Charnley, S., Collins, B.M., Kline, J.D., Leahy, J.E., Littell, J.S., Millington, J.D.A., Nielsen-Pincus, M., Olsen, C.S., Paveglio, T.B., Roos, C.L., Steen-Adams, M.M., Stevens, F.R., Vukomanovic, J., White, E.M., Bowman, D.M.J.S., 2016. Wildfire risk as a socioecological pathology. *Front. Ecol. Environ.* 14, 276–284.
- Gill, A.M., Christian, K.R., Moore, P.H.R., Forrester, R.I., 1987. Bush fire incidence, fire hazard and fuel reduction burning. *Aust. J. Ecol.* 12, 299–306.
- Guzy, M.R., Smith, C.L., Bolte, J.P., Hulse, D.W., Gregory, S.V., 2008. Policy research using agent-based modeling to assess future impacts of urban expansion into farmlands and forests. *Ecol. Soc.* 13, 37. <http://www.ecologyandsociety.org/vol13/iss1/art37/>.
- Halofsky, J.E., Creutzburg, M.K., Hemstrom, M.A., 2014a. Integrating Social, Economic, and Ecological Values Across Large Landscapes. USDA Forest Service, Pacific Northwest Research Station, Portland, OR p. 206.
- Halofsky, J.S., Halofsky, J.E., Burcu, T., Hemstrom, M., 2014b. Dry forest resilience varies under simulated climate-management scenarios in a central Oregon, USA landscape. *Ecol. Appl.* 24, 1908–1925.
- Haugo, R., Zanger, C., DeMeo, T., Ringo, C., Shlisky, A., Blankenship, K., Simpson, M., Mellen-McLean, K., Kertis, J., Stern, M., 2015. A new approach to evaluate forest structure restoration needs across Oregon and Washington, USA. *For. Ecol. Manag.* 335, 37–50.
- Holsinger, L., Parks, S., Miller, C., 2016. Weather, fuels, and topography impede wildland fire spread in western US landscapes. *For. Ecol. Manag.* 380, 59–69.
- Hulse, D., Branscomb, A., Enright, C., Bolte, J., 2009. Anticipating floodplain trajectories: a comparison of two alternative futures approaches. *Landsc. Ecol.* 24, 1067–1090.
- Hulse, D., Branscomb, A., Enright, C., Johnson, B., Evers, C., Bolte, J., Ager, A., 2016. Anticipating surprise: using agent-based alternative futures simulation modeling to identify and map surprising fires in the Willamette Valley, Oregon USA. *Landsc. Urban Plan.* 156, 26–43.
- Kalabokidis, K., Palaiologou, P., Gerasopoulos, E., Giannakopoulos, C., Kostopoulou, E., Zerefos, C., 2015. Effect of climate change projections on forest fire behavior and values-at-risk in Southwestern Greece. *Forests* 6, 2214–2240.
- Kalabokidis, K., Ager, A.A., Finney, M.A., Athanasis, N., Palaiologou, P., Vasilakos, C., 2016. AEGIS: a wildfire prevention and management information system. *Nat. Hazards Earth Syst. Sci.* 16, 643–661.
- Kalies, E.L., Yocom Kent, L.L., 2016. Tamm review: are fuel treatments effective at achieving ecological and social objectives? A systematic review. *For. Ecol. Manag.* 375, 84–95.
- Keane, R.E., McKenzie, D., Falk, D.A., Smithwick, E.A., Miller, C., Kellogg, L.-K.B., 2015. Representing climate, disturbance, and vegetation interactions in landscape models. *Ecol. Model.* 309, 33–47.
- Kline, J.D., White, E.M., Fischer, A.P., Steen-Adams, M.M., Charnley, S., Olsen, C.S., Spies, T.A., Bailey, J.D., 2017. Integrating social science into empirical models of coupled human and natural systems. *Ecol. Soc.* 22, 25. <http://dx.doi.org/10.5751/ES-09329-220325>.
- Knight, I., Coleman, J., 1993. A fire perimeter expansion algorithm based on Huygens' wavelet propagation. *Int. J. Wildl. Fire* 3, 73–84.
- Koutsias, N., Kalabokidis, K.D., Allgöwer, B., 2004. Fire occurrence patterns at landscape level: beyond positional accuracy of ignition points with kernel density estimation methods. *Nat. Resour. Model.* 17, 359–375.
- Krawchuk, M., Cumming, S., Flannigan, M., Wein, R., 2006. Biotic and abiotic regulation of lightning fire initiation in the mixedwood boreal forest. *Ecology* 87, 458–468.
- LANDFIRE, 2013. *LANDFIRE 40 Scott and Burgan Fire Behavior Fuel Models*. (30 August 2016). <http://www.landfire.gov/NationalProductDescriptions2.php>.
- Littell, J.S., McKenzie, D., Peterson, D.L., Westerling, A.L., 2009. Climate and wildfire area burned in western U.S. ecoprovinces, 1916–2003. *Ecol. Appl.* 19, 1003–1021.
- Loehman, R.A., Keane, R.E., Holsinger, L.M., Wu, Z., 2017. Interactions of landscape disturbances and climate change dictate ecological pattern and process: spatial modeling of wildfire, insect, and disease dynamics under future climates. *Landsc. Ecol.* 32, 1447–1459.
- Loudermilk, E.L., Stanton, A., Scheller, R.M., Dilts, T.E., Weisberg, P.J., Skinner, C., Yang, J., 2014. Effectiveness of fuel treatments for mitigating wildfire risk and sequestering forest carbon: a case study in the Lake Tahoe Basin. *For. Ecol. Manag.* 323, 114–125.
- Lozano, F.J., Suárez-Seoane, S., de Luis, E., 2007. Assessment of several spectral indices derived from multi-temporal Landsat data for fire occurrence probability modelling. *Remote Sens. Environ.* 107, 533–544.
- Martell, D.L., Otukul, S., Stocks, B.J., 1987. A logistic model for predicting daily people-caused forest fire occurrence in Ontario. *Can. J. For. Res.* 17, 394–401.
- McKenzie, D., Littell, J.S., 2017. Climate change and the eco-hydrology of fire: will area burned increase in a warming western USA? *Ecol. Appl.* 27, 26–36.
- Merschel, A.G., Spies, T.A., Heyerdahl, E.K., 2014. Mixed-conifer forests of central Oregon: effects of logging and fire exclusion vary with environment. *Ecol. Appl.* 24, 1670–1688.
- Miller, C., Ager, A.A., 2013. A review of recent advances in risk analysis for wildfire management. *Int. J. Wildl. Fire* 22, 1–14.
- Millington, J.D.A., Wainwright, J., Perry, G.L.W., Romero-Calcerrada, R., Malamud, B.D., 2009. Modelling Mediterranean landscape succession-disturbance dynamics: a landscape fire-succession model. *Environ. Model. Softw.* 24, 1196–1208.
- MTBS Data Access, 2017. *Fire Level Geospatial Data*. (2017, July - Last Revised). (6 November 2017). <https://mtbs.gov/direct/download>.
- Noonan-Wright, E.K., Opperman, T.S., Finney, M.A., Zimmerman, G.T., Seli, R.C., Elenz, L.M., Calkin, D.E., Fiedler, J.R., 2011. Developing the US wildland fire decision support system. *J. Combust.* 168473, 14. <http://dx.doi.org/10.1155/2011/168473>.
- North, M., Collins, B.M., Stephens, S., 2012. Using fire to increase the scale, benefits, and future maintenance of fuels treatments. *J. For.* 110, 392–401.
- North, M.P., Stephens, S.L., Collins, B., Agee, J., Aplet, G., Franklin, J., Fule, P., 2015. Reform forest fire management. *Science* 349, 1280–1281.
- Noss, R.F., Franklin, J.F., Baker, W.L., Schoennagel, T., Moyle, P.B., 2006. Managing fire-prone forests in the western United States. *Front. Ecol. Environ.* 4, 481–487.
- O'Hara, K.L., Nesmith, J.C.B., Leonard, L., Porter, D.J., 2010. Restoration of old forest features in coast redwood forests using early-stage variable-density thinning. *Restor. Ecol.* 18, 125–135.
- Ohmann, J.L., Gregory, M.J., Henderson, E.B., Roberts, H.M., 2011. Mapping gradients of community composition with nearest-neighbour imputation: extending plot data for landscape analysis. *J. Veg. Sci.* 22, 660–676.
- Oliveira, S., Oehler, F., San-Miguel-Ayaz, J., Camia, A., Pereira, J.M.C., 2012. Modeling spatial patterns of fire occurrence in Mediterranean Europe using multiple regression and random forest. *For. Ecol. Manag.* 275, 117–129.
- Oliveira, T.M., Barros, A.M.G., Ager, A.A., Fernandes, P.M., 2016. Assessing the effect of a fuel break network to reduce burnt area and wildfire risk transmission. *Int. J. Wildl. Fire* 25, 619–632.
- Padilla, M., Vega-García, C., 2011. On the comparative importance of fire danger rating indices and their integration with spatial and temporal variables for predicting daily human-caused fire occurrences in Spain. *Int. J. Wildl. Fire* 20, 46–58.
- Parisien, M.A., Snetsinger, S., Greenberg, J.A., Nelson, C.R., Schoennagel, T., Dobrowski, S.Z., Moritz, M.A., 2012. Spatial variability in wildfire probability across the western United States. *Int. J. Wildl. Fire* 21, 313–327.
- Parisien, M.-A., Miller, C., Parks, S.A., DeLancey, E.R., Robinne, F.-N., Flannigan, M.D., 2016. The spatially varying influence of humans on fire probability in North America. *Environ. Res. Lett.* 11, 075005. <http://dx.doi.org/10.1088/1748-9326/11/7/075005>.
- Parks, S.A., Holsinger, L.M., Miller, C., Nelson, C.R., 2015. Wildland fire as a self-regulating mechanism: the role of previous burns and weather in limiting fire progression. *Ecol. Appl.* 25, 1478–1492.
- Parks, S.A., Miller, C., Holsinger, L.M., Baggett, L.S., Bird, B.J., 2016. Wildland fire limits subsequent fire occurrence. *Int. J. Wildl. Fire* 25, 182–190.
- Preisler, H.K., Ager, A.A., 2013. Forest-fire models. In: El-Shaarawi, A.H., Piegorsch, W. (Eds.), *Encyclopedia of Environmetrics*, second ed. John Wiley & Sons, Chichester, U.K, pp. 1081–1088.
- Preisler, H.K., Brillinger, D.R., Burgan, R.E., Benoit, J.W., 2004. Probability based models for estimation of wildfire risk. *Int. J. Wildl. Fire* 13, 133–142.
- Preisler, H.K., Burgan, R.E., Eidenshink, J.C., Klaver, J.M., Klaver, R.W., 2009. Forecasting distributions of large federal-lands fires utilizing satellite and gridded weather information. *Int. J. Wildland Fire* 18, 508–516.
- Prestemon, J.P., Butry, D.T., 2010. Wildland arson: a research assessment. In: Pyne, J.M., Rauscher, H.M., Sands, Y., Lee, D.C., Beatty, J.S. (Eds.), *Advances in Threat Assessment and Their Application to Forest and Rangeland Management*. Gen. Tech. Rep. PNW-802. USDA Forest Service, Pacific Northwest Research Station, Portland, OR, pp. 271–283.
- Prestemon, J.P., Butry, D.T., Abt, K.L., Sutphen, R., 2010. Net benefits of wildfire prevention education efforts. *For. Sci.* 56, 181–192.
- Price, O.F., Pausas, J.G., Govender, N., Flannigan, M., Fernandes, P.M., Brooks, M.L., Bird, R.B., 2015. Global patterns in fire leverage: the response of annual area burnt to previous fire. *Int. J. Wildl. Fire* 24, 297–306.
- Prichard, S.J., Peterson, D.L., Jacobson, K., 2010. Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. *Can. J. For. Res.* 40, 1615–1626.
- Prichard, S.J., Stevens-Rumann, C.S., Hessburg, P.F., 2017. Tamm Review: shifting global

- fire regimes: lessons from reburns and research needs. *For. Ecol. Manag.* 396, 217–233.
- Reilly, M.J., Dunn, C.J., Meigs, G.W., Spies, T.A., Kennedy, R.E., Bailey, J.D., Briggs, K., 2017. Contemporary patterns of fire extent and severity in forests of the Pacific Northwest, USA (1985–2010). *Ecosphere* 8, e01695.
- Reinhardt, E.D., Crookston, N.L., 2003. The fire and fuels extension to the Forest vegetation simulator. Gen. Tech. Rep. RMRS-GTR-116. USDA Forest Service, Rocky Mountain Research Station, Ogden, UT 209 pp.
- Reinhardt, E.D., Keane, R.E., Brown, J.K., 1997. First order fire effects model: FOFEM 4.0 user's guide. Gen. Tech. Rep. INT-GTR-344. USDA Forest Service, Intermountain Research Station, Ogden, UT 65 pp.
- Rollins, M.G., 2009. LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *Int. J. Wildl. Fire* 18, 235–249.
- Roloff, G.J., Mealey, S.P., Clay, C., Barry, J., Yanish, C., Neuenschwander, L., 2005. A process for modeling short- and long-term risk in the southern Oregon Cascades. *For. Ecol. Manag.* 211, 166–190.
- Safford, H.D., Schmidt, D.A., Carlson, C.H., 2009. Effects of fuel treatments on Fire severity in an area of wildland-urban interface, Angora Fire, Lake Tahoe Basin, California. *For. Ecol. Manag.* 258, 773–787.
- Safford, H.D., Stevens, J.T., Merriam, K., Meyer, M.D., Latimer, A.M., 2012. Fuel treatment effectiveness in California yellow pine and mixed conifer forests. *For. Ecol. Manag.* 274, 17–28.
- Salis, M., Ager, A.A., Arca, B., Finney, M.A., Alcasena, F., Bacciu, V., Duce, P., Lozano, O.M., Spano, D., 2014. Analyzing wildfire exposure on Sardinia, Italy. *Geophys. Res. Abst.* 16 EGU2014-11596.
- Salis, M., Laconi, M., Ager, A.A., Alcasena, F.J., Arca, B., Lozano, O., Fernandes de Oliveira, A., Spano, D., 2016. Evaluating alternative fuel treatment strategies to reduce wildfire losses in a Mediterranean area. *For. Ecol. Manag.* 368, 207–221.
- Scheller, R.M., Mladenoff, D.J., 2004. A forest growth and biomass module for a landscape simulation model, LANDIS: design, validation, and application. *Ecol. Model.* 180, 211–229.
- Scheller, R.M., Mladenoff, D.J., 2007. An ecological classification of forest landscape simulation models: tools and strategies for understanding broad-scale forested ecosystems. *Landsc. Ecol.* 22, 491–505.
- Scheller, R., Domingo, J.B., Sturtevant, B.R., Williams, J.S., Rudy, A., Gustafson, E., Mladenoff, D.J., 2007. Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. *Ecol. Model.* 201, 409–419.
- Scheller, R.M., Spencer, W.D., Rustigian-Romsos, H., Syphard, A.D., Ward, B.C., Strittholt, J.R., 2011. Using stochastic simulation to evaluate competing risks of wildfires and fuels management on an isolated forest carnivore. *Landsc. Ecol.* 26, 1491–1504.
- Scheller, R.M., Kretchun, A.M., Loudermilk, E.L., Hurteau, M.D., Weisberg, P.J., Skinner, C., 2017. Interactions among fuel management, species composition, bark beetles, and climate change and the potential effects on forests of the Lake Tahoe Basin. *Ecosystems* 1–14.
- Scott, J.H., Burgan, R.E., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. Gen. Tech. Rep. RMRS-GTR-153. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO 72 pp.
- Shindler, B., Spies, T., Bolte, J., Kline, J., 2017. Integrating ecological and social knowledge: learning from CHANS research. *Ecol. Soc.* 22, 26. <http://dx.doi.org/10.5751/ES-08776-220126>.
- Short, K.C., 2014. A spatial database of wildfire in the United States, 1992–2011. *Earth Syst. Sci. Data* 6, 1–27.
- Spies, T.A., White, E.M., Kline, J.D., Fischer, A.P., Ager, A.A., Bailey, J., Bolte, J., Koch, J., Platt, E., Olsen, C.S., Jacobs, D., Shindler, B., Steen-Adams, M.M., Hammer, R., 2014. Examining fire-prone forest landscapes as coupled human and natural systems. *Ecol. Soc.* 19, 9. <http://dx.doi.org/10.5751/ES-06584-190309>.
- Spies, T., White, E., Ager, A., Kline, J.D., Bolte, J.P., Platt, E.K., Olsen, K.A., Pabst, R.J., Barros, A.M.G., Bailey, J.D., Charnley, S., Koch, J., Steen-Adams, M.M., Singleton, P.H., Sulzman, J., Schwartz, C., Csuti, B., 2017. Using an agent-based model to examine forest management outcomes in a fire-prone landscape in Oregon, USA. *Ecol. Soc.* 22, 25.
- Steelman, T., 2016. U.S. wildfire governance as a social-ecological problem. *Ecol. Soc.* 21, 3. <http://dx.doi.org/10.5751/ES-08681-210403>.
- Stephens, S.L., Collins, B.M., Biber, E., Fulé, P.Z., 2016. US federal fire and forest policy: emphasizing resilience in dry forests. *Ecosphere* 7, e01584.
- Stevens, J.T., Collins, B.M., Long, J.W., North, M.P., Prichard, S.J., Tarnay, L.W., White, A.M., 2016. Evaluating potential trade-offs among fuel treatment strategies in mixed-conifer forests of the Sierra Nevada. *Ecosphere* 7 (9), e01445. <http://dx.doi.org/10.1002/ecs2.1445>.
- Syphard, A.D., Keeley, J.E., 2015. Location, timing and extent of wildfire vary by cause of ignition. *Int. J. Wildl. Fire* 24, 37–47.
- Syphard, A.D., Scheller, R.M., Ward, B.C., Spencer, W.D., Strittholt, J.R., 2011. Simulating landscape-scale effects of fuels treatments in the Sierra Nevada, California, USA. *Int. J. Wildland Fire* 20, 364–383.
- Theobald, D.M., Romme, W.H., 2007. Expansion of the US wildland–urban interface. *Landsc. Urban Plann.* 83, 340–354.
- USDA Forest Service, 1990. Deschutes National Forest: Land and Resource Management Plan. USDA Forest Service, Pacific Northwest Region, Portland, OR.
- USDA Forest Service, 2014. The National Strategy: The Final Phase in the Development of the National Cohesive Wildland Fire Management Strategy. p. 93.
- USDA Forest Service, 2015. From Accelerating Restoration to Creating and Maintaining Resilient Landscapes and Communities Across the Nation: Update on Progress from 2012. FS-1069.
- Wells, G., 2009. A powerful new planning environment for fuels managers: the inter-agency fuels treatment decision support system. *Fire Science Digest* December 2009, 1–12.
- Westerling, A.L., 2016. Increasing Western US forest wildfire activity: sensitivity to changes in the timing of spring. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* 371, 20150178. <http://dx.doi.org/10.1098/rstb.2015.0178>.
- Western Regional Climate Center, 2014. RAWs USA Climate Archive. (1 October 2015). <http://www.raws.dri.edu/>.
- Wood, S.N., 2006. Generalized Additive Models: An Introduction With R. Chapman and Hall/CRC.