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Improving long-term fuel treatment effectiveness in the National Forest System through quantitative prioritization

Ana M. G. Barros[a,*], A.A. Ager[b], M.A. Day[a], P. Palaiologou[c]

[a] Oregon State University, College of Forestry, Department of Forest Ecosystems & Society, United States
[b] USDA Forest Service, Rocky Mountain Research Station, United States
[c] USDA Forest Service International Visitor Program, Oregon State University, College of Forestry, Department of Forest Engineering, Resources & Management, United States

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ABSTRACT

Predicting the efficacy of fuel treatments aimed at reducing high severity fire in dry-mixed conifer forests in the western US is a challenging problem that has been addressed in a variety of ways using both field observations and wildfire simulation models. One way to describe the efficacy of fuel treatments is to quantify how often wildfires are expected to intersect areas prioritized for treatment. In real landscapes treatments are static, restricted to a small portion of the landscape and against a background of stochastic fire and dynamic vegetation, thus the likelihood of fire encountering a treatment during the period treatments remain effective is small. In this paper we simulate a wide range of different treatment prioritization schemes using the forest landscape simulation model Envision to examine 50 years of fire-treatment interactions and forest succession. We first reviewed 47 fuel management projects in Oregon, USA to build prioritization schemes that addressed different fuel management objectives. We then simulated different priority schemes in the 18 planning areas of the Deschutes National Forest in central Oregon and measured potential fire-treatment interactions over time. Simulated annual area burned was used to calculate the success odds for each priority scheme and planning area. Out of the ten metrics considered only three had higher success odds than a random prioritization of planning areas. Spatial allocation of projects based on burn probability and transmitted wildfire had the highest success odds among the tested metrics. However, success odds declined sharply as desired success levels increased suggesting that fuel management goals need to be tempered to consider the stochastic nature of wildfire. Meeting long-term multiple management goals over time can benefit from consideration of short- and long-term tradeoffs from different treatment prioritization schemes. Our work contributes towards a better framing of both management and public expectations regarding the performance of fuel treatments programs.

1. Introduction

In the western US, wildfire is an important agent of landscape change, and forest management is used to mitigate the negative ecological, economic and social impacts of wildfire. On public lands, the task faced by forest and fire managers is daunting. Many national forests are coupled human-natural systems where the effects of wildfire and forest management are multidimensional (e.g., wildfire exposure, carbon, habitat, visual amenities, and timber) and interact over various spatiotemporal scales. Understanding and managing such a level of complexity is outside the realm of field experiments (Shifley et al., 2006) and requires simulation models capable of linking fire behavior, spread and effects with vegetation and succession, and empirical based knowledge on forest management goals and silvicultural impacts (He et al., 2008; Gustafson et al., 2010; Spies et al., 2018). Models that simulate forest landscape succession and disturbance improve our understanding of the roles that natural and human processes play in ecosystem change and can support informed management decisions. For example, modeling landscape trajectories in response to public forest restoration policies in the western US (Stephens et al., 2016) contributes to the evaluation of management programs and can help shape future decision making in the face of uncertainty and imperfect information (Millar et al., 2007).

When managers are preparing landscapes to receive fire, treatment location and size matter. Project planning may rely on potential wildfire exposure maps, yet benefits on real landscapes are hard to realize given the highly stochastic nature of wildfire (Jones et al., 2004). For example, fuel reduction treatments typically involve removal of

* Corresponding author.
E-mail address: ana.barros@oregonstate.edu (A.M. G. Barros).

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aboveground carbon by thinning of small diameter trees, followed by pile and burn or prescribed fire (Stephens et al., 2012). Offsetting removed carbon is contingent on a future reduction in burn severity, thus the degree to which fuel treatments can offer carbon benefits depends on how much wildfire actually occurs on the landscape (Ager et al., 2010; Ryan et al., 2010; Chiono et al., 2017; Krofcheck et al., 2017). In fact, based on historical fire and forest management records the majority of treatments are rarely intersected by wildfire (Barnett et al., 2016), and simulation has shown similar low fire-treatment interactions (Ager et al., 2017a; Barros et al., 2018). Models that can account for the stochastic nature of wildfire, are paramount to understanding how wildfire coupled with vegetation succession, determines whether treatments meet management goals and are well suited to support forest and fuel management prioritization.

Forest landscape simulation models (FLSM) are a tool for understanding alternative successional pathways in forest ecosystems by employing simulation of long-term landscape-scale processes such as wildfire, insect and disease outbreak, management and climate change (He et al., 2008). Furthermore, temporally explicit modeling of forest vegetation and fuel dynamics presents avenues to explore the potential for the unintended consequences of long-term public policies aiming to promote healthy and resilient forests, biodiversity and human well-being (Nelson et al., 2009). Actions that seek to mitigate wildfire risk and exposure are associated with short- and long-term tradeoffs and concessions may be required to meet the long-term goals of fuel management programs (Ager et al., 2013; Vogler et al., 2015; Creutzburg et al., 2017). For example, in fire-adapted dry-mixed conifer forests, tolerating a short-term increase in smoke production from restoration fires may be necessary to increase forest resilience over time (Ryan et al., 2013; Barros et al., 2018).

In this paper, we describe the application of an FLSM to examine the performance of landscape prioritization metrics on ecological restoration and fire protection objectives. First, we surveyed 47 fuel management projects on national forests in Oregon, delineated a classification of management objectives, and defined a suite of landscape prioritization metrics that can be used to map fuel treatment priorities. Secondly, we used the agent-based FSLM, Envision (Bolte et al., 2004), to simulate how often wildfire returns to areas prioritized for treatment over the course of 50 years. Envision is an FLSM capable of simulating forest succession and disturbance over time. It has been applied to a range of landscape management problems including restoration of fire-adapted forests (Barros et al., 2017; Spies et al., 2017). We propose that based on vegetation succession and the random nature of wildfire there is an implicit *a priori* limitation to how often wildfires can return to areas prioritized for treatment, i.e., before treatments are implemented. Our primary objective was to quantify how uncertainty associated with wildfire ignition and spread, combines with vegetation dynamics to determine how often wildfire returns to areas prioritized for treatment based on different management goals. Thus, we do not simulate fuel treatments nor do we quantify post-management fire-treatment interactions. Our results should be interpreted as a baseline for potential future fire-treatment interactions. This work contributes to a further understanding of how wildfire uncertainty and forest succession interact over time to limit the efficacy of fuel management projects aimed at increasing forest resilience, reducing risk to high-value resources and sustaining the provision of ecosystem services.

2. Methods

2.1. Study area

The study area is comprised of 1.2 million ha of public and private land along the eastern slope of the Cascade Mountains in central Oregon (Fig. 1A). Potential vegetation types vary along a high to low elevation and moisture gradient, from subalpine forest to moist-mixed conifer (*Abies grandis*, *Abies concolor*, *Pseudotsuga menziesii* var. *menziesii*, *Pinus ponderosa* var. *ponderosa,* and *Larix occidentalis*) and dry-mixed conifer (including species in moist-mixed forest in addition to *Pinus contorta* var. *contorta*, *Picea engelmannii* var. *engelmannii*, *Calocedrus decurrens*, *Pinus lambertiana* and *Pinus monticola*), respectively (Fig. 1B). Along the east boundary of the study area, vegetation is dominated by juniper (*Juniperus occidentalis* var. *occidentalis*) woodlands and arid lands (Fig. 1B).

The Deschutes National Forest (DNF) covers 60% of the study area (Fig. 1C). The DNF was divided into planning area polygons based on approximate hydrologic units. The resulting layer consisted of 18 planning areas, ranging from 15,338 ha to 66,400 ha (Fig. 1C). Planning area polygons cover the DNF entirely and can include other land tenures when these are surrounded by national forest, and wilderness areas where mechanical treatments are restricted. We kept planning areas as integral geographic units to provide a continuous matrix for wildfire spread and resulting spatial intersections between fire perimeters and planning areas.

2.2. Classification of fuel management objectives in NEPA documents

We analyzed National Environmental Policy Act (NEPA) documents that describe fuel management projects within the National Forest System (USDA Forest Service, 2018a). The NEPA of 1969 determines that management actions on federal land must follow an interdisciplinary approach to assess the risk and adverse consequences of proposed actions, in a thoughtful and publicly open planning and decision-making process (NEPA, 1969). The NEPA process and resulting documentation provide the best-available roadmap to the purpose, need and type of management actions implemented within national forests. We selected projects that were: (1) located in the state of Oregon, (2) > 10,000 ha in area, (3) approved after 2010, and (4) categorized as fuel management. These criteria resulted in 47 projects, covering 11 national forests (Appendix A). Our objective was to collect, for each project, information on purpose, type of treatment, and the area proposed for each treatment action. Based on data gathered from NEPA documents available for each project we defined nine overall objectives for fuel management projects (Table 1). Our analysis excluded treatment objectives that directly addressed wildlife, specific habitat needs (e.g., removing conifer encroachment in riparian areas), roadless areas, improved hydrology, salvage logging and specific forest health issues (e.g., eliminating trees affected by bark beetle infestation). This resulted in five main objectives represented in the majority of NEPA projects surveyed (Table 1).

A general description of the analysis and modeling work is provided in the sections below (Fig. 2). We proposed metrics to allocate priorities to treat that reflect the objectives identified in the NEPA documents (Table 2, Fig. 2A). Metrics associated with each objective were calculated for each planning area at initial conditions, resulting in one ranking for each prioritization metric - each ranking consisting of 18 planning areas (Fig. 2B). Once rankings were established we identified highest ranking planning areas (or blocks, see sections below) until 10% of the national forest area was prioritized for treatment (Fig. 2C). We then used the forest landscape simulation model Envision to model forest succession and wildfire over time (Fig. 2D). The same vegetation and fuel initial conditions used to calculate metrics and rank planning areas were used as inputs for the Envision model. We overlapped simulated annual fire perimeters from Envision runs with prioritized planning areas to calculate success odds for each metric (Fig. 2E). Success odds were calculated for different success thresholds ranging between 1 and 100%. Success thresholds are interpreted as different levels of success. For example, a success threshold of 0.35 defines success as having at least 35% of the total area burned in the prioritized areas. Thus, for a given metric, if success odds are 5:1 it means that having a minimum of 35% of the area burned within the 10% of the national forest prioritized for management is five times more likely than not (failure).

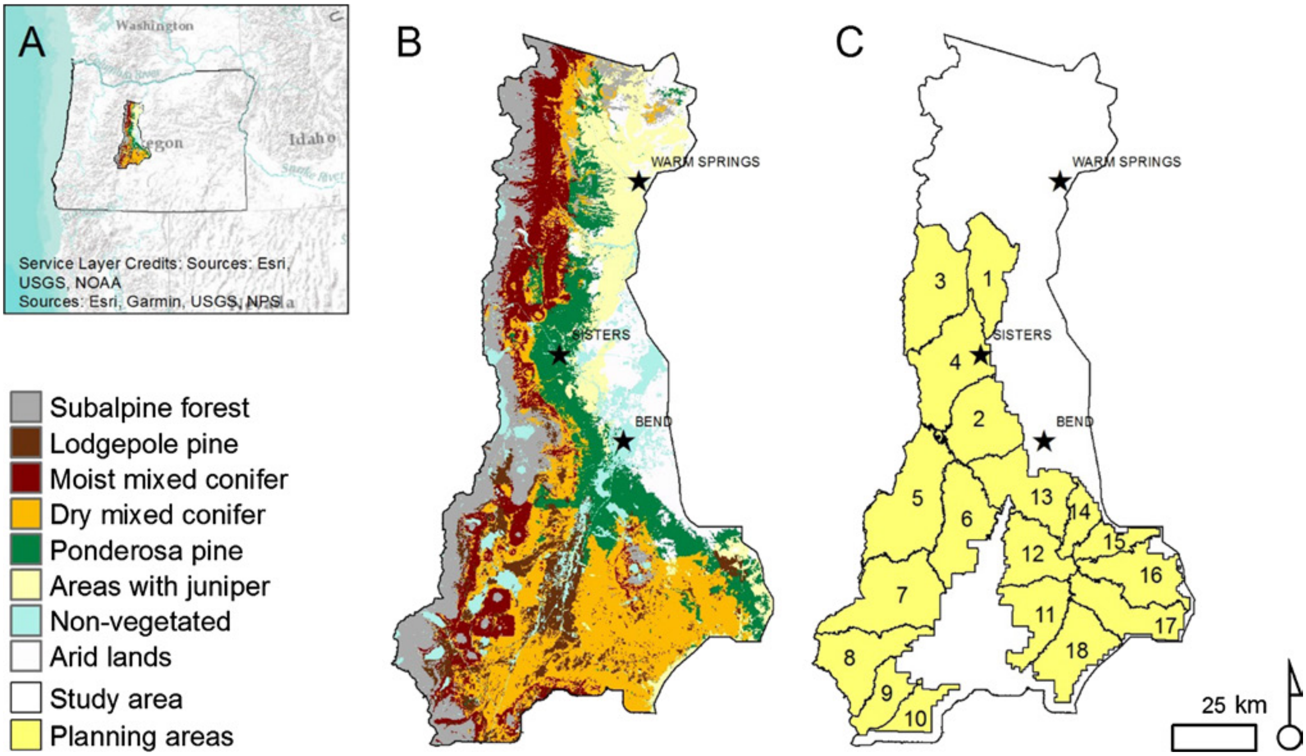

Fig. 1. Location of the study area in central Oregon (A), potential vegetation types (B, following Halofsky et al. (2014)) and distribution of the 18 planning areas on the Deschutes National Forest (C).

Table 1
Forest and fuel management objectives and number of projects that reference each objective. Note that a given project can include multiple objectives.

Objective	Number of projects
Forest structure, composition and resilience	39
Wildfire exposure and the likelihood of high-severity fires	34
Local economies, wood, and fiber products	26
The ecological role of fire	11
Facilitate suppression	9

2.3. Link management goals to prioritization metrics

2.3.1. Forest structure, composition, and resilience

In NEPA documents, forest resilience is often described in terms of forest structure, density, and composition that resembles the historical range of variability (HRV), i.e., before significant management and land use change. The concept of HRV relates closely with LANDFIRE vegetation departure data, an index ranging from 0 to 100 that characterizes how current vegetation regarding species composition, structural condition, and canopy closure deviates from an estimated historical baseline considered more resilient (LANDFIRE, 2013b). Thus, vegetation departure can be interpreted as an indicator for forest restoration needs (Table 2). We used ecological departure (Fig. 3A) as a metric to prioritize planning areas with higher vegetation departure (VDEP), calculated as the mean vegetation departure value of all the pixels (90 m) in each planning area.

2.3.2. Wildfire exposure and the likelihood of high-severity fires

We propose six alternative wildfire exposure metrics to prioritize individual planning areas for reduction of wildfire exposure and wildfire severity (Table 2). Specifically we propose to prioritize planning areas with the highest values of average simulated fire size (SIZE), conditional burn probability (BP), conditional burn probability in high flame lengths (flame length ≥ 1.2 m; BP_{high}), conditional flame length (CFL) or area burned (transmitted wildfire) in neighboring planning areas (T_{in} and T_{out}). These wildfire exposure metrics were calculated from outputs of an FConstMTT simulation run spanning 3000 fire seasons. FConstMTT uses the minimum travel time (MTT) algorithm to model individual fire perimeters for a set of ignitions and associated burning conditions described in lists (hereafter firelists). Firelists were generated from a spatiotemporal ignition prediction model calibrated using historical (1992–2009) patterns of fire occurrence and fire size in the study area. Each ignition listed in a firelist is associated with a day of year, location, energy release component (ERC), wind speed, wind direction and expected fire size. A detailed description of firelists and the ignition prediction model can be found in Ager et al. (2018).

We ran a firelist with 3000 ignition replicates in a single season. Replicates represent different samples of fire ignition locations but are derived from the same spatiotemporal statistical models based on historical data. In FConstMTT surface and canopy fuels remain the same in every simulated year. The only variables changing among fire years were ignition location, ERC, fuel moisture, wind speed, and direction. Thus, we refer to FConstMTT runs as static as opposed to dynamic runs with Envision (described below) where vegetation condition is updated at the end of each annual time step to reflect changes due to vegetation growth (succession) and disturbance (wildfire).

Outputs from an FconstMTT run included simulated fire perimeters for each ignition and pixel-level (90-m) conditional burn probability (BP) (Fig. 3B) and burn probability in six flame length (FL) classes (FL1 = 0–0.6 m, FL2 = 0.6–1.2 m, FL3 = 1.2–1.8 m, FL4 = 1.8–2.4 m, FL5 = 2.4–3.7 m, and FL6 > 3.7 m). Flame length grids were used to calculate CFL (Fig. 3C) and BP_{high} (Appendix B).

Metrics describing wildfire transmission included identifying planning areas that either transmit fire (T_{out}) or receive fire (T_{in}). Wildfire transmission captures the shared dynamics of wildfire risk (Ager et al., 2018). It parses total burned area in a given planning area, based on its origin inside or outside the planning area and identifies neighboring planning areas that act as a source or sink for transmitted fire. We were interested in understanding how transmission concepts can contribute

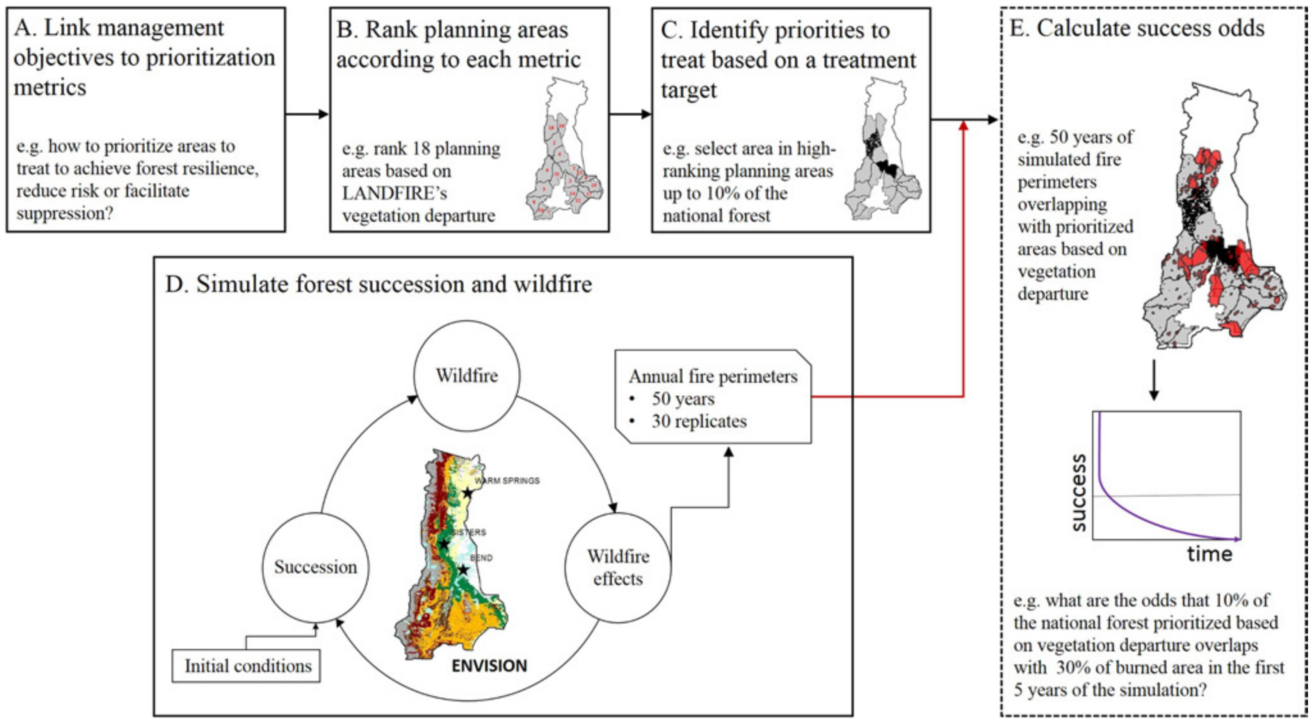

Fig. 2. Diagram showing components of the analysis which includes linking management objectives with spatial prioritization metrics (A), ranking planning areas based on each metric (B), selecting priority areas to treat according to each metric and treatment target for the national forest (C), and simulation of spatiotemporal forest succession and wildfire with Envision (D). Success odds were calculated by overlapping annual fire perimeters simulated for 60 replicates with 50 years each with prioritized areas (E). We calculated odds based on the proportion of burned area in the national forest that was within prioritized areas for different success thresholds and prioritization metrics.

to the delineation of fuel and forest management projects. For example, what would be more successful in reducing area burned: to manage fuels in planning areas that receive fire or planning areas that transmit fire? We ranked planning areas based on the total amount of annual incoming fire (ha/yr) and outgoing fire (ha/yr).

2.3.3. Local economies, wood and fiber products

The treatment availability metric quantifies the amount of area that is available for mechanical thinning in each planning area (THIN, Fig. 3E). The criteria used to select areas suitable for mechanical thinning were based on current management practices on the national forest. Specifically, mechanical thinning can take place in dry mixed conifer forests (ponderosa pine or lodgepole pine) with diameter at breast height (dbh) > 25 cm, in stands with multiple canopies and where canopy closure > 60%. High elevation forest, wilderness areas, reserves established to protect endangered habitat, roadless and steep areas were excluded from THIN. Note that treatment availability refers only to national forest lands, i.e., while planning areas may include other ownerships, these areas were excluded from thinning availability.

2.3.4. The ecological role of fire

Treatment availability for fire (FIRE, Fig. 3F) combines areas where restoration wildfire can be used and areas that meet the ecological constraints for prescribed fire on the DNF. Restoration wildfire refers to the management of natural ignitions for ecological benefit. Areas where restoration wildfire can potentially be used were delineated based on information from managers on the DNF coupled with a 2-km protection buffer outside the wildland urban interface (WUI) (Barros et al., 2018). Prescribed fire can occur in dry mixed conifer and ponderosa pine forest with dbh > 25 cm, single canopies and open story where the last prescribed fire was more than nine years before (Barros et al., 2017).

2.3.5. Facilitate suppression

To address the objective of minimizing risk to the WUI and facilitate

Table 2
Proposed metrics to rank planning areas on the Deschutes National Forest as a function of the different project objectives described in Table 1.

Objective	Metric	Planning area rank based on
Forest structure, composition and resilience	Vegetation departure (VDEP)	Mean vegetation departure of all pixels in the planning area
Wildfire exposure and the likelihood of high-severity fires	Fire size (SIZE)	Mean fire size of all fires that ignited within the planning area
	Burn probability (BP)	Mean burn probability of the planning area (excludes unburnable pixels)
	Burn probability in high flame length (BP_{high})	Mean burn probability with flame length ≥ 1.2 m (excludes unburnable pixels)
	Conditional flame length (CFL)	Mean conditional flame length (m) of all pixels within the planning area (excludes unburnable pixels)
	Incoming transmitted fire (T_{in})	Sum of incoming fire (ha) associated with the planning area
	Outgoing transmitted fire (T_{out})	Sum of outgoing fire (ha) associated with the planning area
Local economies, wood and fiber products	Merchantable timber (THIN)	Sum of area (ha) available for mechanical thinning of merchantable timber
The ecological role of fire	Restoration and prescribed fire (FIRE)	Sum of area (ha) available for prescribed fire and restoration wildfire
Facilitate suppression	Wildfire transmission to communities (T_{com})	Number of housing units exposed from transmitted wildfire originating in the planning area

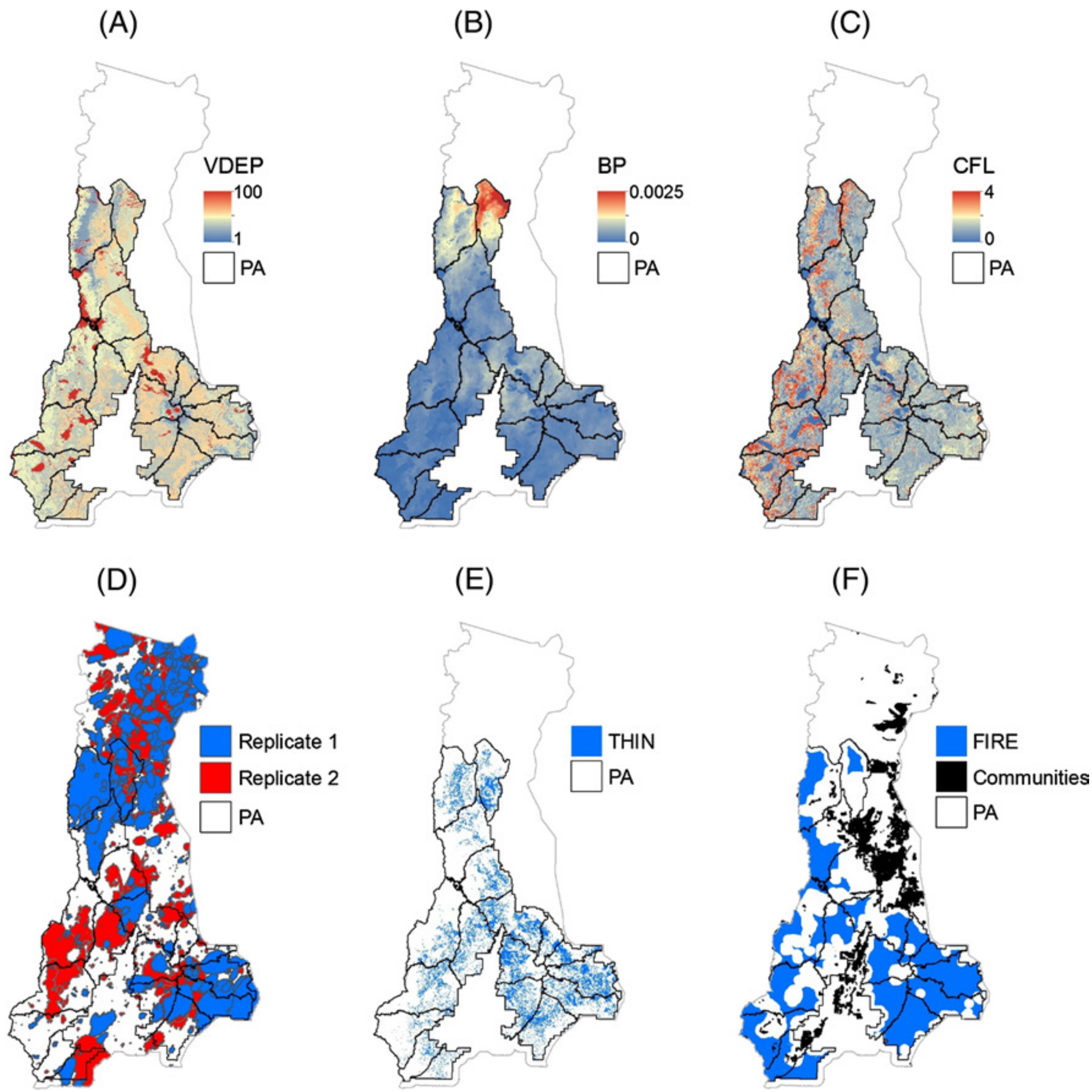

Fig. 3. Vegetation departure (A), conditional burn probability (B), conditional flame length (C), and simulated wildfire perimeters for two replicates (D). The full set of perimeters (60 replicates) was used to calculate mean fire size per planning area, fire transmission between planning areas (PA) (incoming and outgoing transmitted fire) and the number of structures exposed to fire based on the communities map (F). Also shown is the area suitable for merchantable thinning (E) and restoration wildfire and prescribed fire (F).

suppression we prioritized planning areas based on wildfire transmission into communities (T_{com}). This metric quantifies fire transmitted from each planning area to the communities in the study area in terms of the number of structures exposed per year. Community boundaries (Fig. 3F) were defined as the areas that intersect the USA Census Bureau populated places layer (community cores, US Census Bureau, 2016), and SILVIS WUI layer polygons with > 2 housing units per km^2 (SILVIS Lab, 2012) that fall within a 45-minutes' drive time distance from the community cores. We intersected simulated perimeters (Fig. 3D) with community boundaries (Fig. 3F) to obtain the portion of each perimeter that entered a community and recorded the corresponding planning area where ignition occurred. The abovementioned methods were described in detail in previous work (Ager et al., 2017b).

2.4. Rank planning areas based on individual prioritization metrics

We calculated the prioritization metrics at the pixel level and averaged to the planning area. We then ranked planning areas according to each metric, which resulted in 10 alternative rankings (Fig. 2B). Rankings determine priorities to treat at initial conditions. We identified correlated rankings using the Spearman rank correlation test at alpha = 0.05. All calculations were done with MatLab (Mathworks, 2016).

2.5. Identify priorities to treat based on a treatment target

On average, managers on the DNF treat 1.2% of the landscape per year in a combination of mechanical actions and prescribed fire. Our simulation scenario diverged from current practice on the DNF in two ways. First, it assumes that 10% of the DNF would be prioritized for treatment each year which is substantially above the current treatment rate (1.2% per year). Secondly, within high-ranking planning areas, we selected area to treat until the 10% treatment target was met and assumed that treatments were restricted to selected locations throughout 50 years. In other words, once priorities were established, they remained the same until all area was treated. Once all area is treated, management is directed at long-term treatment maintenance, i.e., second and third entries in restored areas with a combination of mechanical actions and fire. Our modeling approach differs from the current practice where projects are spatially allocated irrespective of other potential alternative project locations, previous projects or long-term maintenance schedules. We acknowledge that this simplification implies that the entire area in each planning area can be treated which is not the case in real landscapes, where operational and logistical constraints limit the location, rate, and type of treatment.

To assure that rankings associated with different metrics had the same amount of area we divided planning areas into 100-ha blocks and randomly selected blocks from the first-ranked planning area until the area target was fully met. If the area in the highest ranking planning area was not sufficient to meet the area target, we randomly selected blocks from the second-highest planning area and so forth until 10% of the national forest was selected for management.

2.6. Simulate forest succession and wildfire

2.6.1. Envision

We used the agent-based landscape model Envision to simulate annual area burned in each planning area. Envision models the interactions of fire, vegetation growth and forest management over space and time. In Envision, the landscape is dynamic, and at the end of each annual time step, changes in vegetation carry over to the following time step. The model has been used previously to study the effects of increased levels of forest management and wildfire on future fire regimes and ecosystem processes in the study area (Ager et al., 2017a; Barros et al., 2017; Spies et al., 2017).

Envision runs on an annual time-step, and changes to vegetation structure due to disturbance (wildfire and management) and succession occur at the spatial scale of individual decision unit (IDU) polygons. IDUs range between 1 and 10 ha and result from the intersection between tax lot counties and potential vegetation types. Each IDU polygon is associated with a vegetation structural state characterized by the following attributes: dominant and codominant tree species, canopy cover, tree size and canopy layers. In addition to the structural state, each IDU is associated with a fuel model, canopy height, canopy base height, canopy bulk density, aspect, elevation, and slope. Fuel models and canopy fuels were derived from Forest Vegetation Simulator runs using tree lists representative of structural states in the study area. Topographic variables were obtained from digital elevation model data from the USGS National Map Seamless Server.

In each simulation time-step, Envision evaluates potential changes to the IDU structural attributes. If a disturbance leads to changes in any of the IDU attributes a transition is triggered leading to a new structural state defined by the new class attributes. Examples of changes to an IDU structure class include vegetation growth over time resulting in a new size class, or the development of an understory layer of vegetation that triggers a transition from a single to multilayer stand. Rules that define succession-related transitions were modeled based on a state-and-transition model developed for Oregon, Washington, Arizona and New Mexico (Hemstrom et al., 2004). This model includes probabilistic and deterministic rules of transition that reflect our empirical understanding of succession trajectories for the potential vegetation types in the study area.

Disturbances can also trigger changes in an IDU structure class, depending on the disturbance's intensity and whether one or more of the structural attributes changes. In cases where the vegetation structure class remains the same after disturbance, the fuel model associated with the disturbed IDU will change to reflect the effect of disturbance on understory fuel but not the IDU structural attributes. For example, a low severity fire will reduce understory fuel load without changing the number of layers, canopy closure or tree size. This will trigger a change in fuel model, but not in the IDU vegetation class. Envision classifies fire severity into three classes, surface, mixed-severity and stand-replacing fire, based on simulated flame length. Fire severity was determined by comparing simulated flame length in each burned IDU with the flame length threshold above which expected tree mortality is 20% (surface fire), 20–80% (mixed-severity) or above 80% (stand-replacing fire). Flame length thresholds were determined with the FVS-Fire and Fuels Extension (Reinhardt and Crookston, 2003) using tree lists representative of each structure class.

Envision models fire growth and fire intensity of individual fire events using the minimum travel time (MTT) algorithm integrated into a wildfire submodel that shares the same code libraries as the FlamMap program (Finney, 2006). The wildfire submodel uses firelists that follow the format and methods described in the previous section. It follows that both static (FconstMTT) and dynamic (Envision) runs rely on the same spatiotemporal ignition prediction methods to generate firelists. In Envision, we ran 60 replicates with 50 fire seasons each. Each of the 60 replicates had the same initial conditions (landscape at year 0) which will go through changes through the course of 50 years as a function of the interaction between alternative wildfire and succession pathways. At the end of each annual run, changes in each IDU vegetation structure from fire and vegetation succession carry over to the following year and annual fire perimeters are recorded.

2.6.2. Initial conditions

IDUs were populated with potential vegetation data from the gradient nearest neighbor analysis structure and species maps corresponding to 2006 (LEMMA, 2014). Within the DNF, fuel models were based on the fuel model layer for the national forest, and on LANDFIRE data elsewhere (LANDFIRE, 2013a). We ran Envision for six annual cycles to update vegetation states from 2006 to 2012. Historical fires between 2006 and 2012 were also considered by updating burned IDUs using the Monitoring Trends in Burn Severity layer (National Geospatial Data, 2009). As a result, initial conditions are representative of the best available information on vegetation, fuels and fire as of 2012 (simulation year zero). This landscape was used to calculate SIZE, BP, BP_{high}, T_{com}, T_{in}, T_{out}, FIRE and THIN and as initial conditions for the Envision runs. Vegetation departure (VDEP) was based on the estimated departure of the 2014 succession class relative to historical conditions.

2.7. Calculate success odds

We used simulated annual fire perimeters over 50 years and 60 replicates to estimate success to failure odds of each metric when 10% of the landscape was targeted for treatment. We defined a metric as successful if, in any given 5-year period, the area burned in prioritized areas was above a specific success threshold. The rationale behind success thresholds it to reflect diverse management styles. Ambitious managers may require that a given metric prioritizes at least 60% of all area burned in the DNF within a 5-year window (success threshold = 0.6). However, a more moderate management expectation may be that only 30% of the area burned (success threshold = 0.3) is within the areas prioritized for treatment. Failure corresponded to having less area burned than the success threshold for the same 5-year period. The underlying assumption is that for a prioritization metric to be successful, areas treated ought to be intersected by wildfire. The potential for fire-treatment interaction requires fire and treatments to occur in the same space and within close succession. Thus, it is possible to determine an *a priori* success rate of different metrics by determining how often selected areas for treatment reburn. Our measure of success describes how often (odds) a given metric gets future fire occurrence "right," for different levels of "right" (success threshold). To calculate the success relative to failure odds we defined a success threshold on a continuous scale, from 0 to 1 in 0.1 increments as:

$$success\quad threshold = \frac{AB_{10\%}}{AB_{DNF}} \tag{1}$$

where $AB_{10\%}$ corresponds to area burned within a 5-year window that overlaps prioritized areas based on a treatment target of 10% of the study area and AB_{DNF} corresponds to total area burned in the DNF within the same period. We overlapped annual fire perimeters with areas identified as a priority for treatment and with the 18 planning areas to calculate $AB_{10\%}$ and AB_{DNF}, respectively. Proportions were calculated within a five-year moving window starting at year 2 and ending at year 47. This resulted in 27,000 sample points used to calculate success odds for each metric in Table 2, and success threshold according to:

$$odds = \frac{P_x}{1 - P_x} \tag{2}$$

where Px is the number of times the metric was successful, divided by the sample size.

2.7.1. Null model of random prioritization

To test whether the selected metrics perform better than a random ranking of planning areas, we generated an empirical distribution of the success to failure odds under the assumption of randomly generated rankings ($odds_{rand}$). We created 5000 rankings by sampling random combinations of the 18 available planning areas and calculated $odds_{rand}$ according to Eq. (2). To determine whether the odds obtained with the prioritization metrics could be achieved by chance alone, we compared the statistical significance of odds distributions for each metric relative to the odds distribution under random prioritization. The probability of having an $odds_{rand} \geq$ odds was used to determine the significance of the odds for each priority metric and success threshold (North et al., 2002). An estimate of the empirical p-value can be obtained, based on Davidson and Hinkley (1997) as:

$$p = \frac{r + 1}{n + 1} \tag{3}$$

where p is the p-value, r is the number of random replicates with $odds_{rand} \geq$ odds and n is the number of replicate samples under random allocation. All calculations were performed with MatLab R2016b (Mathworks, 2016).

3. Results

3.1. Correlation among rankings based on alternative prioritization metrics

Planning area rankings obtained with metrics focusing on different management objectives showed evidence of correlation. Correlation between rankings suggests that it is possible to identify locations where fuel management projects can meet multiple goals. Results for the Spearman rank correlation test among the ten rankings using the full set of 18 planning areas (Table 3) showed evidence of correlation between rankings based on burn probability (both BP and BP_{high}), fire size (SIZE), transmitted fire (T_{in} and T_{out}) and area suitable for restoration wildfire and prescribed fire (FIRE). Other correlated rankings included conditional flame length (CFL) and fire transmitted to communities (T_{com}). The latter was also correlated with the ranking obtained based on area suitable for thinning (THIN), suggesting that prioritizing planning areas based on merchantable timber harvest (THIN) can be reconciled with community protection (T_{com}).

When only a small percentage of high-ranking planning areas was prioritized for treatment, correlated rankings showed a similar distribution of prioritized areas. When 10% of the national forest was prioritized using BP, BP_{high} and T_{in}, only two planning areas were selected for treatment during the course of 50 years (Fig. 4C, D, F). For the three abovementioned metrics this included planning area #1 in addition to random blocks in planning area #3, up until the 10% area threshold was met. Prioritization based on vegetation departure (Fig. 4A), fire size (Fig. 4B) conditional flame length (Fig. 4E), outgoing fire (Fig. 4G), merchantable timber (Fig. 4H), potential for restoration wildfire and prescribed fire use (Fig. 4I) and transmitted fire to communities (Fig. 4J) resulted in distinct spatial patterns of planning areas targeted for management.

3.2. Comparison of success odds obtained with metrics based on management objectives and random prioritization

Comparison between prioritization metrics and the null model showed that only three out the ten metrics tested performed significantly better than a random allocation of priorities (Fig. 5). Prioritization based on burn probability (BP, BP_{high}) and transmitted fire (incoming, T_{in}) had higher success odds than random allocation of priorities to treat ($P < 0.05$). Burn probability was based on the simulation of fire spread and it is expected to capture the spatial patterns of activity in the study area. T_{in} identifies planning areas that receive wildfire, also directly capturing spatial variability in the success metric, i.e., how often fire reoccurs on a given planning area. Using fire size (SIZE) and outgoing transmitted fire (T_{com}) to prioritize management performed better than random, albeit with mixed results depending on the metric and success threshold (Fig. 5). Metrics emphasizing vegetation condition (VDEP), potential fire behavior (CFL), potential for merchantable timber harvest (THIN) and forest restoration using prescribed and restoration wildfire (FIRE) have significantly lower odds than the null model for all success thresholds (Fig. 5). These results indicated that allocating priorities to treat based on chance alone had higher odds of fire-treatment interactions than based on VDEP, CFL, FIRE and THIN.

When the success threshold = 1, there was no significant difference between individual prioritization metrics and the null model of random prioritization (Fig. 5). This resulted from testing a null hypothesis of random prioritization having the same, or higher success odds than each alternative criteria, i.e., $odds_{rand} \geq$ odds. Therefore, cases where $odds_{rand}$ = odds counted as success cases in favor of the random model. When success threshold = 1, success means that all the area burned in a 5-year period was within the 10% of the DNF that was prioritized for

Table 3
P-values associated with the null hypothesis of no correlation among rankings, calculated using the Spearman rank correlation test ($^*P \leq 0.05$). Columns/rows show alternative prioritization metrics with VDEP = vegetation departure, SIZE = average fire size, BP = burn probability, BP_{high} = burn probability in high flame length, CFL = conditional flame length, T_{in} = incoming wildfire, T_{out} = outgoing wildfire, THIN = area suitable for merchantable thinning, FIRE = area suitable for restoration wildfire/prescribed fire and T_{com} = transmitted fire to communities.

	VDEP	SIZE	BP	BP_{high}	CFL	T_{in}	T_{out}	THIN	FIRE	T_{com}
VDEP	–	0.256	0.150	0.889	0.477	0.748	0.102	0.767	0.563	0.314
SIZE	0.256	–	0.850	0.047*	0.100	0.126	0.831	0.889	0.282	0.417
BP	0.150	0.850	–	0.039*	0.487	0.306	0.436	0.876	0.264	0.889
BP_{high}	0.889	0.047*	0.039*	–	0.348	0.004*	0.067*	0.331	0.005*	0.436
CFL	0.477	0.100	0.487	0.348	–	0.558	0.366	0.005*	0.407	0.219
T_{in}	0.748	0.126	0.306	0.004*	0.558	–	0.171	0.876	0.013*	0.767
T_{out}	0.102	0.831	0.436	0.067	0.366	0.171	–	0.503	0.344	0.961
THIN	0.767	0.889	0.876	0.331	0.005*	0.876	0.503	–	0.656	0.006*
FIRE	0.563	0.282	0.264	0.005*	0.407	0.013*	0.344	0.656	–	0.662
T_{com}	0.314	0.417	0.889	0.436	0.219	0.767	0.961	0.006*	0.662	–

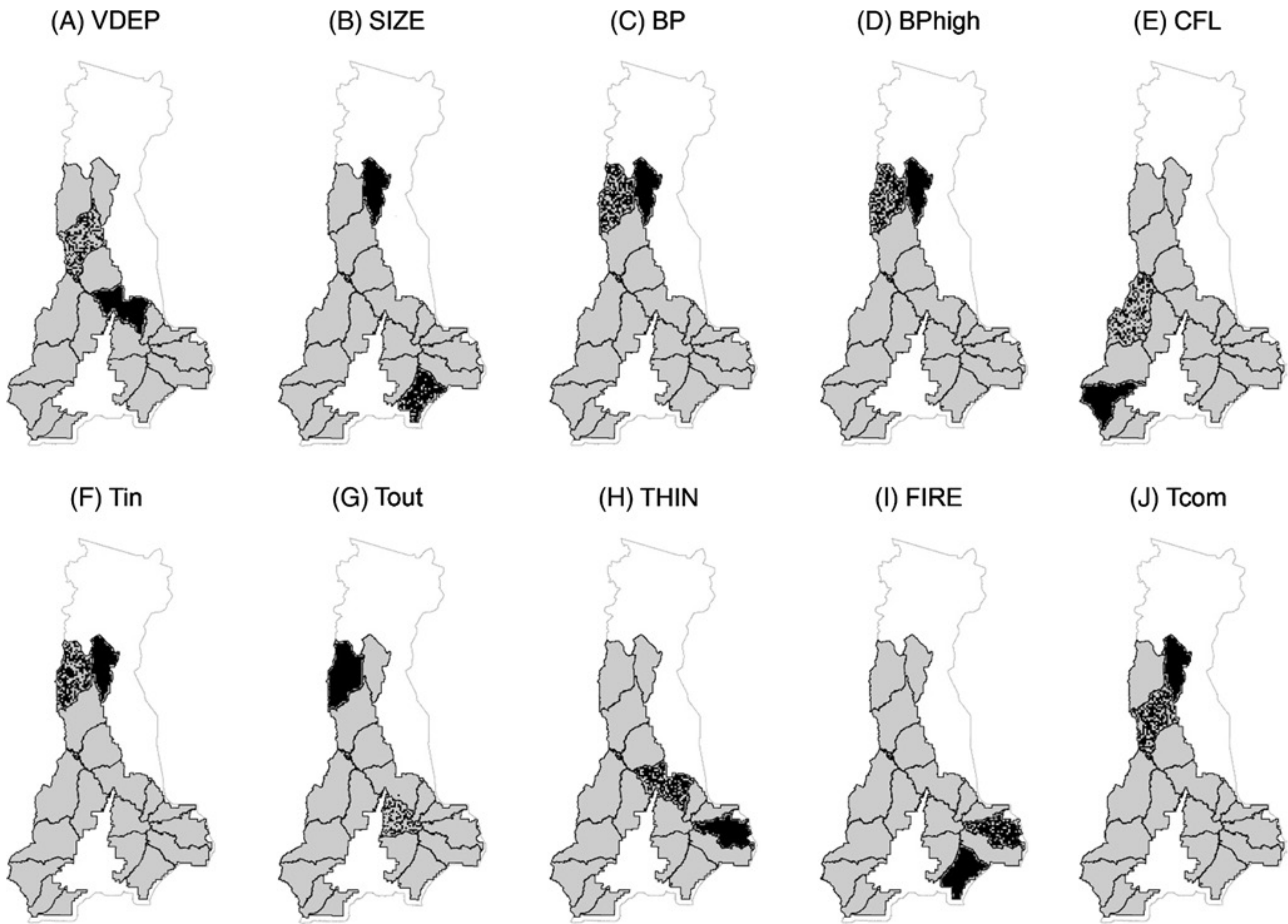

Fig. 4. Blocks selected for treatment when the treatment target corresponds to 10% of the national forest. Blocks are selected individually from planning areas starting with the first highest ranking planning area. Within a planning area blocks are selected randomly and new blocks are continuously selected following the priority ranking until the treatment target is met. VDEP = vegetation departure, SIZE = average fire size, BP = burn probability, BP_{high} = burn probability in high flame length, CFL = conditional flame length, T_{in} = incoming transmitted wildfire, T_{out} = outgoing transmitted wildfire, THIN = area suitable for merchantable thinning, FIRE = area suitable for restoration wildfire/prescribed fire and T_{com} = wildfire transmitted to communities.

treatment. The likelihood of this level of success for any metric considered including random allocation is zero, resulting in $P = 1$ (Eq. (3)).

3.3. Success odds over time

When 10% of the DNF was prioritized for treatment, overall success odds were small and declined sharply when the success threshold increased (Fig. 6) and over the course of the 50-yr simulation period (Fig. 7). Burn probability (BP, BP_{high}) and incoming fire (T_{in}) had the highest success odds. When the success threshold = 0.10, the odds in favor of a positive outcome, i.e., > 10% of total area burned during any 5-year period occurred in prioritized areas, were 5:1 for BP/BP_{high}/T_{in}. Doubling the success threshold, i.e., moving from 0.1 to 0.2 resulted in a reduction in odds from 5:1 to 1:1, meaning odds in favor were the same as odds against success. As the success threshold further increased, reflecting more ambitious management goals, success odds declined sharply. Achieving higher success odds when the success threshold was > 0.2 would require prioritizing more area to treat, i.e., increasing the simulated target of 10% of the national forest treated.

Allocating priorities to treat based on merchantable timber (THIN), vegetation departure (VDEP), area suitable for prescribed fire and restoration wildfire (FIRE) and conditional flame length (CFL) had similar or lower success odds than random allocation (Fig. 6).

Metrics with higher overall success odds also performed better over time. When the success threshold = 0.2, annual success odds for burn probability metrics (BP/BP_{high}) were higher during the first ten years of the 50-year simulation period and declined afterward (Fig. 7). Annual success odds for BP and BP_{high} were 5:1 and the highest among all metrics (Fig. 7C–D). Odds for T_{in} and T_{com} were also higher during the first decade, about 4:1 and 3:1, respectively (Fig. 7F and J), after which a decline in success odds was observed. We interpret the reduction in odds over time as the result of early wildfire occurrence in prioritized areas resulting in lower fuel loads in subsequent years. As vegetation regrows these previously burned areas become available to burn again, as indicated by the small increase in annual odds around simulation year 35. However, success odds did not return to the same levels as the early years suggesting wildfire can be used to maintain restored areas. Annual success odds based on random allocation (dashed), VDEP, CFL, THIN and FIRE were small suggesting low potential for interaction between wildfire and treatments over time.

4. Discussion

Our results show that the choice of metric used to select fuel management locations matters when it comes to maximizing the potential for wildfire-treatment encounters over time. However, even the best-performing metrics showed only modest success odds that declined sharply as management goals became more ambitious. We showed that project allocation based on vegetation departure or potential for merchantable timber harvest resulted in lower potential for fire-treatment interaction than with random assignment. We also quantified the degree to which wildfire and vegetation succession affect the success odds

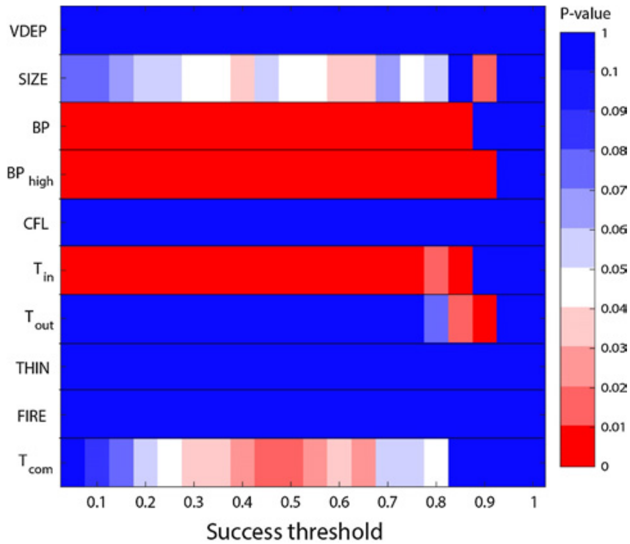

Fig. 5. Empirical P-values associated with testing the null hypothesis of random allocation of planning areas having greater or equal success odds than each prioritization metric (rows) at different success thresholds (columns). A small P-value ($P \leq 0.05$, red to white) indicates strong evidence against the null hypothesis. Rows represent prioritization metrics where VDEP = vegetation departure, SIZE = average fire size, BP = burn probability, BP_{high} = burn probability in high flame length, CFL = conditional flame length, T_{in} = incoming transmitted wildfire, T_{out} = outgoing transmitted wildfire, THIN = area suitable for merchantable thinning, FIRE = area suitable for restoration wildfire/prescribed fire and T_{com} = wildfire transmitted to communities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

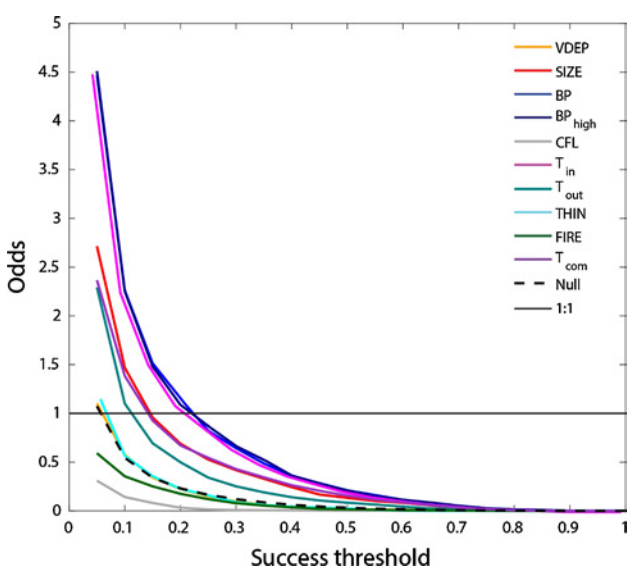

Fig. 6. Success to failure odds associated with randomly selecting 10% of the national forest for management (dashed line) or according to metrics based on project objectives (Table 2). Odds were calculated on a 5-year moving window over 50 years and for different success thresholds (x-axis). The horizontal line represents 1:1 success odds, indicating equal odds in favor or against. VDEP = vegetation departure, SIZE = average fire size, BP = burn probability, BP_{high} = burn probability in high flame length, CFL = conditional flame length, T_{in} = incoming transmitted wildfire, T_{out} = outgoing transmitted wildfire, THIN = area suitable for merchantable thinning, FIRE = area suitable for restoration wildfire/prescribed fire and T_{com} = wildfire transmitted to communities.

of alternative spatial allocation metrics over time. We found that allocating landscape-scale management priorities based on conditional burn probability (or burn probability in high flame length) and transmitted fire (planning areas with higher incoming fire) resulted in higher success odds particularly during early simulation years, i.e., when vegetation conditions are similar to the planning year. These results reinforce the need to incorporate probabilistic wildfire exposure and wildfire transmission concepts into forest management planning at the landscape scale (Calkin et al., 2014; Ager et al., 2017b).

We quantified the success odds of alternative metrics for the spatial allocation of fuel treatment actions that reflect different objectives for fuel management programs. We defined success based on each metric's ability to prioritize planning areas for treatment that maximize fire-treatment interactions over time. Other measures of short- and long-term performance are possible such as carbon sequestration, timber production or compound indices that capture ecological benefits, management effort and the feasibility of long-term management (Creutzburg et al., 2017; Krofcheck et al., 2017), and a similar analysis could be used to quantify performance over time of alternative metrics. Our choice of a success measure was based on the assumption that meeting fuel management objectives over time relies on future fires intersecting past treatments within a timeframe in which they are still considered effective. Low frequency of fire-on-treatment interaction results from the small amount of area treated relative to the area needing treatment (Barnett et al., 2016), the criteria used to spatially allocate treatments (Barros et al., 2017) and the intrinsic uncertainty of wildfire occurrence and spread (Jones et al., 2004). Whether the objective is to restore forest structure and composition in fire-adapted forest and the ecological role of fire or to protect communities from fire, the long-term achievement of treatment goals is limited by spatial misalignments between treatment placement and wildfire occurrence. Allocation of projects in locations that are suboptimal to modify fire growth and behavior may result in actions that are only effective for a few years, compromising long-term forest resilience and raising questions regarding the validity of initial investments.

Our results show that when 10% of the Deschutes National Forest was targeted for management, prioritized areas based on conditional burn probability increased the odds of fire-treatment interactions. Burn probability (BP) is a component of risk and wildfire exposure assessments and correlates with transmitted wildfire (incoming, T_{in}) and conditional burn probability in high flame lengths (BP_{high}). Correlation among metrics that share similar odds allows for flexibility when comparing and choosing metrics that better reflect local context and management objectives. For example, the counterpart to incoming fire is outgoing fire (T_{out}), used to prioritize planning areas where ignitions burn proportionally more outside the planning area, i.e., planning areas that on a proportional basis "give" more fire to neighboring areas. T_{out} had lower success odds than T_{in} and BP, but higher than random allocation. In planning areas that are near private lands or communities, prioritizing management based on T_{out} may provide a better compromise between success rate and the reduction of transmitted risk to areas outside the national forest.

Prioritizing areas to treat based on non-fire risk metrics had little impact on overall area burned, giving further support to the need to incorporate wildfire exposure and risk concepts into the planning process of fuel management programs. This need has been recognized in both fire and landscape management literature (Sampson and Sampson, 2005; Ager et al., 2014; Calkin et al., 2014), and national policy documents (O'Laughlin, 2005; USDA Forest Service, 2015). However, in real landscapes, decisions regarding the size and location of fuel management projects are often independent of quantitative risk, and a function of economic and operational constraints, public support and management style (MacGregor and Seesholtz, 2008). Incorporating risk

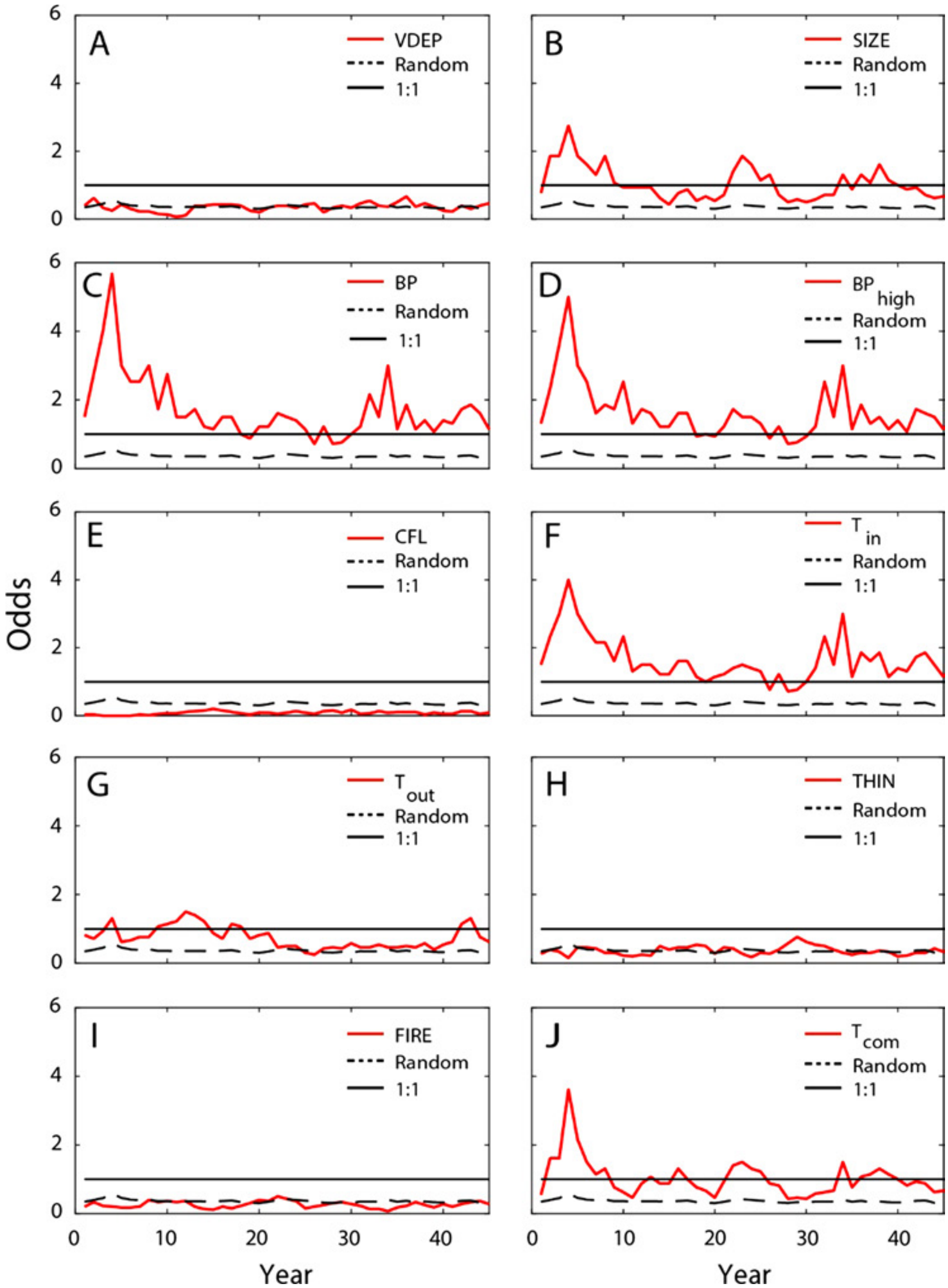

Fig. 7. Success to failure odds over time assuming the success threshold = 0.2 for each metric and random allocation (dashed). Solid black line corresponds to the 1:1 success odds. The x-axis indicates the mid-position year in the 5-year window used to calculate the odds. VDEP = vegetation departure, SIZE = average fire size, BP = burn probability, BP_{high} = burn probability in high flame length, CFL = conditional flame length, T_{in} = incoming transmitted wildfire, T_{out} = outgoing transmitted wildfire, THIN = area suitable for merchantable thinning, FIRE = area suitable for restoration wildfire/prescribed fire and T_{com} = wildfire transmitted to communities.

into forest planning is challenging because risk management must balance the need to suppress fire where expected losses are high, with the need to promote wildfire where positive impacts are expected (Borchers, 2005). The observed correlation between priority rankings developed with different metrics suggests that at least a few locations can be managed to meet multiple management objectives. Spatial optimization frameworks capable of incorporating uncertainty and representing multiple - and sometimes conflicting management goals - can facilitate the delineation of effective multi-objective projects (Vogler et al., 2015; Ager et al., 2016; Krofcheck et al., 2017).

Forest landscape simulation models with the ability to simulate natural and human disturbance and vegetation succession are needed to address landscape management problems. Models such as Envision, LANDIS, and iLand can be used to analyze tradeoffs among multiple, competing, ecological and management objectives (e.g., Scheller et al., 2011; Seidl et al., 2016). Risk tradeoffs or "competing risks" from fuel management programs, i.e., the relative effects of short-term adverse impacts to ecological values (e.g., 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 (Scheller et al., 2011; Loudermilk et al., 2014), or factored it as an exogenous process (Roloff et al., 2005). We showed how risk tradeoffs are impacted by the choice of metric used to prioritize and select treatment areas. For example, in some areas, selecting planning areas based on merchantable timber may generate positive economic outcomes in the short term but is unlikely to positively affect longterm forest resilience (measured as future fire-treatment intersection). In fact, our results show that random allocation of treated areas would be equally effective at promoting future fire-treatment intersection.

We used historical (1992–2009) fire data to calibrate our ignition prediction and fire size model, which bears significant implications to our findings. Much of the dry and mixed conifer forest in the study area is running at a fire-deficit (Parks et al., 2015) as a consequence of past management practices and fire exclusion policy. By replicating contemporary fire regimes to model future wildfire occurrence, we assumed that the current fire-deficit would persist, resulting in spatio-temporal patterns of fire occurrence in the next 50 years that are similar to historical. Under alternative future scenarios, where spatial and temporal distributions of fire occurrence differ substantially from historical, estimates of success odds may change (Krawchuk et al., 2009; Kim et al., 2018). Potential changes in future fire regimes are likely to affect odds in different ways. If the spatial pattern of fire occurrence remains similar and fire occurrence increases then success odds are expected to increase, without changes to the relative performance of allocation metrics. However, if under future fire regimes the spatial distribution of area burned is significantly different from historical, then the performance of the different metrics analyzed is likely to differ from our results. For example, projected climate change effects on the length of growing season (Kim et al., 2018) and amount of snowmelt (Westerling et al., 2006) can shift current species distribution, including creating conditions that favor invasive grasses (Abatzoglou and Kolden, 2011). Such changes in vegetation composition and distribution can alter contemporary patterns of wildfire ignition and spread. The empirical nature of Envision's state-and-transition model used to simulate vegetation succession does not account for potential shifts in vegetation distribution. While this is a known caveat of the model, it does not detract from our results given previous work showing that within the 50-year timeframe of our simulation significant changes in the distribution of potential vegetation types are unlikely (Halofsky et al., 2013).

To our knowledge, this study was the first effort to systematize a classification of forest management project objectives based on implemented NEPA projects. The survey of NEPA documents revealed that there is not always a strong linkage between management objectives, proposed treatment actions, project location and performance metrics trackable over time. We adopted a top to bottom approach from management objectives to spatial allocation metrics to priority rankings of planning areas. Prioritizing goals associated with fuel management programs is driven by federal forest policy and locally influenced by the public, stakeholders and public managers' background. Regardless of what is expected from federal forests, linking management goals to landscape intervention, and monitoring performance over time requires metrics that establish a nexus between a projects purpose and location. Outcome-based performance metrics at project, regional and national scales are needed to allow managers (and the public) to track whether treatments are meeting their intended purpose(s) over time and if necessary, correct course (Gaines and Lurie, 2007). Quantifying project effectiveness is challenging because: (1) there are often multiple objectives associated with each project, (2) different objectives may be accomplished at a different pace, and (3) multiple objectives may result in potentially different criteria to monitor progress. Our results emphasize how wildfire randomness can limit the efficacy of projects in meeting their stated goals. In this context, incorporating uncertainty and risk concepts can advance project planning and evaluation by establishing a realistic baseline for project performance and contributing to build public trust (but see Germain et al. (2001)). Federal agencies have recognized the need to learn from past experiences, address the evolving societal demands of public accountability, but also achieve a reasonable balance between much-needed forest management, environmental protection, public involvement and economic efficiency (GAO, 1997). Expectations for public lands change over time and understanding why and where to treat hazardous fuels is a key management practice, particularly given new federal land management initiatives that will increase funding, flexibility and opportunities for shared stewardship (USDA Forest Service, 2018b).

5. Conclusion

In the western USA, sustaining resilient federal forests, maintaining biodiversity, conserving habitat and fostering the economic health of communities are long-term challenges with both short- and long-term tradeoffs. Taken collectively our results show that wildfire stochasticity strongly determines the success odds of forest management programs when success is predicated on potential fire-treatment interactions. Land and fire management decisions with potentially risky outcomes must reconcile multiple and sometimes conflicting objectives and uncertain information, and are often biased by overly risk-averse decision-processes. Because uncertainty cannot be eliminated from natural systems a better management approach is to quantify and incorporate uncertainty into the decision process. Forest landscape simulation models provide a framework for long-term scenario planning of alternative fuel management strategies and potential feedbacks with natural disturbance. In an environment of increased social demand on ecosystems services and need for resource protection, establishing clear management priorities and defining science-based, trackable criteria for project performance will improve public accountability and promote better decision-making. Ultimately, this can contribute to positive policy feedbacks to help sustain public support for investing in fire-adapted communities and fire resilient landscapes.

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Appendix A

See Table A1.

Table A1
Project location within the National Forest System, project name and type of NEPA document analyzed: Decision Notice (DN), Finding Of Non-Significant Impact (FONSI), Environmental Assessment (EA), Record of Decision (ROD), Decision Memo (DM), Final Environmental Impact Statement (FEIS).

National Forest	Project name	NEPA document
Malheur	Damon Wildland Urban Interface	DN/FONSI
Malheur	Starr Aspen	DN/FONSI
Malheur	Soda Bear	DN/FONSI
Malheur	Marshall Devine Hazardous Fuel Reduction	DN/FONSI

(*continued on next page*)

Table A1 (*continued*)

National Forest	Project name	NEPA document
Malheur	Upper Pine Hazardous Fuel Reduction	EA
Malheur	Galena	ROD
Malheur	Wolf Vegetation Management	DN/FONSI
Malheur	Magone	ROD
Malheur	Dove Vegetation Management	DN/FONSI
Deschutes	West Bend Vegetation Management	ROD
Deschutes	Ogden Vegetation Management	ROD
Deschutes	Marsh	DN/FONSI
Deschutes	Rim-Paunina	ROD
Deschutes	Prescribed Fire Maintenance	DM
Deschutes	Junction Vegetation Management	DN
Deschutes	Flat Vegetation Management	DN
Fremont-Winema	Westside Fuels Reduction	DN/FONSI
Fremont-Winema	Black Hills	DN/FONSI
Fremont-Winema	Bluejay Vegetation Management	DN/FONSI
Fremont-Winema	Red Knight Restoration	DN/FONSI
Fremont-Winema	Oatman Restoration	DN/FONSI
Fremont-Winema	Deuce Fuels Reduction and Vegetation Management	DN/FONSI
Umatilla	Wildcat II Fuels Reduction and Vegetation Management	DN/FONSI
Umatilla	South George Vegetation and Fuels Management	ROD
Umatilla	Tollgate Fuels Reduction	ROD
Umatilla	Asotin Creek Prescribed Fire	DM
Wallowa-Whitman	Rooster Vegetation Management	DN/FONSI
Wallowa-Whitman	Puderbaugh Vegetation Management	DN/FONSI
Wallowa-Whitman	East Face Vegetation Management	DN
Wallowa-Whitman	Snow Basin Vegetation Management	ROD
Wallowa-Whitman	Trail Vegetation Management	DN/FONSI
Wallowa-Whitman	Sandbox Vegetation Management	DN/FONSI
Wallowa-Whitman	Little Dean Fuels Vegetation Management	DN/FONSI
Wallowa-Whitman	Cove II WUI Fuels Reduction	DN/FONSI
Wallowa-Whitman	Limber Jim/Muir Fuels Reduction	DN
Wallowa-Whitman	Lower Joseph Creek Restoration	ROD
Mt. Hood	The Dalles Watershed Phase II Hazardous Fuels Reduction	DN/FONSI
Mt. Hood	Lava Restoration	DN/FONSI
Ochoco	Upper Beaver Creek Vegetation Management	ROD/FEIS
Rogue River-Siskiyou	Bybee Vegetation Management	DN/FONSI
Siuslaw	North Fork Siuslaw Landscape Management	DN
Willamette	Outlook Landscape Diversity	DN/FONSI
Willamette	Bachelor Bear	DN/FONSI
Willamette	Goose	ROD
Umpqua	Elk Creek Watershed Restoration	DN/FONSI
Umpqua	Loafer Timber Sale	DN/FONSI
Umpqua	2010 North Umpqua Zone Precommercial Thin/Fuels Treatment	DM

Appendix B

Eq. (B1). Conditional burn probability

$$BP = \frac{TB}{NR} \tag{B1}$$

where *BP* is defined as the conditional burn probability at a specific pixel and *TB* is the number of times the pixel burned over NR simulated fires.

Eq. (B2). Conditional burn probability in high flame length

$$BP_{high} = BP \times \frac{TB_{high}}{TB} \tag{B2}$$

where BP_{high} is the probability of any given pixel burning with a flame length ≥1.2 m. BP is the conditional burn probability at the pixel level (Eq. (B1)), $\mathrm{TB_{high}}$ is the number of times the pixel burned with flame ≥1.2 m, and TB is the number of times the pixel burned (Eq. (B1)).

Eq. (B3). Conditional flame length

$$CFL = \sum_{1}^{k} BP_k \times FIL_k \tag{B3}$$

where CFL is conditional flame length (m) at the pixel level, and BP_k is burn probability in flame length class k, where $k = (1, 2, \ldots 6)$, and FIL_k is the midpoint flame length of class k. Flame length classes are FIL1 = 0–0.6 m, FIL2 = 0.6–1.2 m, FIL3 = 1.2–1.8 m, FIL4 = 1.8–2.4 m, FIL5 = 2.4–3.7 m and FIL6 > 3.7.

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