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Optimising fuel treatments over time and space

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Abstract. Fuel treatments have been widely used as a tool to reduce catastrophic wildland fire risks in many forests around the world. However, it is a challenging task for forest managers to prioritise where, when and how to implement fuel treatments across a large forest landscape. In this study, an optimisation model was developed for long-term fuel management decisions at a landscape scale. Using a simulated annealing algorithm, the model optimises locations and timing of fuel treatments, while considering changes in forest dynamics over time, fire behaviour and spread, values at risk, and operational feasibility. The model employs the Minimum Travel Time algorithm in FlamMap and the Fire and Fuels Extension to the Forest Vegetation Simulator to assess spatial and temporal effects with and without fuel treatments. The objective function is set to minimise total expected loss from a landscape due to wildfires throughout the planning horizon. The model was applied to a 14 000-ha study landscape located on the west side of the Bitterroot Valley in Montana. Comparisons between the optimised and random solutions show that the model was able to strategically locate and schedule fuel treatments to efficiently reduce expected loss from the landscape.

Additional keywords: fire behaviour, fuels reduction, heuristic optimisation, minimising expected loss, minimum travel time.

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Introduction

There is a recognised need to apply and maintain fuel treatments to reduce catastrophic wildland fires in forests (Pollet and Omi 2002; Agee and Skinner 2005; Prichard *et al.* 2010). However, treating all of the forest lands considered at risk would be costly and impractical. Forest managers, who are faced with limited budgets, narrow burning windows, air quality issues and concerns about treatment effects on other critical forest resources, must establish priorities for where, when and how to implement fuel treatments. Science-based as well as field-applicable guidelines are necessary to strategically locate, schedule and apply fuel treatments to effectively reduce catastrophic fire and restore ecosystem health on landscapes over time (Collins *et al.* 2010).

Several models and decision tools have been developed for addressing various aspects of fuel treatments while accounting for other important resource-management issues and constraints. These models operate on a variety of geographic scales, varying from an individual stand to an entire landscape composed of many stands. Some models operate only on current conditions, whereas others span multiple decades. For example, most of the existing fire behaviour models, such as NEXUS (Scott 1999), FIREHARM (Keane *et al.* 2010), FARSITE (Finney 2004*a*) and FlamMap (Finney 2006), are able to compute fire behaviour and spread at a stand level or across stands at a landscape level. However, there is no temporal component to these analyses that reflects how the effectiveness of treatments changes over time with vegetative growth. In contrast, the Fire and Fuels Extension (FFE) to the Forest Vegetation Simulator (FVS; Reinhardt and Crookston 2003) evaluates the effectiveness of proposed fuel treatments in the context of potential fire effects on short- and long-term stand dynamics, but does not simulate fire spread between stands or have the ability to strategically locate fuel treatments.

Recent modelling efforts have addressed placement of fuel treatments across a landscape. Some studies evaluated the effects of spatial treatment patterns on changes in fire behaviour and spread at a landscape scale (Palma *et al.* 2007; Schmidt *et al.* 2008; Kim *et al.* 2009), whereas other studies attempted to optimise placement of fuel treatments in a multi-objective decision-making framework (Nalle *et al.* 2004; Kennedy *et al.* 2008; Konoshima *et al.* 2010). However, most optimisation methods developed for treatment placement in the past have ignored temporal aspects or employed simple fire-spread logic with a hypothetical setting of treatment units in order to simplify the problem.

Finney (2004*b*) developed an optimisation method that can strategically place fuel treatments across a landscape to efficiently disrupt the growth or movement of large fires. The method was then employed in a simulation system developed by Finney *et al.* (2007) to place fuel treatments over multiple time periods to minimise undesired fire behaviour. Using a sequential process of spatial optimisation and temporal simulation of fuel treatments, the system selects treatment locations for one planning period at a time, and then projects the post-treatment landscape to the next planning period for treatment decisions for that period. Although the system is able to produce fuel treatment schedules over multiple time periods, it places treatments in a given period without taking into account their continuing effects in subsequent periods. Owing to this sequence of simulations, treatment decisions made in early periods easily dominate decisions to be made in later periods. This one-way influence can narrow down the solution space of the scheduling problem, and thus may result in inferior solutions. In addition, the simulation system did not consider several practical factors that might be critical in treatment design and ground implementation, such as pre-existing treatment unit boundaries, ownerships, land classes and relative values.

Despite the aforementioned modelling efforts to address the strategic placement of fuel treatments, there still exists a considerable gap between modelling fuel treatments and actually implementing such treatments on the ground (Collins *et al.* 2010). In the present study, we developed an optimisation model for long-term fuel-management decisions at a landscape scale with a hope of reducing the gap between modelling and ground implementation of treatments. The model optimises locations and timing of fuel treatments, while considering changes in forest dynamics over time, fire behaviour and spread across a landscape, values at risk, treatment proportions and practical treatment unit boundaries. Similar to the simulation system developed by Finney *et al.* (2007), our model employs the Minimum Travel Time algorithm in FlamMap (FlamMap-MTT) and FFE-FVS to assess spatial and temporal effects with and without treatments. However, using an iterative search algorithm, our model simultaneously optimises treatment locations over multiple time periods while considering continuing and cooperative effects of treatments across time and space. Treatment decisions in one period can thus mutually influence decisions in other periods. The model sets the objective function to minimise total expected loss from a given landscape due to wildfires throughout the planning horizon, and considers user-defined treatment units as binary decision variables that are selected for treatment as either an individual polygon or a group of treatment units. Simulated annealing (SA), a metaheuristic search algorithm, is employed in the model to solve this challenging combinatorial optimisation problem of placement and scheduling of fuel treatments.

This paper presents the concept and structure of the optimisation model and provides an application example for proof of concept. The model has been incorporated into a spatial decision-support system, known as OptFuels, for other applications (Jones and Chung 2011). The system can be downloaded from the US Forest Service (USFS) Rocky Mountain Research Station website (http://www.fs.fed.us/rm/human-dimensions/optfuels/main.php, accessed 20 May 2013).

Methods

Structure of optimisation model

The optimisation model developed in this study consists of three main functional components: vegetation simulator for treatment effects and stand dynamics, fire simulator for fire behaviour and spread, and heuristic solver for spatiotemporal optimisation of fuel treatments (Fig. 1).

The main spatial data required for the optimisation model include treatment units or stand polygons in a vector form with associated attributes of current vegetation and fuel conditions, and terrain information in a raster form with attributes of elevation, slope and aspect. The model employs FFE-FVS to project stands into the future with and without fuel treatments and compute the fuel parameters needed for fire behaviour modelling. The heuristic solver, equipped with a SA iterative search algorithm, generates and evaluates a large number of alternative fuel treatment arrangements over time and space (i.e. alternative solutions). At each iteration, the solver develops one alternative solution, virtually composes a landscape per time period by filling it with FFE-FVS results of treatment units, and rasterises the landscapes to build FlamMap-ready landscape files for each time period. These landscape files reflect the effects of selected treatments and dynamic changes of vegetation and fuels over time. FlamMap is then used to evaluate the alternative solution in terms of treatment effects on changing fire behaviour and spread across the landscape, and thus on reduction of the total expected loss from the landscape due to potential wildland fires over time. To model a future fire, FlamMap analyses a user-defined fire scenario that specifies wind direction and speed, fuel moisture conditions, ignition locations and other necessary fire parameters.

The heuristic solver uses the FlamMap results to guide the solution search in finding a near-optimal fuel treatment solution that minimises the expected loss across a landscape from a modelled future fire. A user-specified maximum allowable treatment area is considered as an area constraint in the optimisation model. The solver outputs include the schedule and placement of fuel treatments selected by the solver, the associated expected loss value, total treatment areas computed for the area constraint and FlamMap-ready landscape files for both untreated and treated landscapes for each planning period. Details on each functional component of the model are described below.

Simulation of treatment effects and forest dynamics using FFE-FVS

FFE-FVS has been widely used by federal, state and tribal government agencies to evaluate the effectiveness of proposed fuel treatments in the context of potential fire effects on short- and long-term stand dynamics (Crookston and Dixon 2005; Johnson *et al.* 2011). FFE-FVS provides the capacity of FVS to project vegetation changes due to growth, mortality, disturbance and treatment, while incorporating additional data and models to predict fuel parameters for the projected stands. FFE-FVS

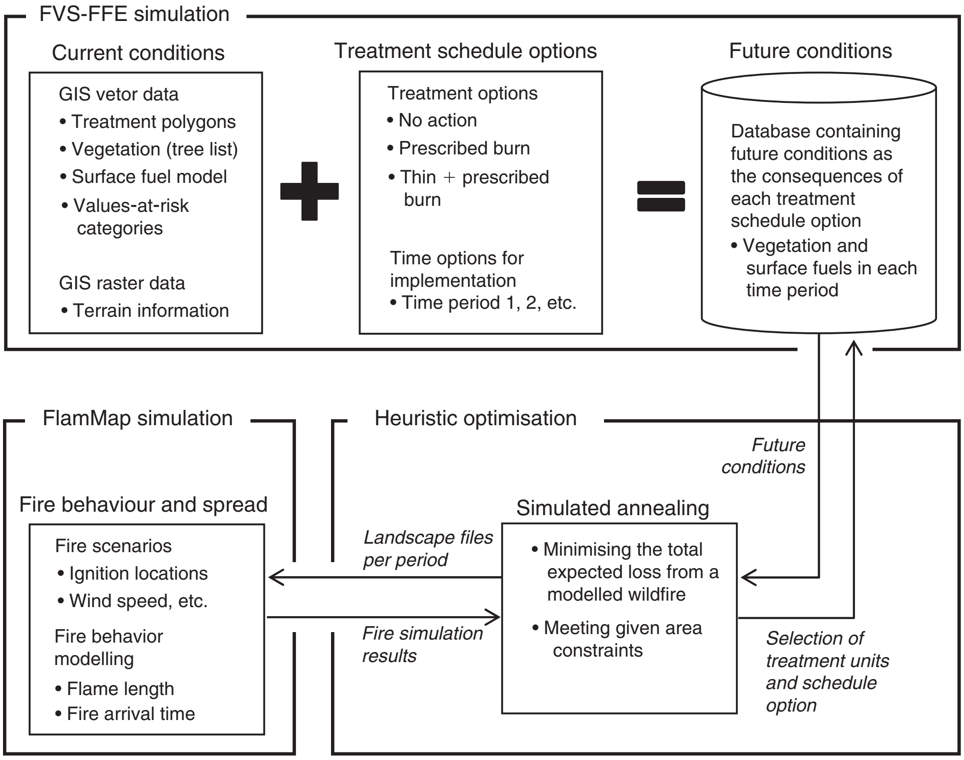

Fig. 1. Overview of the optimisation model, OptFuels, consisting of three simulation and optimisation components: vegetation and fuel treatment simulation using FVS-FFE, fire behaviour and spread simulation with FlamMap, and a heuristic solver to schedule fuel treatments to minimise the total expected loss over the planning horizon.

requires a tree-list assigned to each stand, which can be obtained from existing stand inventory data or imputation of tree-lists from the representative Forest Inventory and Analysis (FIA) plots as suggested by Crookston *et al.* (2002).

A treatment schedule option comprises a sequence of treatment activities that may extend over multiple planning periods to represent scheduled retreatments of the same location or a one-time treatment occurring in a single planning period. Treatment schedule options are assigned to the stand polygons based on the vegetation and fuel conditions present in the polygon, as well as the management zone where it resides. For example, a mechanical treatment can be limited to a zone where road access exists or to specific stand conditions. In the same manner, individual treatments can be excluded as options in riparian areas or other restrictive land-management zones. No action throughout the planning horizon is always considered as an eligible option for all stand polygons to be analysed.

After treatment schedule options are assigned to each stand or group of similar stands, each option is simulated with FFE-FVS for the sequence of treatments specified in the schedule. These simulations define the fuel conditions required in fire behaviour modelling for the future planning periods. To improve the efficiency of FFE-FVS simulation, multiple treatment units with similar vegetative characteristics may be stratified and FFE-FVS simulation is run for each stratum. The results are then stored in a relational database for data sharing among multiple treatment units within the stratum.

Simulation of fire behaviour and spread across a landscape using FlamMap

FlamMap is a fire behaviour mapping and analysis program that computes potential fire behaviour characteristics in terms of spread rate, flame length and fire-line intensity over an entire landscape (Finney 2006). In addition, the MTT option (Finney 2002) employed in FlamMap calculates a fire arrival time for each grid cell on a landscape. This arrival time represents the minimum time span required for fire to move from an ignition location across a landscape to a grid cell under a given fire scenario. An absence of fire suppression is assumed in this travel time calculation.

Our optimisation model evaluates the effects of various placements and schedules of fuel treatments in terms of the fire intensity and spread calculated by FlamMap-MTT for each planning period. Specifically, the effects of treatments are measured using two FlamMap-MTT outputs: (1) node flame length (which is computed from fire-line intensity to capture flame length associated with the direction of fire movement, e.g. backing, flanking or head fire) and (2) fire travel time. We use node flame length as a surrogate measure of fire severity within individual treatment units or stands, while using fire travel time to estimate the likelihood of fire arriving at each grid cell across a landscape. These two measures are used for calculation of the total expected loss from a modelled fire across a given landscape, which is the heuristic solver's objective function.

Optimisation of fuel treatments using simulated annealing

The heuristic solver developed in this study is designed to determine the most effective spatial and temporal distribution of fuel treatments that minimises the total expected loss across a landscape. It also considers user-defined treatment area limits for each time period in each management zone as problem constraints. Expected loss value for a grid cell on a landscape is calculated as a product of user-defined value at risk of the grid cell, percentage loss varying with fire intensity and a probability that fire duration is long enough for a modelled fire to reach the grid cell. The total expected loss from a given entire landscape is then summed across the grid cells representing the landscape.

Expected loss of a grid cell from a modelled fire is measured in terms of loss value relative to no fire occurring (Calkin *et al.* 2010). The user provides relative value-at-risk categories, and the amount of loss expected from fire within each category varies with the level of fire intensity (i.e. flame length; Table 1). The user also provides fire duration probabilities indicating the probability a modelled fire would last over a specific time span (Table 2). Fire duration probabilities may be developed by analysing the duration of past fires, or through using historical weather data to estimate the probability of weather patterns over various numbers of days that would allow fire suppression efforts to contain a fire. We recognise that MTT in FlamMap calculates fire spread assuming constant fire scenario conditions (Finney 2002). However, fire-spreading weather is not continuous in reality, but rather occurs only in blocks of time. Days of fire duration are thus converted to minutes of active fire spread for fire behaviour modelling by estimating the average number of active spread hours in a 24-h day.

Using the results of the FlamMap-MTT simulation (i.e. estimated node flame length and fire arrival time in each grid cell), the solver selects a percentage loss and a fire duration probability for each grid cell and calculates its loss value. The sum of losses across grid cells on a given landscape becomes the total expected loss of the landscape due to the modelled fire (Eqn 1). Therefore, a high loss value occurs in an area that has a high value at risk and is expected to burn with high intensity or when the modelled fire quickly moves across the landscape to that area.

The heuristic solver employs a SA solution search algorithm. The solver develops several alternative fuel treatment solutions and selects the most effective fuel treatment placement and schedule that minimises the total expected loss across the landscape while meeting given area constraints. Through dynamic link libraries (DLLs), the solver automatically runs FlamMap-MTT in real time on landscape files developed for each time period for solution evaluation. The solution is also evaluated for its feasibility against any given area constraints. If the solution violates any of the constraints, it is penalised by an additional loss calculated as the total amount of deviation from the violated constraints multiplied by an arbitrary large factor (Eqn 1). This penalty prevents infeasible solutions from being selected as the best solution.

$$Minimise \sum_{t\in T}\sum_{c\in C} P_{c,t} \times W_r \times Loss_{c,r,f,t} + PF \times Dev \quad (1)$$

where c is an index of grid cells, t is a time period, r is an index of risk category, f is an index of flame length category, $P_{c,t}$ is the probability of grid cell c being burned from a fire modelled in time period t. The probability depends on fire arrival time at the cell and user-defined fire duration probability (see Table 2), W_r is the weight factor for risk category r, $Loss_{c,r,f,t}$ is the loss value at risk category r of grid cell c given predicted flame length category f in time period t, PF is the user-defined penalty factor, and Dev is the total amount of deviation from the violated constraints.

SA is a metaheuristic search technique that has been widely used to solve large combinatorial optimisation problems in various fields (Kirkpatrick *et al.* 1983). The ideas that form the basis for SA were first published by Metropolis *et al.* (1953) in an algorithm to simulate the cooling of materials in a heat bath – a process known as annealing. The approach is a variation of the Monte Carlo method that uses a local search in which a subset of solutions is explored by moving from one solution

Table 2. An example of fire duration probabilities
A probability of 0.9 at 300 min of active spread time indicates that there is a 90% chance that the modelled fire lasts for 300 active fire-spread minutes

Active spread time categories (min)	Fire duration probability
300	0.9
600	0.8
900	0.7
1200	0.6
1500	0.5
1800	0.4
2100	0.3
2400	0.2
2700	0.1
3000	0.0
3300	0.0
3600	0.0

Table 1. An example of relative value at risk varying with flame-length categories
The relative loss value of a grid cell is calculated as its loss index multiplied by its weight

Value-at-risk category	Area (ha)	Weights	Loss index per flame length category based on a 90 × 90-m grid cell				
			Low (0–0.3 m)	Medium (0.3–1.0 m)	High (1.0–2.0 m)	Very high (2.0–4.0 m)	Extreme (4.0 m+)
Residential	1711	8	5	10	30	50	80
Wildland–urban interface	3343	8	2.5	5	15	25	40
Other forested land	8948	1	0	10	20	30	30

to a neighbouring solution. To avoid becoming trapped in a local optimum, the procedure provides for an occasional acceptance of an inferior solution to allow it to move away from a local optimum. Temperature and cooling rate are algorithm parameters that control the number of iterations and range of acceptable solution values. The chance of accepting inferior solutions becomes large at a high temperature, which allows search across a broad solution space. The chance gets smaller as temperature decreases, which reduces solution variability and thus allows a narrow and intensive search for a better solution. The SA algorithm employed in the heuristic solver is illustrated in Fig. 2. Readers are encouraged to refer to Kirkpatrick *et al.* (1983) for details on the theory of the algorithm.

Clustering adjacent stand polygons for a large treatment area

Spatial representation of a landscape using forest stand boundaries often results in many small stand polygons (e.g. <5 ha), but treating small treatment units sporadically across a landscape might not be cost-effective or effective at changing fire behaviour on a landscape (Ritchie *et al.* 2007). In the current study, we developed a polygon-clustering algorithm and incorporated the algorithm into the heuristic solver to group adjacent polygons with treatments in the same period into larger, contiguous treatment areas (Fig. 3).

With the polygon clustering algorithm, the heuristic solver takes a two-phase approach to generate and modify alternative solutions. In Phase I, the solver begins with developing a

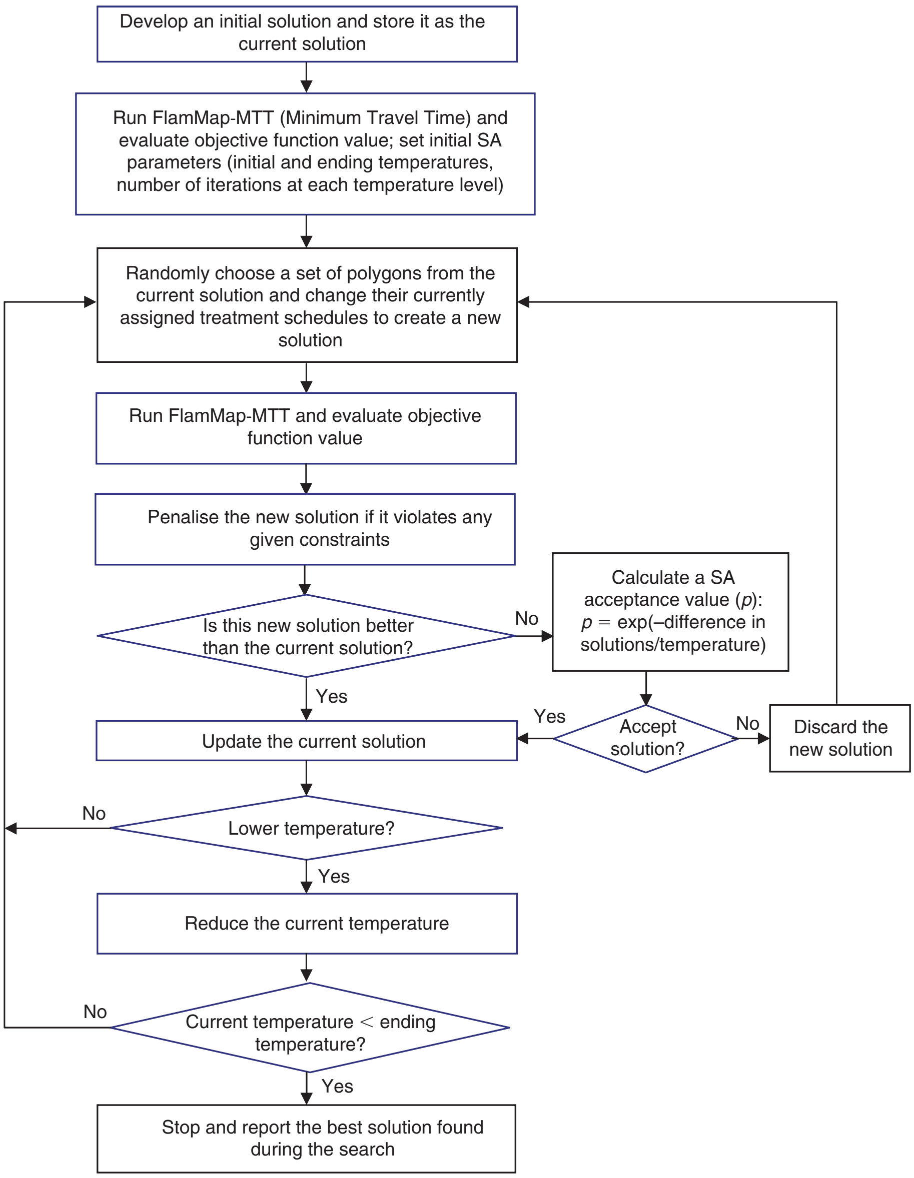

Fig. 2. A simulated annealing (SA) algorithm employed in the heuristic solver to optimise fuel treatment locations and schedule.

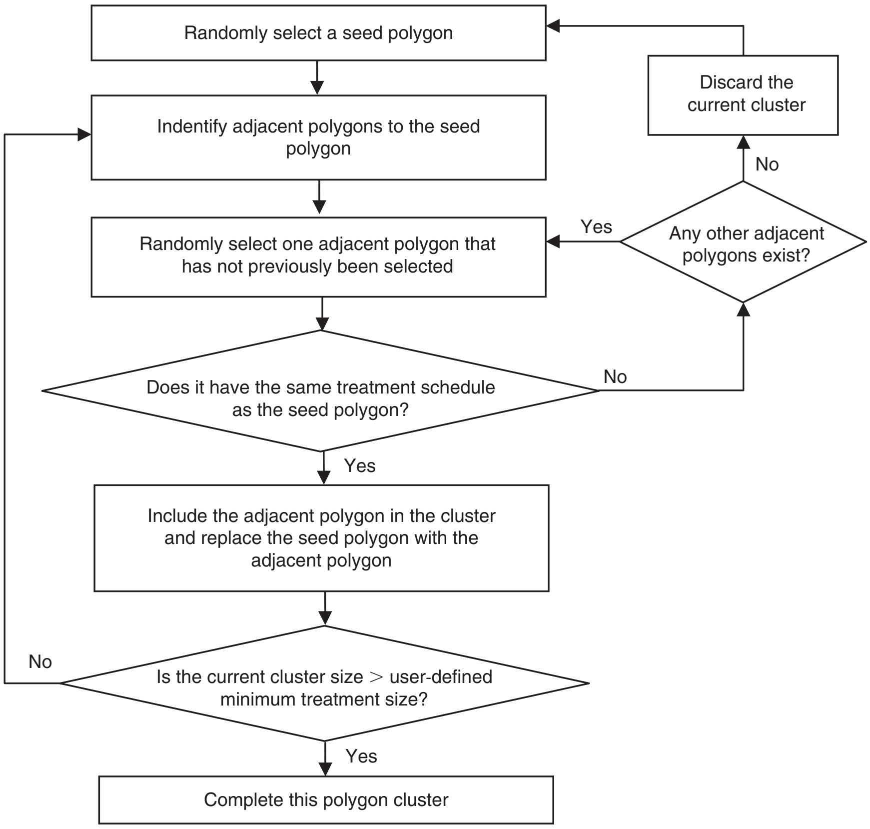

Fig. 3. A polygon-clustering algorithm developed to combine adjacent stand polygons into a larger contiguous treatment unit.

'no-action' scenario as an initial solution where no treatment is scheduled across the landscape throughout the planning horizon. This solution provides the worst-case scenario with the maximum possible amount of expected loss from the landscape. The solver then builds polygon clusters and adds the clusters into the solution for treatments. This process is repeated until the total number of hectares selected for treatment reaches the maximum allowable area constraint per planning period. Once the area constraints are reached closely, Phase II begins where the solver implements the SA algorithm to improve the solution by iteratively generating and examining neighbouring solutions. To generate a neighbouring solution, a single polygon cluster is randomly selected and the fuel treatment schedule assigned to the cluster is removed. Then, a new cluster is formed in a different location and assigned one of the available treatment options. This solution refinement process continues until the SA algorithm ends.

Application

Study landscape

We applied the optimisation model to a 14 000-ha study landscape located on the west side of the Bitterroot Valley in Montana (Fig. 4*a*). Private property and state lands border the project area to the east and the Selway–Bitterroot Wilderness bounds the project area to the west. Approximately 70% of the study landscape is a part of the USFS Bitterroot National Forest, whereas the rest of the landscape is private land with residential development.

The vegetation structure in the majority of the project area has grown into overstocked, dense stands that are at increased risk of stand-replacing crown fires or intensities that cannot be directly attacked by firefighters. The increased inter-tree competition in these dense stands can make the larger, overstorey trees more susceptible to insects and disease and increase mortality of the subdominant trees (Hummel and Agee 2003). Eighty-two per cent of the project area is in fire regime condition class 3 (highly departed from historical fire frequency and severity) and 18% is in fire regime condition class 2 (moderately departed from historical fire frequency and severity). These fire regime condition classes have the greatest deviation from natural fire regimes and are most in need of treatment (Hardy *et al.* 2001; Schmidt *et al.* 2002). Existing fuel loads (including live trees) pose a threat to the public, firefighters and natural resources. Any large fire (>40 ha) or multiple ignitions in one day on the Bitterroot Face have the potential to overwhelm suppression forces and travel unimpeded to the Forest Service–private boundary and onto private property.

Forest stand delineations on the study landscape were obtained from R1-VMP, a Geographic Information System-based forest vegetation classification system, produced by the Northern Region of the USDA Forest Service (Brewer *et al.* 2004). R1-VMP categorises polygons based on dominant and

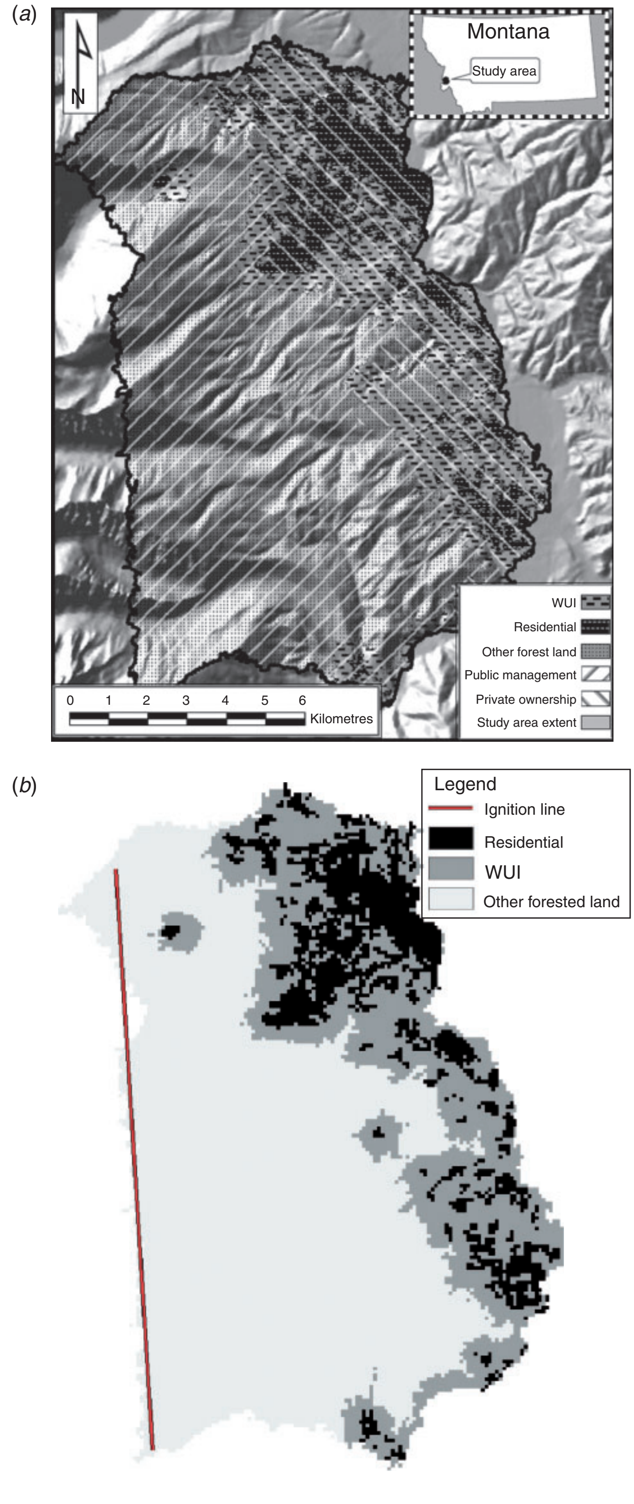

Fig. 4. A study landscape located in western Montana shown with land classes (*a*) and a rasterised landscape with the value-at-risk category attributes and the ignition line location (*b*) (WUI, wildland–urban interface).

co-dominant tree species, stand size class and stand density as measured by percentage canopy cover. R1-VMP, however, does not provide inventory data for the forest vegetation classes. Inventory data were assigned to the R1-VMP polygons using the k-nearest neighbour imputation method (Crookston and Finley 2008). In this process, FIA plots were imputed to polygons based on the similarity of zonal statistics computed for the stand polygons and FIA plot locations from Landsat spectral imagery (http://landsat.gsfc.nasa.gov/, accessed 20 May 2013). The plots used in this process included FIA plots from four counties in Western Montana with forest conditions similar to the study area and intensified grid plots collected by the Bitterroot National Forest staff with sample techniques similar to FIA. Only the 188 plots measured in the early 2000s were used to correspond with the 2002 Landsat imagery.

The Northern Idaho–Inland Empire variant of the FVS (www.fs.fed.us/fmsc/fvs, accessed 20 May 2013) was used to simulate applying prescribed burn only, and thin and prescribed burn treatments to the plots. Using *Suppose* (http://www.fs.fed.us/fmsc/fvs/software/suppose.php), separate FVS runs were made for applying each treatment to each plot that met the treatment criteria in each planning period. FVS runs were also made for ‘no action’ (no treatment applied) to project the untreated plot data through future planning periods. FFE-FVS was used in these simulations to predict the following fuel parameters for fire behaviour modelling: crown base height, stand height, crown bulk density and percentage crown closure.

FFE-FVS also assigns surface fuel models to projected forest stands, but we found that these fuel model assignments did not result in modelled fire behaviour that matched observed fire behaviour of past fires in western Montana. Others have encountered similar problems with the FFE-FVS fuel model assignments in other studies (Seli *et al.* 2008; Collins *et al.* 2011). We chose instead to use the LANDFIRE fuel model assignments (http://www.landfire.gov/datatool.php) for existing conditions, which we assumed continued through the 20-year planning horizon for the no-action alternative. For post-treatment fuel parameters, we used the ‘Low-load Compact Conifer Litter’ fuel model (Scott and Burgan 2005) following treatment to reflect the fuel treatment objectives.

The fuel treatment scheduling approach presented here was designed for use by federal, state and tribal agencies. Thus, we restricted the fuel treatment options in the study area to non-reserved public lands managed by the USFS and the State of Montana. There exist a total of 4894 stand polygons representing the entire study landscape, with an average size of 3 ha (Table 3).

Treatment options and model parameters

For the study landscape, we identified the following two fuel treatment options that are known to be effective at mitigating fire severity in dry western forests (Prichard *et al.* 2010): prescribed burn only and thin and prescribed burn. Depending on the current stand density of individual forest stands, one of the two options was assigned to each stand as a treatment option. A total of 3274 ha (or 840 stand polygons) were identified as the area where a prescribed burn could not be accomplished without thinning to reduce ladder fuels. The prescribed-burn only option was assigned to the rest of treatable stands (6252 ha) where the stand density was low or shrub dominated (Table 3). The thinning prescription was designed to reduce stand density to $\sim 17\,m^2$ of basal area per hectare. Two time periods were considered with a 10-year time span in each time period. It was assumed that the same area could be treated only once over the 20-year planning horizon.

All the stand polygons in the study landscape were classified into the following three value-at-risk categories: (1) parcel that contains residential structures; (2) wildland–urban interface (WUI) defined as polygons within one-half mile (~805 m) of residential structures; and (3) forest lands not included in any other risk category (Table 1 and Fig. 4*b*). Loss response functions from Calkin *et al.* (2010) provided the basis for assigning percentage loss by flame-length categories. Residential and WUI parcels received an importance weight of 8 per 90×90-m grid cell, whereas non-WUI forest land received a weight of 1 per grid cell (Table 1).

The modelled fire scenario includes a line of ignition on the west boundary of the study landscape with winds blowing from the west at 20 miles h^{-1} (~8.94 m s^{-1}) (Fig. 4*b*). Fuel moistures by fuel category were 4% for 1-h, 5% for 10-h, 7% for 100-h, 50% for live herbaceous and 90% for live woody fuels, with foliar moisture set at 100%. Active spread time categories and fire duration probabilities were developed for the study landscape based on the frequency of past weather patterns that would be expected to allow fire suppression efforts to be successful in containing a wildland fire (Table 2). FireFamily Plus (Bradshaw and McCormick 2000) was used to analyse the frequency of one-half inch (~12.7 mm) or more of precipitation occurring over 3-consecutive-day periods, starting on 15 July and continuing through September. The time frame for these probabilities was converted to the measure of time used in FlamMap-MTT (active spread minutes) based on the percentage of time when winds approximating the wind speed used for our fire spread modelling (20 miles h^{-1}, ~8.94 m s^{-1}) were present at weather stations in the study area vicinity.

The SA algorithm requires user-defined algorithm parameters, such as initial temperature (T_{init}), ending temperature (T_{end}), cooling rate and number of iterations at each temperature level. For this application, an initial temperature was set at 60% of the objective function value of the initial solution (i.e. no-action scenario) and an ending temperature was set at 0.05% of the initial temperature (Table 4).

Model implementation and runs

For the optimisation model, graphic user interfaces were developed to facilitate data input and data transfer among the model components (Fig. 1). Coded in Microsoft Visual C++, the heuristic solver was designed for multiple-processor computers to simultaneously run FlamMap DLLs on multiple landscape files. A desktop computer with a 2.83-GHz, 8-processor CPU and 8 GB of RAM was used to run the heuristic solver in this application.

Four different area proportions were considered in this application as area constraints to analyse the effectiveness of varying amounts of treatment on changing fire behaviour and reducing expected loss across the study area. The treatment intensity scenarios considered are: 0 (no action), 20, 40 and 60% of the total treatable areas (Table 5).

To measure the relative effectiveness of the optimised solutions, a total of 30 random solutions were developed under each treatment intensity scenario. In each random solution, clusters of

Table 4. Simulated annealing algorithm parameters
T_{init}, initial temperature; T_{end}, ending temperature

Algorithm parameter	Value
T_{init}	1 007 627
T_{end}	504
Cooling rate	0.95
Number of iterations at each temperature level	20
Minimum size of treatment unit (cluster size)	20 ha

Table 5. Four treatment intensities modelled in this study
Treatment intensity is defined as the proportion of treated areas relative to the total treatable areas in the study landscape

Period	Treatment intensity			
	0% (0% per period)	20% (10% per period)	40% (20% per period)	60% (30% per period)
1	0 ha	930 ha	1860 ha	2790 ha
2	0 ha	930 ha	1860 ha	2790 ha

Table 3. Fuel treatment and timing options assigned to stand polygons in the study landscape
WUI, wildland–urban interface

Ownership	Stand type		Number of polygons	Area (ha)	Available fuel treatment options
Forest Service	Tree-dominated	Non-WUI	743	2869	• no action
		WUI	97	405	• thin and prescribed burn in period 1
					• thin and prescribed burn in period 2
	Low-density tree- or shrub-dominated	Non-WUI	1928	5727	• no action
		WUI	169	525	• prescribed burn only in period 1
					• prescribed burn only in period 2
Private land	WUI		1821	4124	• no action
	Others		136	352	• no action
Total			4894	14 002	

treatment units were randomly constructed and distributed across the treatable areas of the landscape until the maximum allowable areas set for each time period were closely met. Treatment effects of each random solution were then simulated by FlamMap-MTT and their total expected losses were calculated for comparison.

Results and discussion

Optimised fuel treatment location and timing

Locations and timing of fuel treatment were optimised under each treatment intensity scenario to minimise total expected loss from the study landscape due to the modelled wildfire (Fig. 5). The total number of hectares selected for treatment ranged from 1859 to 5581 across the treatment intensity scenarios (Table 6). These treatment areas were evenly distributed between the two time periods and close to the upper limit of the area constraints established for each scenario (Table 5). The results show that the total amount of expected loss decreased as more areas were treated (Table 6). The reduction in loss, however, decreased for each 20% increment in treatment areas, indicating a diminishing marginal return for additional areas treated beyond 20% of the landscape. When time periods were compared, there was a substantially larger decrease in expected loss in period 2 than period 1, albeit the total treatment areas being more or less the same in both time periods (Fig. 6). It appears that some effects of treatments scheduled in period 1 continued through the subsequent period, and were cooperatively coupled with treatments in period 2, resulting in greater effects of treatments in period 2.

There seems to be no apparent spatial pattern of treatment units across the landscape in the solutions. However, there exist several concentrated areas of treatment, especially in the upper and mid-west areas of the landscape in the solutions for the 20 and 40% treatment scenarios (Fig. 5). Results of an independent FlamMap-MTT run on the untreated landscape reveal that the upper and mid-west areas of the landscape serve as the roots of major fire paths that move across private residential and WUI areas located in the eastern portion of the landscape (Fig. 7). Although the heuristic solver was not designed to place fuel treatments to directly disrupt major fire paths, it appears that the solver was able to find treatment locations in treatable forested lands that effectively change fire behaviour and paths that could otherwise negatively affect high-value yet non-treatable areas, such as residential areas and WUI in our application.

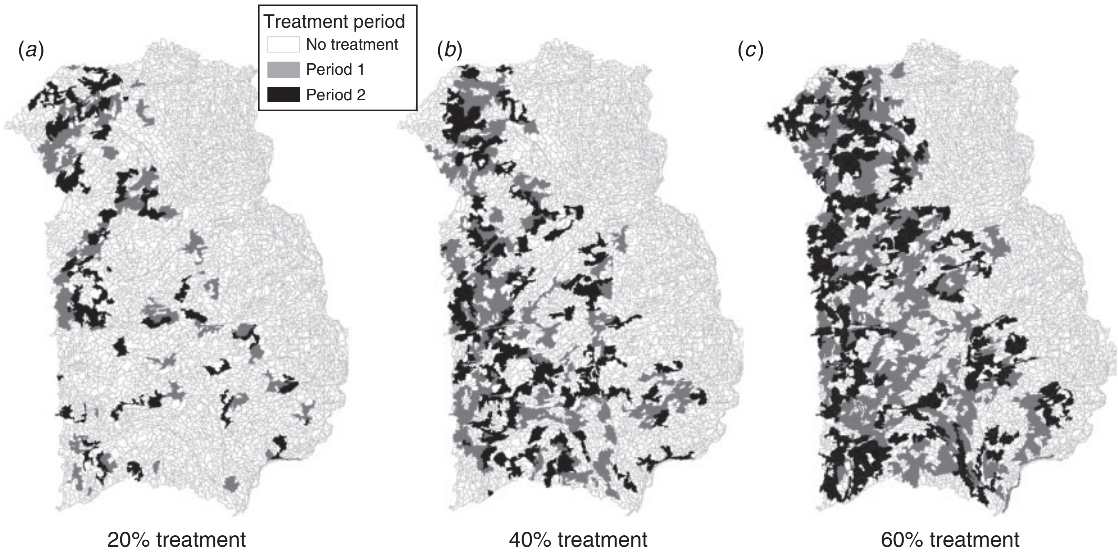

Fig. 5. Optimised fuel treatment locations and implementation time periods under each treatment intensity.

Table 6. Solutions from each treatment intensity scenario in terms of expected loss, number of hectares and polygons selected for treatments per time period

Treatment intensity	Treatment area				Total expected loss		
	Period 1		Period 2				
	Area (ha)	Number of polygons	Area (ha)	Number of polygons	Value	Percentage of no-action	Incremental reduction in loss value
No action	0	0	0	0	1 679 378	100	
20%	930	300	929	305	1 023 361	61	656 017
40%	1859	593	1860	576	640 018	38	383 343
60%	2790	867	2790	823	399 622	24	240 396

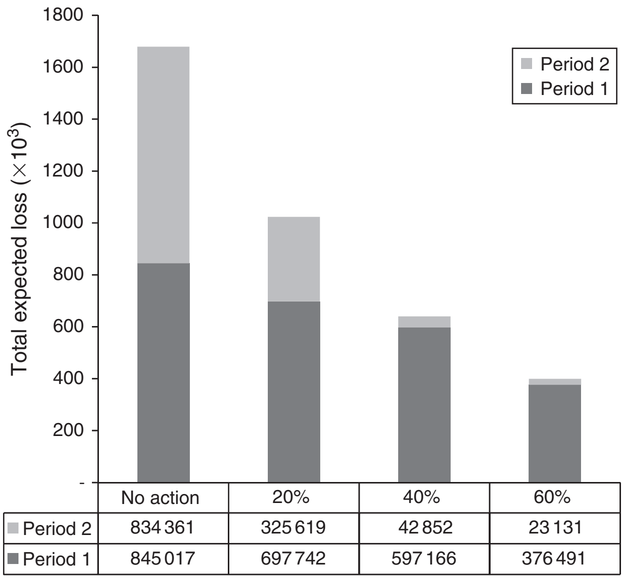

Fig. 6. Expected loss per time period under each treatment intensity scenario.

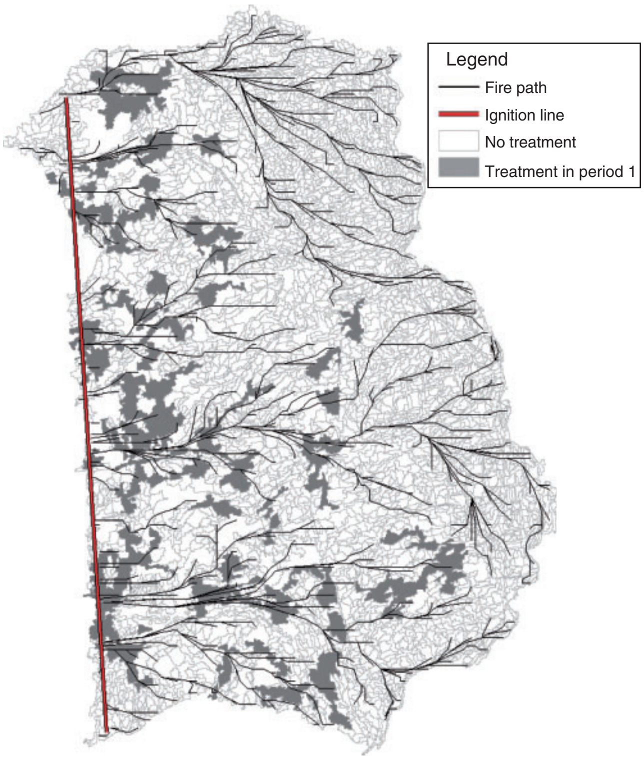

Fig. 7. Treatment units selected for period 1 under the 40% treatment scenario overlaid with major fire paths modelled by FlamMap-MTT (Minimum Travel Time) on the untreated landscape in period 1. It appears that the treatment units are located to intercept the major fire paths.

It is worthwhile to note that some of the treatment units selected for period 1 under the 20% treatment scenario (e.g. 20% treatment) were not reselected in the other scenarios where more treated areas were allowed. The heuristic solver schedules fuel treatments while considering accumulative and cooperative effects of treatments across time and space. Because such effects dynamically change with the total areas of treatment, the best set of treatment units selected for the 20% treatment scenario might no longer serve as the best when additional units can be treated.

Table 7. Statistics of fire arrival time, flame length and expected loss per grid cell under each treatment intensity scenario

The study landscape is represented by a grid with 17 288 grid cells of 90 by 90 m in size

	Treatment level							
	Period 1				Period 2			
	No action	20%	40%	60%	No action	20%	40%	60%
Arrival time (min)								
Maximum	3791	4188	5282	5636	4014	6586	7343	8850
Mean	441	628	871	1380	466	1272	2664	3831
Minimum	0	0	0	0	0	0	0	0
s.d.	298	391	519	798	318	1205	1171	1638
Flame length (m)								
Maximum	14.2	13.0	13.6	15.9	31	11.5	12.3	12.6
Mean	1.9	1.7	1.5	1.3	2.1	1.5	1.2	0.9
Minimum	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
s.d.	1.5	1.4	1.3	1.2	4.4	1.3	1.1	1.0
Expected loss								
Maximum	576	576	512	448	512	384	84	36
Mean	51	42	36	23	50	20	3	1
Minimum	0	0	0	0	0	0	0	0
s.d.	71	59	55	38	72	26	5	3

Spatial and temporal effects of fuel treatments

To observe the spatial and temporal effects of selected fuel treatments, we display the distribution of flame length, fire arrival time and expected loss across the study landscape for each time period using the FlamMap-MTT and heuristic solver output files. Statistics of these fire behaviour measures and expected loss across the landscape are presented in Table 7.

Fig. 8 compares the effects of the selected fuel treatments on flame length across different levels of treatment intensity and time periods. The FlamMap simulations show the fuel treatment options modelled in this application (i.e. prescribed burn only and thin and prescribed burn) were able to reduce flame length within treatment units. Comparisons across the treatment intensity scenarios indicate that the more areas were treated, the more areas fell into low flame-length categories. However, the effects of treatment on flame length were seen primarily within treated units. Flame lengths on the grid cells associated with untreated units in a treatment scenario are only affected by changes in the direction of fire movement on those untreated grid cells, for example changing what was a head fire for the no-action scenario to a flanking or backing fire in a treatment scenario.

Fire arrival time simulated by FlamMap-MTT changed significantly not only within treated units, but also in surrounding untreated areas (Fig. 9). Comparisons across the treatment intensity scenarios show there were obvious increases in fire arrival time as more areas were treated. Due to the continuing effects of the first-period treatments, there were larger effects in period 2 across the landscape.

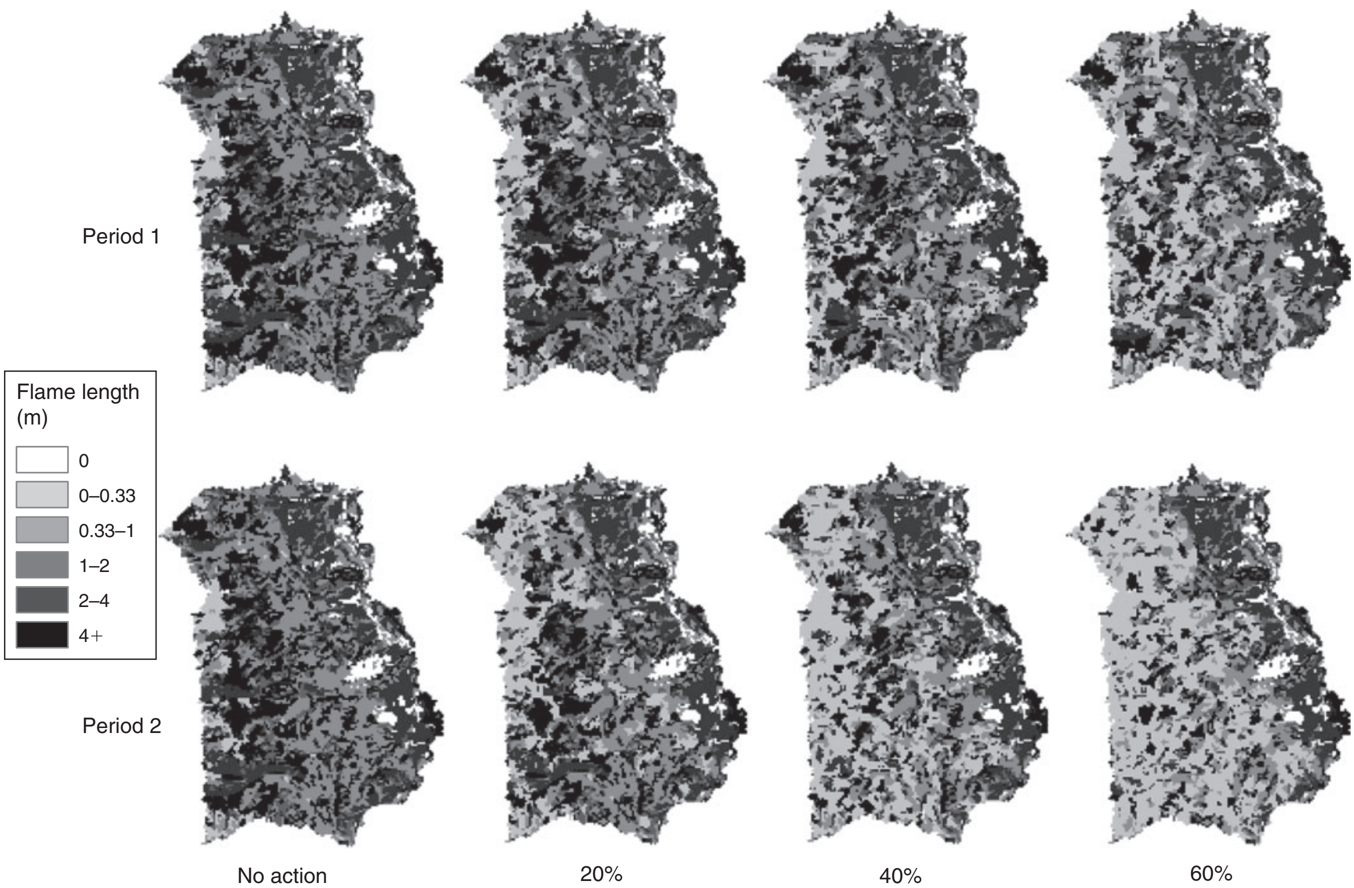

Fig. 8. Changes in flame length due to scheduled fuel treatments in time periods 1 and 2.

Changes in flame length and fire arrival time across the landscape over time were reflected in the expected loss calculation and distribution. The more areas were treated, the more reductions in expected loss across the landscape were realised (Fig. 10). The accumulated effects of treatments throughout the two time periods caused a substantially large reduction of expected loss in period 2. However, not everywhere in the landscape realised a reduction in expected loss compared with the no-action scenario. Depending on spatial and temporal arrangement of fuel treatments, some areas might experience a shorter fire arrival time due to potential changes in fire paths caused by the selected treatments. In our application, most of the landscape experienced a decrease in expected loss as the effects of treatment, but there were some marginal areas that experienced an increase of expected loss due to the selected treatments (Fig. 11).

It is noteworthy that even though most areas selected for treatment existed in the Other Forest Lands value-at-risk category (Fig. 12) owing to the fact that candidate treatments were restricted to federal and state public lands (only a few polygons had treatment options in the WUI and Residential categories), most of the reduction in loss per grid cell occurred in Residential and WUI value-at-risk categories (Fig. 13). This result indicates that the solver was able to develop a spatial and temporal arrangement of treatment units across the treatable areas in a way to protect high-value areas. Similar results were observed in Fig. 7 where treatment units were located to intercept major fire paths to private residential and WUI areas.

Performance of the heuristic solver

Comparisons between the optimised and random solutions confirm the ability of the optimisation algorithm employed in the solver to strategically locate and schedule fuel treatments in a way to improve the effectiveness and efficiency of treatments in achieving the given objective (i.e. minimising expected loss). Compared with the no-action scenario, the optimised solutions reduced the total expected loss by 39, 62 and 76% under respective 20, 40 and 60% treatment scenarios, whereas the average reductions of expected loss from 30 random solutions developed for each of the respective treatment scenarios were only 10, 21 and 35% (Table 8).

The total number of iterations performed by the heuristic solver increased with the number of treatment hectares in a scenario because of Phase I of the solution process where random polygon clusters were developed and added to the solution (Table 9). A larger number of iterations was needed to build more treatment clusters as the maximum allowable treatment areas increased. However, solution times required for the heuristic solver did not always increase as the number of iterations increased. The solution time for the 40% treatment scenario was slightly larger than that of 20% treatment, whereas the 60% treatment scenario required the least amount of solution

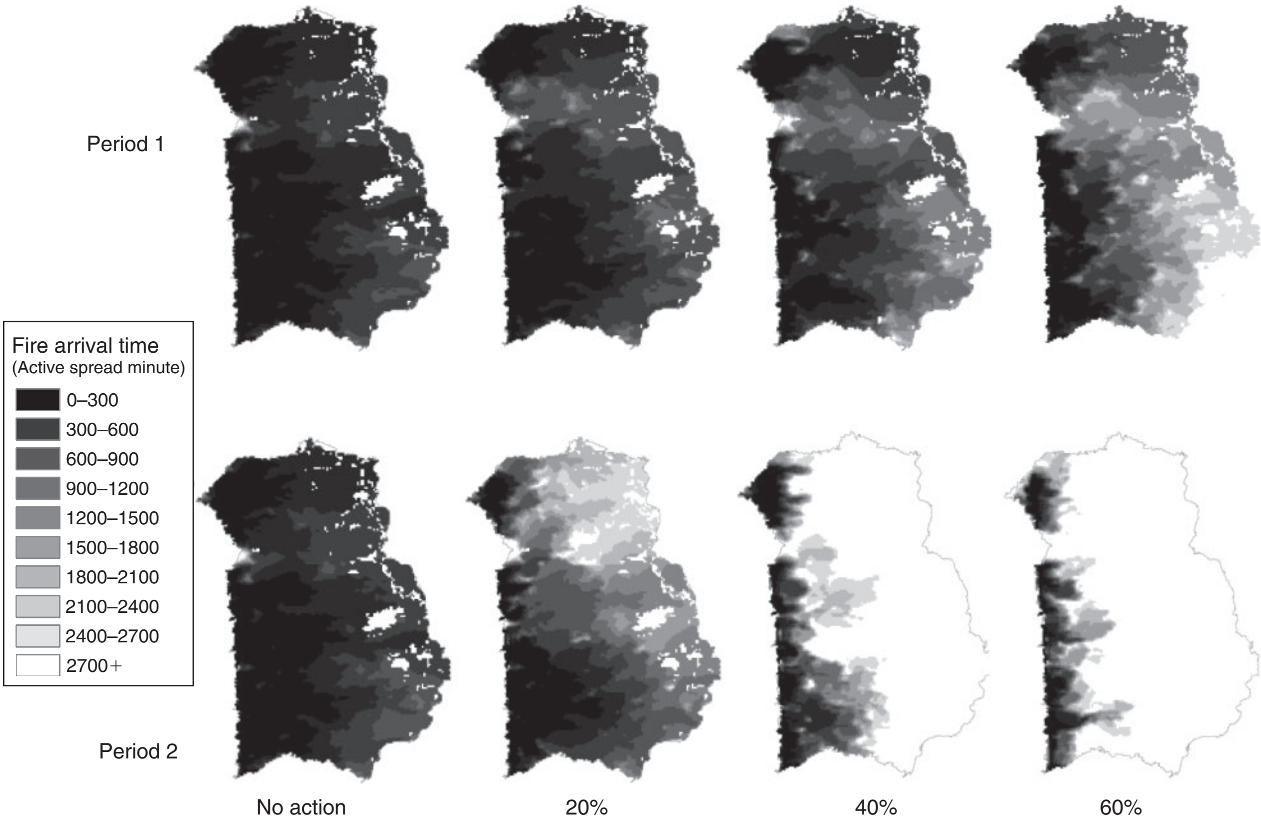

Fig. 9. Changes in fire arrival time due to scheduled fuel treatments in time periods 1 and 2.

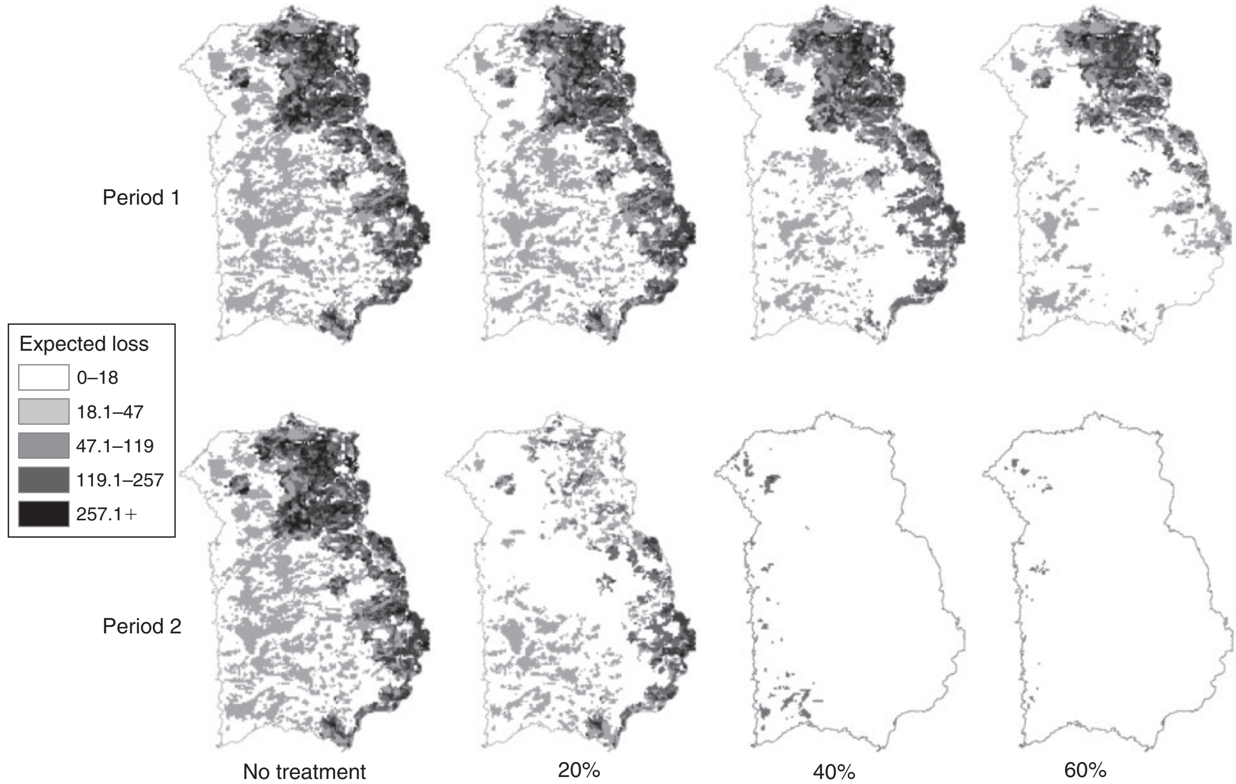

Fig. 10. Changes in expected loss value due to scheduled fuel treatments in time periods 1 and 2.

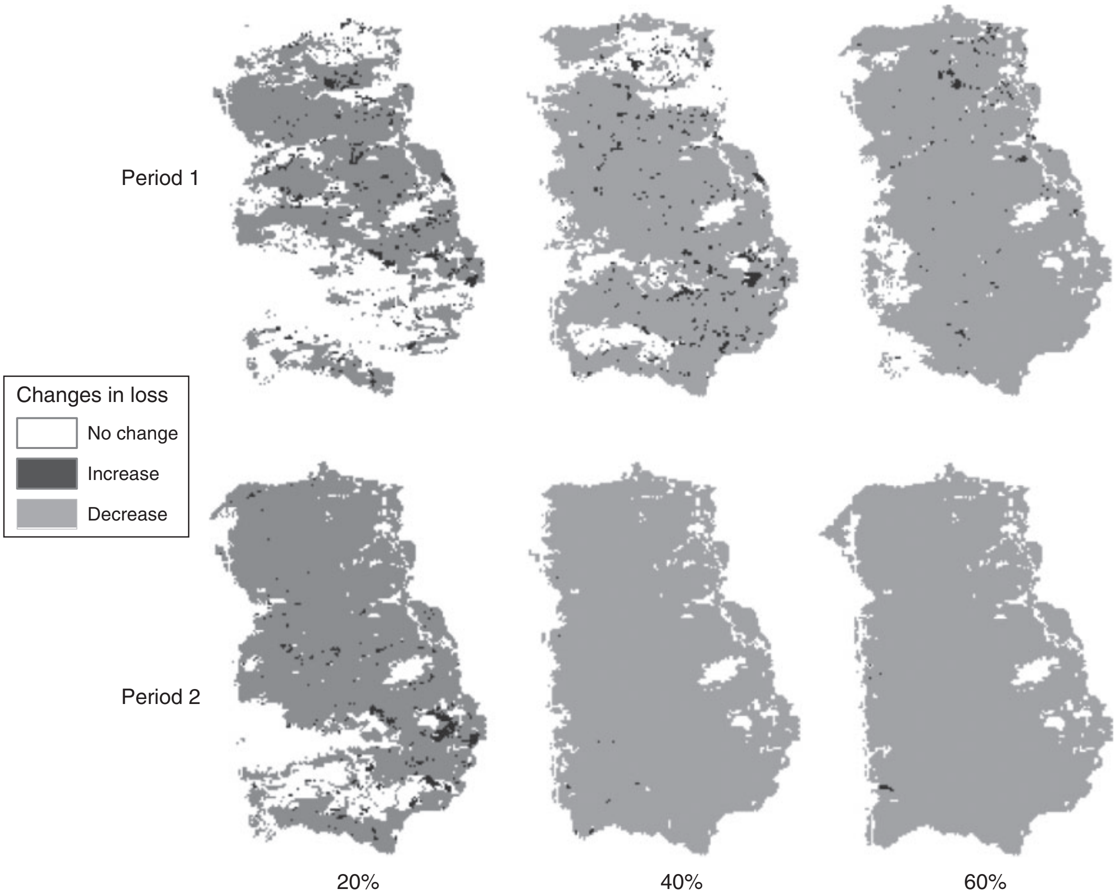

Fig. 11. Changes in the expected loss value per grid cell relative to the no-action scenario. Grey areas indicate a decrease of expected loss, whereas black areas indicate an increase of loss due to scheduled treatments.

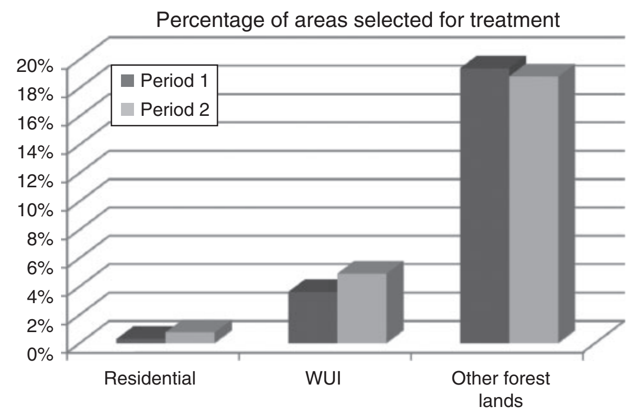

Fig. 12. Percentage of areas selected for treatment in each value-at-risk category in periods 1 and 2 (WUI, wildland–urban interface).

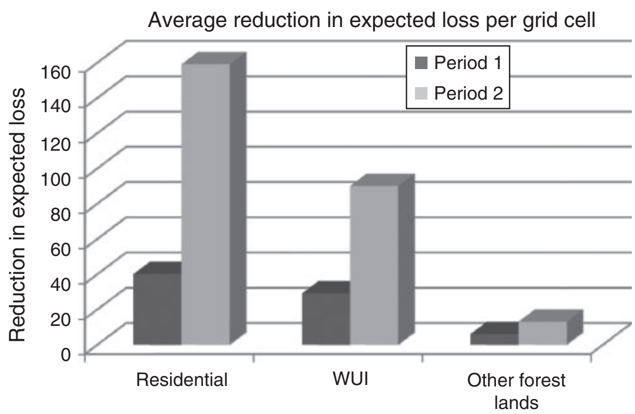

Fig. 13. Average reduction in loss value across value-at-risk categories in periods 1 and 2 (WUI, wildland–urban interface).

time among the three scenarios. This was because the 60% treatment scenario provided a simpler landscape from the fire-growth modelling standpoint than the other two scenarios. As an example, FlamMap-MTT did not have to simulate fire spread for the entire landscape for period 2 in the 60% treatment scenario because the majority of the landscape was beyond the limit of fire arrival time set in FlamMap-MTT for this application (Fig. 9). This limit on arrival time was based on when the probability of fire duration drops to zero (Table 2). The solver runs FlamMap-MTT in each iteration to evaluate solution

Table 8. Comparison of total expected loss between the optimised solution and the average of 30 random solutions under each treatment intensity scenario

Treatment intensity	Optimised solutions		Average of random solutions	
	Expected loss	Percentage reduction from no action loss	Average expected loss	Percentage reduction from no-action loss
No action	1 679 378	0	1 679 378	0
20%	1 023 361	39	1 504 343	10
40%	640 018	62	1 318 626	21
60%	399 622	76	1 095 141	35

Table 9. Solution time required for the heuristic solver
The average solution time per iteration was 32 s on a 2.83-GHz computer with 8-processor CPU and 8 GB of RAM

Treatment intensity	Total number of iterations	Solution time (h)
20%	3063	29.2
40%	3147	31.1
60%	3231	24.7

alternatives and FlamMap-MTT runtime is indeed the most time-consuming part of the search process owing to the computationally intensive nature of fire-growth modelling.

Fig. 14 graphically shows the performance of the heuristic solver in terms of improving solution quality throughout the search process. During Phase I, the solution improves as more treatment clusters are added to the solution. The SA algorithm begins in Phase II when it starts relocating clusters and evaluating new alternative solutions. Wide and narrow pulses of solution quality across iterations in Fig. 14 indicate that the SA algorithm occasionally accepts a worse solution (i.e. higher expected loss) and then quickly jumps to a better solution. The amplitude of pulses decreases as the algorithm moves towards the end because the probability of accepting a worse solution in the SA algorithm diminishes as temperature cools down towards the end of the search process. The algorithm stops when the temperature goes below the user-defined minimum temperature and the best solution found throughout the search process is reported as the final solution.

It is noteworthy that most solutions developed during Phase II for a treatment scenario have more or less the same number of hectares selected for treatment. However, the results in Fig. 14 show wide ranges of expected loss among the alternative solutions. In addition to what was observed from the comparisons against random solutions, the wide range of alternative solutions also confirms that strategically located and scheduled fuel treatments may greatly improve the effectiveness and efficiency of such activities in achieving desirable goals.

Conclusion

This study has developed an optimisation model to simultaneously schedule fuel treatments across time and space. Even though fuel treatment planning is a computationally challenging problem, the model, using a meta-heuristic algorithm for solving the large combinatorial optimisation problem, was able to find effective arrangements of fuel treatments for the study landscape compared with random solutions. Earlier approaches to multi-period fuel treatment planning scheduled fuel treatments for one planning period at a time without considering continuing effects of treatments over time.

The model's ability to consider area constraints allows quantifying trade-offs among various fuel treatment scenarios and thus helps informed decision-making. For example,

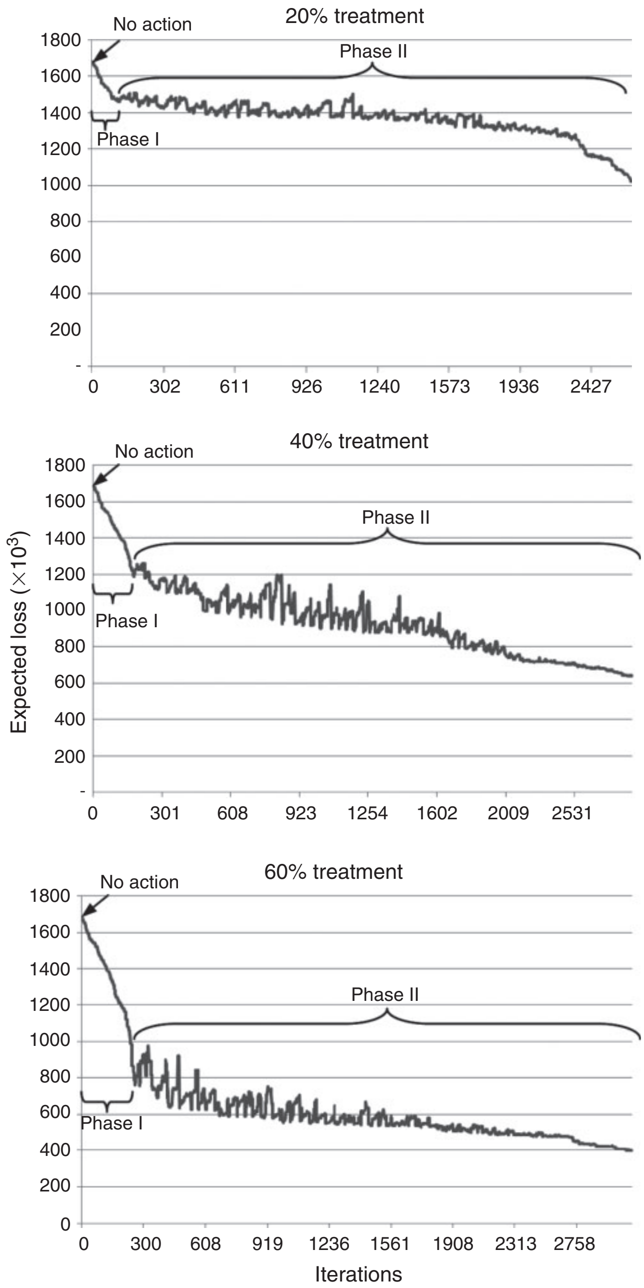

Fig. 14. Performance of the simulated annealing algorithm in finding less-expected loss solutions throughout the search process.

multiple runs of the model with increasing maximum allowable treatment areas can be used to assess the additional fuel treatment benefits that can be achieved by additional treatment areas. In addition, FVS simulation in the model provides the ability to estimate other outputs or outcomes of the fuel treatment activities, such as timber products and woody biomass. This additional information can be then used to analyse trade-offs between fuel treatment and other resource management objectives, as well as to conduct financial analysis of fuel treatment projects.

It should be noted that the effects of fuel treatments in earlier planning periods are reflected in the vegetation and fuels parameters predicted by FFE-FVS for one or more subsequent periods. However, unplanned disturbances, namely wildland fire and insect outbreaks, are not reflected in the forest vegetation simulation. The presence of such disturbances would necessitate re-planning the spatial and temporal fuel treatments on an affected landscape.

One notable limitation to using the optimisation model developed in this study is that FVS-ready tree list and stand data are not readily available. Our model, as well as any planning process that utilises FFE-FVS to predict temporal changes of vegetation and fuels, requires FVS-ready inventory data that accurately represent each stand polygon in a planning landscape. One must develop such inventory data for the landscape before planning fuel treatments using our model if the data do not exist. The best option for accomplishing this appears to be imputation, which in essence matches available inventory plots (e.g. FIA plots) with stand polygons. In addition, surface fuel models serve as the primary input for fire behaviour calculation in the optimisation model, and therefore should be carefully determined and examined for reliable fire behaviour predictions.

Another limitation is that a large amount of solution time is required for model runs owing to the computationally intensive process of fire-growth modelling. Because of this limitation, we modelled only one fire scenario in our application and used it for solution evaluation. However, modelling multiple fires with different weather and fire scenarios would certainly help us better address uncertainties related to fire ignitions and weather conditions. In addition, the degree of uncertainty in the future is often greater than the present, but our model does not take into account this growing uncertainty. Future study should investigate methods to reflect growing uncertainty on the objective function of the model.

Lastly, the optimisation model developed in this study works based on two already-complex simulation systems: FFE-FVS and FlamMap. Each system has its own assumptions and limitations. Potential users of the model should fully understand both simulation systems, as well as data and assumptions used in simulation, for proper use and maximum benefit from the model.

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