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Prioritising fuels reduction for water supply protection

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Abstract. Concerns over wildfire impacts to water supplies have motivated efforts to mitigate risk by reducing forest fuels. Methods to assess fuel treatment effects and prioritise their placement are needed to guide risk mitigation efforts. We present a fuel treatment optimisation model to minimise risk to multiple water supplies based on constraints for treatment feasibility and cost. Risk is quantified as the expected sediment impact costs to water supplies by combining measures of fire likelihood and behaviour, erosion, sediment transport and water supply vulnerability. We demonstrate the model's utility for prioritising fuel treatments in two large watersheds in Colorado, USA, that are critical for municipal water supply. Our results indicate that wildfire risk to water supplies can be substantially reduced by treating a small portion of the watersheds that have dense, fire-prone forests on steep slopes that drain to water supply infrastructure. Our results also show that the cost of fuel treatments outweighs the expected cost savings from reduced sediment inputs owing to the low probability of fuel treatments encountering wildfire and the high cost of thinning forests. This highlights the need to expand use of more cost-effective treatments, like prescribed fire, and to identify fuel treatment projects that benefit multiple resources.

Additional keywords: erosion, fuel treatment effectiveness, sediment, spatial optimisation, wildfire risk assessment.

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Introduction

Communities that rely on surface water from fire-prone watersheds are at risk of wildfire-related increases in peak flows, sediment, debris, organic matter and other constituents that may damage water infrastructure, complicate water treatment and reduce reservoir storage capacity (Moody and Martin 2001; Martin 2016; Nunes *et al.* 2018). In the western USA, proactive fuels reduction has emerged as a popular strategy to mitigate wildfire risk to water supplies (Huber-Stearns 2015; Ozment *et al.* 2016). Fuel reduction treatments, such as forest thinning and prescribed fire, are projected to reduce fire severity (Graham *et al.* 2004; Agee and Skinner 2005; Reinhardt *et al.* 2008; Martinson and Omi 2013) and therefore post-fire runoff, erosion and debris flows (Benavides-Solorio and MacDonald 2001, 2005; Cannon *et al.* 2010). However, watershed investment programs have been challenged to quantify fuel treatment effects on water supply risk and to prioritise fuel treatment locations (Ozment *et al.* 2016). Quantifying fuel treatment effects is fundamental to outcome-based investment strategies for land management that emphasise clearly articulated goals and spatial prioritisation (USDA Forest Service 2018). Assessment and planning tools are needed to characterise water supply risk, quantify the potential risk reduction from fuel treatments, and prioritise fuel treatment type and location across large watersheds.

In the western USA, wildfire affects water supplies primarily by increasing sediment supply, including ash, which can harm infrastructure and impair water quality. Exposure to post-fire sediment can therefore serve as a useful metric of water supply impact (Buckley *et al.* 2014; Elliot *et al.* 2016; Jones *et al.* 2017).

High-severity wildfire reduces surface cover and alters soil properties, leading to substantial increases in runoff and erosion (DeBano *et al.* 2005; Shakesby and Doerr 2006; Moody and Martin 2009). Burn severity and correlated metrics, like percentage bare soil, are strong predictors of erosion (Benavides-Solorio and MacDonald 2001, 2005; Schmeer *et al.* 2018). Climate, topography, soils and vegetation also influence erosion potential at landscape to regional scales (Shakesby and Doerr 2006; Moody and Martin 2009). Water supply consequences are further mediated by sediment transport processes that determine the connectedness of sediment-producing uplands to downstream water supplies. Spatial variability in factors affecting fire and watershed processes suggests there may be high value in spatially prioritising risk mitigation.

Wildfire risk to water supplies varies across large landscapes owing to the likelihood and intensity of fire, erosion potential and connectivity to water supplies (Scott *et al.* 2012; Thompson *et al.* 2013*a*, 2013*b*, 2016). Relative measures of risk have been quantified by combining spatial predictions of fire likelihood and intensity with expert-defined functions of relative water supply loss (value change) by watershed exposure to broad classes of fire intensity (Scott *et al.* 2013). This approach emphasises fire intensity as the primary driver of water supply impact, although multivariate response functions have been used to account for variable erosion potential due to soils and slope steepness (Thompson *et al.* 2013*a*, 2013*b*, 2016). Relative measures of water supply risk can be useful for prioritising fuels reduction at broad scales, but they do not communicate the potential magnitude of water supply disruption and water quality impairment. Without concrete metrics of water supply risk, it is difficult for water managers to justify the need for risk mitigation, set objective mitigation goals and evaluate the effectiveness of different mitigation strategies.

Spatially explicit erosion and sediment transport models have been used to assess the potential erosion and water supply consequences of future fires using modelled fire behaviour metrics that approximate burn severity (Miller *et al.* 2011; Buckley *et al.* 2014; Tillery *et al.* 2014; Elliot *et al.* 2016; Sidman *et al.* 2016; Jones *et al.* 2017). Spatial watershed models improve on multivariate response functions (Thompson *et al.* 2013*a*, 2013*b*, 2016) by providing quantitative predictions of post-fire erosion and sediment delivery that account for the influence of surface cover, rainfall, topography and soils. Sediment yield is a useful metric to water managers because it can be translated into water supply consequences such as dredging or replacement costs for reservoirs, maintaining or repairing conveyance infrastructure, and water treatability (Oropeza and Heath 2013; Buckley *et al.* 2014; Elliot *et al.* 2016; Jones *et al.* 2017). Using this framework, fuel treatment effects can be quantified as the difference between predicted post-fire sediment delivery to water supplies for current and simulated post-treatment fuel conditions (Buckley *et al.* 2014; Elliot *et al.* 2016; Sidman *et al.* 2016; Jones *et al.* 2017). Fuel treatment targeting may be improved by considering the variation in treatment effects due to starting fuel conditions, the intensity of treatment, topography and fire weather (Graham *et al.* 2004; Agee and Skinner 2005; Reinhardt *et al.* 2008; Martinson and Omi 2013).

Fuels reduction must be prioritised because treating entire watersheds is cost-prohibitive and almost certainly would conflict with other land-management objectives. It is therefore important to consider fuel treatment costs, legal and administrative restrictions, operational constraints and social acceptance (North *et al.* 2015). Buckley *et al.* (2014) relied primarily on wildfire risk analysis and local stakeholder knowledge of forest conditions and fuel treatment constraints to prioritise one landscape-scale fuel treatment scenario. Their analysis provided rich details on the potential effects of this single fuel treatment scenario, but at the expense of characterising different levels of investment or placement strategies. Jones *et al.* (2017) evaluated a range of treatment scenarios that varied in extent and placement criteria. They found greater benefits when treatments were prioritised using a multiresource risk assessment that included erosion potential compared with those prioritised based on accessibility. The mismatch between where it is best to reduce fuels and where it is easiest to reduce fuels highlights the importance of jointly considering benefits, costs and constraints when prioritising fuels reduction. Furthermore, managers are often considering multiple fuel treatment types that vary in effect, feasibility and cost. Optimisation approaches that explicitly consider the benefits, costs and constraints of fuel treatments (e.g. Ager *et al.* 2013; Thompson *et al.* 2017) are needed to identify the most efficient solutions to these multidimensional problems.

Our goal in the present study was to leverage recent advances in watershed–wildfire risk modelling to prioritise fuels reduction for water supply protection. We introduce a linear program formulation to optimise fuel treatment type and location to maximise avoided sediment costs to water supplies while explicitly considering treatment feasibility and budget constraints. The utility of this approach was tested by using the model to spatially allocate thinning, prescribed fire and combined fuel treatments among planning units in two Colorado watersheds with highly valued water supplies. We also evaluated economic indicators of fuel treatment effectiveness across a wide range of budgets to show how the model can inform water supply protection goals.

Methods

General modelling framework

We developed an optimisation model to prioritise fuel treatment types and locations to maximise wildfire risk reduction to water supplies. We measured risk as the expected fire-related sediment impact costs to water supplies in US dollars (USD) (Buckley *et al.* 2014; Elliot *et al.* 2016; Jones *et al.* 2017). The model focus is prioritising treatment location and type because they are the primary decisions in near-term fuel treatment planning. Treatment location is critical to water supply risk because of spatial variability in fuel conditions, erosion potential and connectivity to water supplies. The model uses the National Hydrography Dataset Plus (NHDPlus; US Environmental Protection Agency (USEPA) and the US Geological Survey (USGS) 2012) catchments as the fuel treatment planning units and routes sediment down the flowline (stream channel) network to water supply infrastructure (see Fig. 1 for spatial topology). NHDPlus catchments have sufficient resolution (mean size ~300 ha) to use as spatial units for large-watershed (>100 km^2) fuel treatment planning. Treatment type is

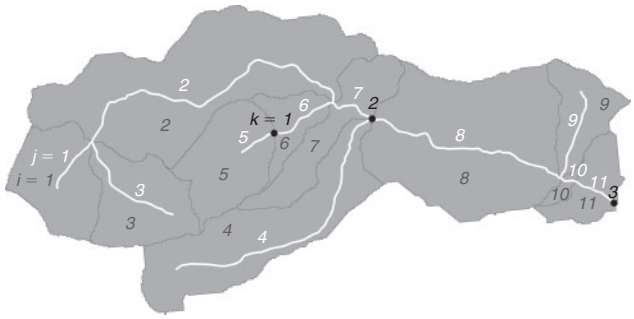

Fig. 1. A portion of the NHDPlus (National Hydrography Dataset Plus; USEPA and USGS 2012) watershed network showing the catchments (numbers in grey) and associated flow lines (in white). Water supply locations are numbered in black and located at the end of the relevant flowline. Sediments produced in upstream catchments are routed to the downstream water supply according to the sediment transport efficiency of the intervening flowlines.

important because thinning, prescribed fire, and other treatments vary in effectiveness, feasibility and cost. We briefly describe the methods used to parameterise the model for our test case in Colorado, but the primary focus here is on the general optimisation approach and application, as different process models, data sources and parameters may be needed to apply the model in other areas.

General model formulations for fuel treatment prioritisation

The linear optimisation model maximises risk reduction (USD) to water supplies for fuel treatment area decisions (ha) by catchment and treatment type during a single fuel treatment planning period. A set of mathematical equations present our logic to prioritise fuel treatments based on spatially explicit estimates of fuel treatment risk reduction to water supplies, feasibility and cost:

Objective function:

$$Maximize \sum_{i=1}^{N} \sum_{t=1}^{P} x_{i,t} \times RR_{i,t} \tag{1}$$

subject to the constraints of:

$$x_{i,t} \leq FE_{i,t} \quad \forall i, t \tag{2}$$

$$\sum_{t=1}^{P} x_{i,t} \leq TotFE_i \quad \forall i \tag{3}$$

$$x_{i,t} \geq MinArea_{i,t} \quad \forall i, t \tag{4}$$

$$x_{i,t} \leq MaxArea_{i,t} \quad \forall i, t \tag{5}$$

$$\sum_{i=1}^{N} \sum_{t=1}^{P} x_{i,t} \times TC_{i,t} \leq Budget \tag{6}$$

$$x_{i,t} \geq 0 \quad \forall i, t \tag{7}$$

Subscript notation:

i is used to index catchments from 1 to N

t is used to index fuel treatment types from 1 to P

Decision variables:

$x_{i,t}$ is the area (ha) of treatment type t scheduled in catchment i

Parameters:

N is the total number of catchments

P is the total number of treatment types

$RR_{i,t}$ is the risk reduction rate (USD ha^{-1}) from treatment type t in catchment i

$FE_{i,t}$ is the feasible and effective area (ha) for treatment type t in catchment i

$TotFE_i$ is the total feasible and effective area (ha) in catchment i for all treatment types combined

$TC_{i,t}$ is the cost (USD ha^{-1}) for treatment type t in catchment i

$MinArea_{i,t}$ is the minimum project area (ha) for treatment type t in catchment i

$MaxArea_i$ is the maximum project area (ha) in catchment i

Budget is the upper bound for the fuel treatment program (USD)

The objective function (Eqn 1) maximises risk reduction to water supplies (USD) from fuel treatment over the planning period. Eqn 2 constrains treatment to the feasible and effective area for each treatment type in each catchment. By 'effective', we mean the treatment meaningfully lowers fire severity by producing a categorical change from high to moderate or moderate to low. The effectiveness constraint is meant to approximate fuels specialist judgement to restrict treatment within heterogeneous planning units from areas that either do not need treatment (e.g. non-forest areas) or treatment is not predicted to alter fire behaviour and severity. Eqn 3 prevents overlapping treatments by restricting treatment to the total feasible and effective area in catchment i. In Eqn 4, the $MinArea_{i,t}$ constraint is used to specify the minimum project size at the catchment level for implementing each treatment type. We expect watershed protection to be one of several management objectives, so the $MaxArea_i$ constraint (Eqn 5) is used to specify the maximum project size (ha). The minimum and maximum area constraints are imposed before model formulation by modifying the $FE_{i,t}$ and $TotFE_i$ parameters. The expected risk reduction to water supplies, $RR_{i,t}$, is calculated as the mean risk reduction for the feasible and effective area for treatment type t in catchment i. Similarly, $TC_{i,t}$ in Eqn 6 is the mean treatment cost for the feasible and effective area for treatment type t in catchment i. Parameterising $RR_{i,t}$, $FE_{i,t}$ and $TC_{i,t}$ requires extensive data and modelling that we introduce through a test case. We emphasise that the model structure, equations and parameters are not universal and may require substantial modification for sites with different vegetation, fuel treatment methods, erosion processes and water supply concerns.

Test case and analysis

We tested our fuel treatment planning approach on the mostly forested, 4809-km^2 upper portions of the Cache la Poudre (CLP) and Big Thompson (BT) Watersheds in northern Colorado, USA (Fig. 2). CLP and BT provide drinking water to over 600 000 residents in Fort Collins, Greeley, Loveland and neighbouring communities. The BT also includes the east slope distribution system of the Colorado–Big Thompson Project (C-BT), which conveys 24700 ha m (200 000 acre-feet) of water annually to water users in the Northern Water Conservancy District. The BT and CLP watersheds range in elevation from 1500 to 4343 m above sea level (ASL). Mean annual temperature varies from

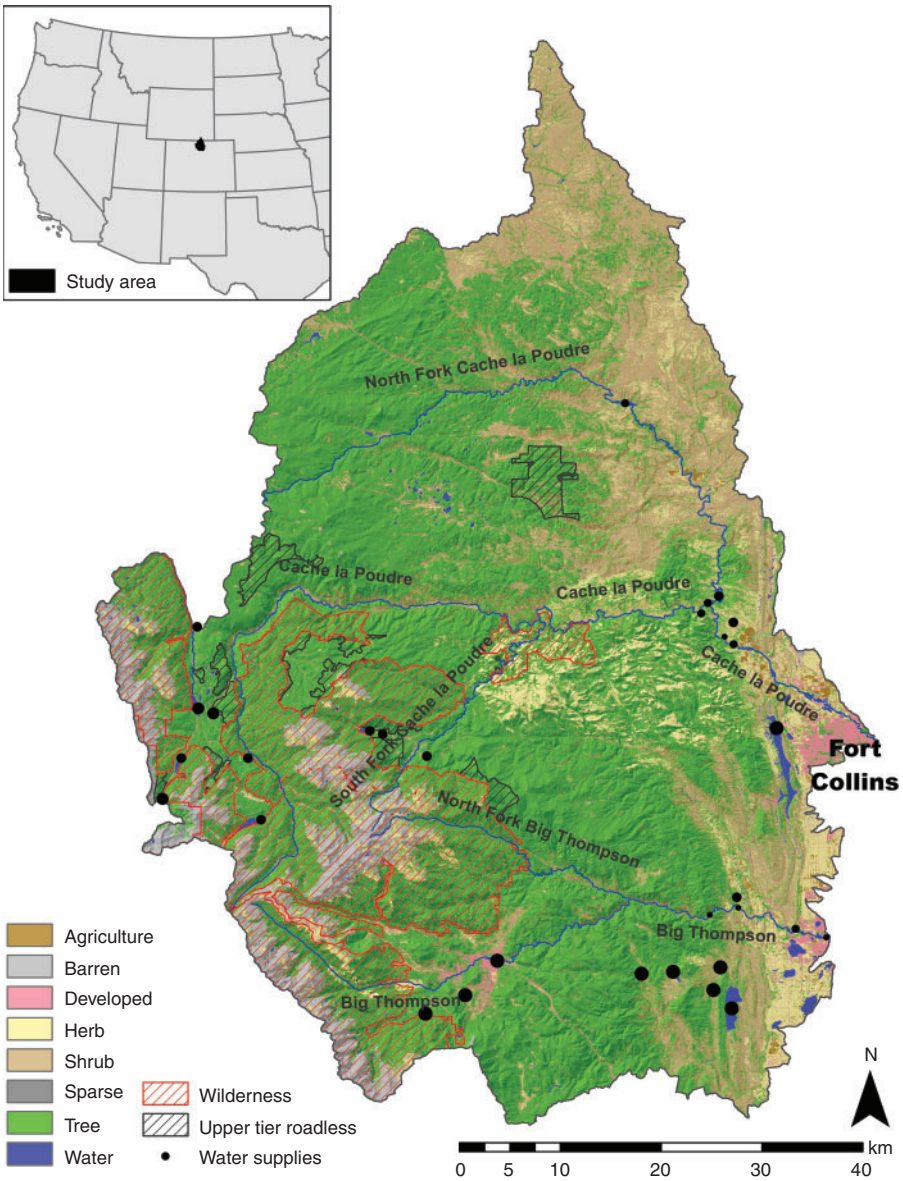

Fig. 2. Test case location including the mainly forested upper portions of the Cache la Poudre and Big Thompson watersheds in northern Colorado. Water supply points are sized based on sediment impact costs (described in the *Sediment cost to water supplies* section). Land cover is from LANDFIRE (2014). The inset map shows the location of the test area in the western United States.

9.9°C in the plains to −4.6°C in the high alpine, and mean annual precipitation increases with elevation from 350 to 1300 mm (PRISM Climate Group 2016). Grass and shrub ecosystems occupy the lowest elevations and montane valleys, the mountains are primarily woodlands and forests, and the highest elevations are alpine tundra or bare rock. There is considerable variation in forest composition and density due to elevational and topographic controls on moisture (Peet 1981). Like much of the western USA, these watersheds have experienced a recent increase in fire activity; since 2000, seven fires larger than 400 ha burned nearly 490 km^2 in the CLP and BT (MTBS 2015). Land ownership is 53.0% federal, 36.5% private, 7.5% state, 1.3% city and 1.0% county. More than 20% of the study area has a protected status that limits active forest management, including 500 km^2 of wilderness in Rocky Mountain National Park and 480 km^2 of wilderness and 100 km^2 of upper-tier roadless area on the Arapaho–Roosevelt National Forest.

Water supply risk and fuel treatment effects

We linked fire, erosion and sediment transport models with sediment impact costs to water supplies to calculate wildfire risk to water supplies from each unit of the landscape (USD ha^{-1}) (Fig. 3). We quantified risk reduction from fuel treatment (USD ha^{-1}) by modelling fire behaviour and effects on water

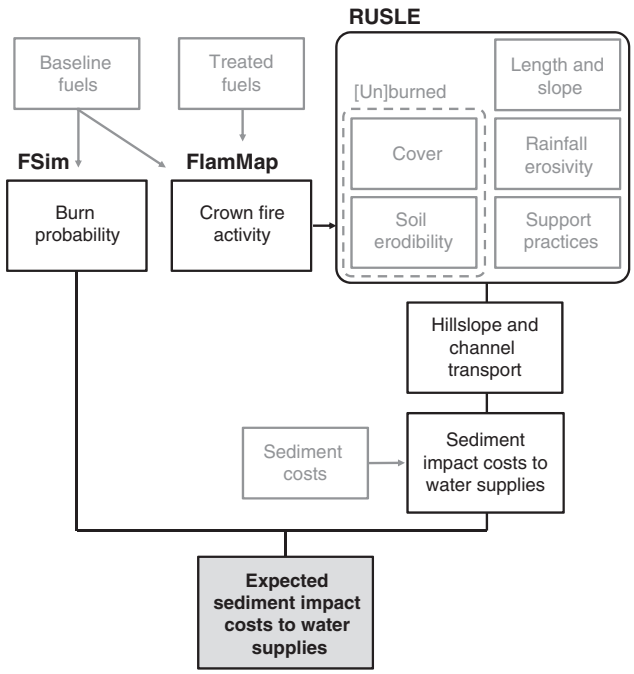

Fig. 3. Fuel treatment effects on wildfire risk to water supplies were quantified by linking models for burn probability (FSim; Short *et al.* 2016), fire behaviour (FlamMap 5.0; Finney *et al.* 2015), erosion (Revised Universal Soil Loss Equation (RUSLE); Renard *et al.* 1997) and sediment transport (Wagenbrenner and Robichaud 2014; Frickel *et al.* 1975) with stakeholder-defined sediment impact costs to water supplies. The output quantifies the expected sediment impact costs to water supplies (i.e. risk) from each unit of the landscape.

supplies for baseline and simulated post-treatment fuel conditions. We did not account for fuel treatment effects on burn probability because the primary objective of fuels reduction is to mitigate fire severity (Graham *et al.* 2004; Reinhardt *et al.* 2008), and fuel treatment has limited effect on landscape-scale burn probability (Thompson *et al.* 2013*c*).

Sediment cost to water supplies

We worked with water managers for Fort Collins, Greeley, Loveland and Northern Water to identify critical water supply infrastructure (hereafter 'water supplies'), including 20 reservoirs and 11 diversions, and map them to flowlines in the NHDPlus watershed network (Fig. 1). Each water supply was assigned a sediment impact cost in US dollars per megagram (1000 kg). The sediment impact costs were used in our analysis to approximate the economic consequence of sediment delivered to a water supply, e.g. the cost to dredge a reservoir, build replacement storage, repair infrastructure, or treat impaired water. Sediment impact costs were calculated as the product of two components: (1) a base cost by water supply type (16 USD Mg^{-1} for reservoirs, 8 USD Mg^{-1} for municipal diversions and 4 USD Mg^{-1} for primarily agricultural diversions), and (2) a relative importance weight of 0 to 1 for low to high importance respectively. The cost of reservoir sedimentation was based on the 25 USD m^{-3} (16 USD Mg^{-1} for a sediment bulk density of 1.6 Mg m^{-3}) reported for dredging costs by Buckley *et al.* (2014), which is also close to the local cost of buying or developing replacement storage. Relative importance weights were assigned by water managers to express the significance of each water supply for their system based on infrastructure characteristics and the volume, priority and timing of water rights. As one water supply can serve several communities, the sum of relative importance weights can exceed 1. The mean sediment impact cost for the 31 water supplies was 18.1 USD Mg^{-1} and the range was from 1.6 to 37.5 USD Mg^{-1}.

Burn probability

Fire likelihood was quantified with a 270-m-resolution national dataset of burn probability (Short *et al.* 2016) modelled with the Large Fire Simulator (FSim; Finney *et al.* 2011). FSim predicts wildland fire occurrence, growth and suppression in response to climate-informed stochastically generated weather streams for tens of thousands of fire seasons. We selected the national FSim burn probability over custom modelling because the FSim fire containment algorithm (Finney *et al.* 2009) produces more reasonable estimates of fire likelihood in the grass and shrub fuel types of our test watersheds. Burn probability was resampled to 30-m resolution using bilinear interpolation to match the resolution of our fire and erosion modelling input data. To simplify accounting of fuel treatment effects, we assume fuel treatments will be implemented immediately and have a constant effectiveness for 25 years. The longevity of fuel treatments is not well constrained, but a similar analysis assumed fuel treatments are effective for 20 years in the western USA (Rhodes and Baker 2008). We lengthened the effective longevity to 25 years for the present study owing to lower forest productivity in the study area (Peet 1981) and results of a stand dynamics modelling study, which suggest forest thinning should reduce torching for ~20 years and active crown fire for ~40 years (Tinkham *et al.* 2016) at the locally observed regeneration density following forest thinning (Francis *et al.* 2018). Therefore, we converted mean annual burn probability (*BP*) from FSim to 25-year *BP* using Eqn 8 and focused on metrics of risk and risk reduction over a 25-year fuel treatment planning period.

$$BP_{25} = 1 - (1 - BP_1)^{25} \tag{8}$$

Fuel treatment simulation

We simulated fuel treatment effects by adjusting spatial fire modelling inputs, including the categorical fire behaviour fuel model (FBFM; Scott and Burgan 2005), canopy base height, canopy height, canopy cover and canopy bulk density. We acquired 30-m raster fuel data from LANDFIRE (2014) and modified them to represent current landscape fuel conditions. Based on our observations of recent fire behaviour and effects in the study area (e.g. the 2012 High Park Fire), we shifted the FBFM for lodgepole pine (*Pinus contorta* subsp. *latifolia*) from moderate load conifer litter to high load conifer litter (Scott and Burgan 2005) and lowered the canopy base height by 20% to increase crown fire potential. Fuels data were also updated with past fuel treatments (Caggiano 2017). We included three common fuel treatment types in the analysis – thinning only, thinning followed by prescribed fire, and prescribed fire only – that

Table 1. Fuel treatment effects on forest structure
Treatment effects adjustment factors used to simulate fuel treatments. Effects were applied as multipliers to the baseline fuel values to calculate the post-treatment conditions

	Treatment effects		
	Thinning	Thinning and prescribed fire	Prescribed fire
Canopy base height	1.20	1.20	1.09
Canopy height	1.20	1.20	1.13
Canopy cover	0.70	0.75	0.95
Canopy bulk density	0.60	0.50	0.92

differ in their effects on surface and canopy fuels (Graham *et al.* 2004; Agee and Skinner 2005; Reinhardt *et al.* 2008). The pretreatment canopy fuel attributes were multiplied by the average proportional change in canopy fuel attributes from studies of hazardous fuel and restoration treatments in dry forests of the western USA (Stephens and Moghaddas 2005; Stephens *et al.* 2009; Fulé *et al.* 2012; Ziegler *et al.* 2017) to estimate post-treatment conditions (Table 1). Treatment effects on surface fuels were simulated by changing the FBFM for the timber understorey and timber litter fuel models (Scott and Burgan 2005). Thinning often increases surface fuel loads, whereas prescribed fire consistently reduces surface fuels (Stephens *et al.* 2009; Fulé *et al.* 2012). We approximated these effects by changing the FBFM to increase surface fire intensity for the thinning treatment, and to decrease surface fire intensity for the prescribed fire treatment. We assumed that the combined thinning and prescribed fire treatment would not change the FBFM because the prescribed fire would consume thinning residues (e.g. branch and litter activity fuels). For grass, grass–shrub and shrub fuel types, we conservatively assumed that none of the treatments would alter the FBFM.

Fuel condition impacts on fire behaviour

Crown fire activity (CFA) (Scott and Reinhardt 2001) was modelled for baseline and post-treatment fuel conditions using FlamMap 5.0 (Finney *et al.* 2015). CFA is a prediction of fire type in categories of unburned, surface fire, passive crown fire and active crown fire, which has been used as a proxy for burn severity in previous watershed risk assessments (e.g. Tillery *et al.* 2014; Haas *et al.* 2017; Jones *et al.* 2017). Large fires driven by very dry and windy conditions are responsible for most of the area burned in the Colorado Front Range (Graham 2003; Sherriff *et al.* 2014; Haas *et al.* 2015), so we assessed risk using fire behaviour modelled under extreme fire conditions. We used FireFamilyPlus 4.1 (Bradshaw and McCormick 2000) to summarise fuel moisture, wind speed and wind direction for the fire season (1 April to 31 October) for three Remote Automated Weather Stations (RAWS) in the study area – Redfeather, Estes Park and Redstone. The mean 3rd percentile fuel moistures for the three stations (1-h 2%, 10-h 3%, 100-h 6%, herbaceous 4%, woody 63%) were used in FlamMap without conditioning. Owing to considerable variability in wind direction, we used the wind blowing uphill option in FlamMap to represent a single worst-case scenario. Wind speed was set to the 97th percentile of the mean 1-min wind speed (Crosby and Chandler 1966) averaged across the three RAWS stations, yielding a value of just under 39 km h^{-1} at 6 m above the ground surface.

Hillslope erosion

We modelled annual soil loss using a geographic information system (GIS) based implementation (Theobald *et al.* 2010) of the Revised Universal Soil Loss Equation (RUSLE), which estimates annual soil loss (A) in megagrams per hectare per year as the product of five subfactors: rainfall runoff erosivity (R), soil erodibility (K), length and slope (LS), cover (C), and support practices (P) (Renard *et al.* 1997). This approach was previously used to estimate wildfire-related erosion in the Southern Rockies for individual wildfire events (Miller *et al.* 2003; Yochum and Norman 2014, 2015) and for future wildfire and climate scenarios (Litschert *et al.* 2014). We chose RUSLE because of its computational efficiency at modelling erosion for multiple treatment scenarios over large landscapes. Although there are uncertainties associated with using a primarily agricultural equation to predict erosion in montane forests, two of the key RUSLE factors have been calibrated for burned forests in the Colorado Front Range (Larsen and MacDonald 2007). The mean performance of RUSLE for recently burned hillslopes in the Colorado Front Range, when grouped by fire and fire severity, was approximately comparable with the more physically based Disturbed Water Erosion Prediction Project (WEPP) model ($R^2 = 0.54$ vs 0.66) (Larsen and MacDonald 2007).

The R factor is the annual sum of total storm energy and maximum 30-min intensity (MJ mm ha^{-1} h^{-1}). The R factor used in our modelling was based on 15-min rainfall data from 11 monitoring stations (Perica *et al.* 2013) that best represent the local climate. These data were assembled for a separate study (Wilson *et al.* 2018) and processed with the Rainfall Intensity Summarisation Tool (Dabney 2016) to calculate rainfall erosivity values for each storm, and these were summed to obtain the annual rainfall erosivity for each year of record and station. This dataset spans the years 1971 to 2010 and includes 403 station-years of annual erosivity observations. Annual rainfall erosivity is highly variable in space and time owing to localised convective thunderstorms typical of the study area (Kampf *et al.* 2016). Rainfall erosivity was therefore treated as a random variable defined by the cumulative frequency distribution of the annual rainfall erosivity observations pooled across stations (Fig. 4). To simplify the analysis, the focus is on risk and risk reduction estimates for median rainfall erosivity of 615 MJ mm ha^{-1} h^{-1}, but uncertainty in these estimates is also communicated by reporting risk reduction for the 5th through 95th percentiles of annual rainfall erosivity.

Soil erodibility (K) was extracted from the Soil Survey Geographic Database (SSURGO), and where necessary the State Soil Geographic Database (STATSGO) (NRCS Soil Survey Staff 2016). We followed the procedures of Yochum and Norman (2014) to calculate a weighted mean of whole-soil K factor (Kwfact) for each map unit. First, we calculated the component depth-weighted mean K for the top 15 cm of soil. We then computed the map unit area-weighted mean K based on the

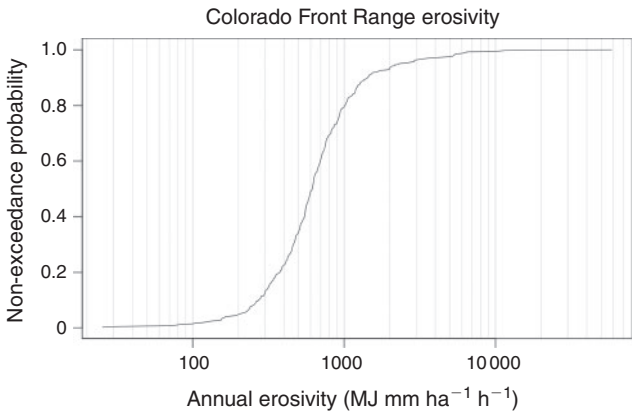

Fig. 4. Empirical cumulative frequency distribution of Colorado Front Range annual erosivity from 403 station-years of annual erosivity observations from 11 NOAA 15-min rainfall stations.

proportional coverage of components. SSURGO map units that were missing K values for more than 50% of their area had gaps filled with equivalent metrics from STATSGO. All K values were converted to metric units (Renard *et al.* 1997).

The combined length and slope (LS) factors were calculated using terrain analysis of a 30-m digital elevation model (DEM) (USEPA and USGS 2012) following Theobald *et al.* (2010). The slope (S) was calculated using Eqn 9 (Nearing 1997) where θ is slope steepness in radians. We capped θ at 55% slope to avoid extrapolating beyond the range of Nearing's data (Theobald *et al.* 2010; Litschert *et al.* 2014).

$$S = -1.5 + \frac{17}{1 + e^{(2.3 - 6.1 \times \sin\theta)}} \tag{9}$$

We then calculated LS using the methods of Winchell *et al.* (2008) (Eqns 10–13) where A is the contributing area to the cell inlet (m^2), D is the cell dimension (m), m is the slope-length exponent, and x is the shape factor calculated as a function of slope aspect (α) in radians. The slope-length exponent (m) is based on the ratio of rill to interrill erosion (β), which is estimated from slope steepness (θ) using Eqn 11 (McCool *et al.* 1989).

$$LS = S \times \frac{(A + D^2)^{m+1} - A^{m+1}}{D^{m+2} \times x^m \times 22.13^m} \tag{10}$$

$$m = \frac{\beta}{1 + \beta} \tag{11}$$

$$\beta = \frac{\frac{\sin\theta}{0.0896}}{3 \times \sin\theta^{0.8} + 0.56} \tag{12}$$

$$x = |\sin\alpha| + |\cos\alpha| \tag{13}$$

Slope steepness (θ), slope aspect (α) and contributing area (A) were each calculated from a 30-m-resolution filled DEM using standard slope, aspect and D8 flow direction (all flow assigned to one of the adjacent or diagonal neighbours) methods in *ArcGIS 10.3*. When calculating LS, we capped A at 0.9 ha to approximate the maximum hillslope length of 300 m as suggested in Renard *et al.* (1997). We also limited LS values to the maximum value of 72.15 listed in Renard *et al.* (1997).

We assigned each existing vegetation type (EVT) from LANDFIRE (2014) an undisturbed cover factor (C) based on previous studies (McCuen 1998; Toy and Foster 1998; Miller *et al.* 2003; Yang *et al.* 2003; Breiby 2006). Baseline C factor values ranged from 0.001 to 0.003 for forests, 0.025 to 0.029 for shrublands, 0.012 to 0.080 for grasslands, and up to 1.0 for the rare barren areas disturbed by agriculture or mining. Barren alpine areas above 2900 m elevation were assigned a C value of 0.002 owing to high rock cover. The C values for unburned forests do not have to be precisely defined, because the C values and predicted erosion rates are very small compared with post-wildfire conditions (Larsen and MacDonald 2007).

Predicting post-fire hillslope erosion

We used CFA (Scott and Reinhardt 2001) modelled with FlamMap 5.0 (Finney *et al.* 2015) as a proxy for burn severity by assuming that surface, passive crown and active crown fire correspond to low, moderate and high burn severity respectively (Tillery *et al.* 2014; Haas *et al.* 2017; Jones *et al.* 2017). Characterising fire effects by burn severity category is consistent with how field-based erosion studies stratified their sampling (e.g. Benavides-Solorio and MacDonald 2005; Larsen and MacDonald 2007) and it is similar to using remotely sensed burn severity to predict post-fire erosion (Miller *et al.* 2016). As post-fire increases in erosion are primarily attributed to decreased surface cover (Larsen *et al.* 2009) and altered soil properties (Shakesby and Doerr 2006), we predicted erosion in the first year after wildfire by modifying the C and K factors. For forests, which were defined as having at least 10% canopy cover, we used the mean first-year post-fire C values by burn severity category from Larsen and MacDonald (2007) (Table 2). Owing to the diversity of non-forest vegetation types and the limited estimates of post-fire cover in these systems (Pierson and Williams 2016), proportional adjustment factors were used to estimate post-fire C values (Table 2). Fire effects on soils are diverse, but generally lead to decreased infiltration and cohesion from a range of processes including deposition of hydrophobic compounds, soil sealing and consumption of organic material (DeBano *et al.* 2005; Shakesby and Doerr 2006). Direct measurements of post-fire K factors are difficult to make, so Larsen and MacDonald (2007) back-calculated a 2.5-fold increase in K for forested areas in the Colorado Front Range that were burned at high severity. Given the uncertainty with back-calculation, we used more conservative proportional adjustment factors that were applied to baseline K factor values to predict post-fire K (Table 2).

In the Colorado Front Range, post-fire hillslope erosion generally returns to pre-disturbance levels within 2–5 years (Benavides-Solorio and MacDonald 2005; Wagenbrenner *et al.* 2006; Robichaud *et al.* 2013*a*). Hillslope erosion rates have been measured for multiple years after burning for 10 fires in the Colorado Front Range (Pietraszek 2006), and these data indicate that the total fire-related sediment yield is ~2.1 times the first-year sediment yield. We used this empirical factor to estimate total post-fire erosion over multiple years from our first-year post-fire erosion predictions.

Table 2. Fire effects on erosion

Mean post-fire cover factor (C) values by burn severity from Larsen and MacDonald (2007) were used to assign post-fire C for forests (≥10% LANDFIRE canopy cover). Fire effects on the C factor for non-forest (<10% canopy cover) were applied as proportional adjustment factors. Fire effects on the soil erodibility factor (K) for all vegetation were applied as proportional adjustment factors

			Fire effects	
Crown fire activity	Burn severity	Forest C	Non-forest C adjustment factor	K adjustment factor
Surface	Low	0.01	1.2	1.5
Passive	Moderate	0.05	1.5	1.75
Active	High	0.20	2.0	2.0

Hillslope sediment transport

We used an empirical model of post-fire hillslope sediment delivery ratio (hSDR) developed for the western USA (Wagenbrenner and Robichaud 2014) to estimate the proportion of gross erosion delivered to streams. When hillslope erosion is the primary source of sediment, unit area sediment yields decline with increasing watershed size (hSDR < 1) because of sediment storage in the watershed (Walling 1983). Post-fire hSDR was estimated with the annual length ratio (LR) model from Wagenbrenner and Robichaud (2014) (Eqns 14 and 15). We used terrain analysis of a 30-m DEM (USEPA and USGS 2012) to calculate the flow path length from each pixel to the nearest channel as the 'catchment length' and the flow path length across the pixel as the 'plot length'.

$$\log(\mathrm{hSDR}) = -0.56 - 0.0094 \times \mathrm{LR} \tag{14}$$

$$\mathrm{LR} = \frac{\textit{Flow path length to nearest channel}}{\textit{Flow path length across pixel}} \tag{15}$$

The moderate-resolution NHDPlus flowline network does not include all channels, which is problematic because of the dramatic headward expansion of the channel network after fires (Wohl 2013). We therefore extended the channel network using a 10.8-ha contributing area threshold (Henkle *et al.* 2011) to define where a channel begins, and this expanded channel network was used to calculate the flow path length from each pixel to the nearest channel. Channel pixels were assigned an hSDR of 1.

Sediment delivery to infrastructure

Sediment transport in streams depends on characteristics of the sediment and water flow. Physically based sediment transport models are sensitive to the magnitude and timing of sediment inputs and flow, which cannot be accurately predicted *a priori*. The overall tendency is for some sediment to be stored in floodplains or channels, resulting in channel sediment delivery ratios (cSDR) less than 1. We used a simple model of cSDR based on Frickel *et al.* (1975) to estimate the proportion of sediment transported through a stream segment as a function of Strahler stream order. Observations from the High Park and other fires (e.g. Miller *et al.* 2017) indicate that the steep, gravel-to-cobble-bed streams typical of the study area are very efficient at transporting sand and finer-grained sediments. Post-fire monitoring in a similar montane watershed confirmed that the silts and clays are efficiently transported even during low-flow conditions, whereas the transport of coarse sand and larger particles occurs primarily during the higher flows associated with snowmelt or larger rainstorms (Ryan *et al.* 2011). We assigned cSDRs per 10 km of stream length of 0.75, 0.80, 0.85 and 0.95 to 1st, 2nd, 3rd, and 4th or higher-order streams respectively. Our assumption is that lower-order streams are less efficient at transporting sediment owing to ephemeral or intermittent flow, high channel roughness and greater proportion of coarse sediment. Sediment transport in the higher-order channels should be more efficient given higher flows, less channel and form roughness, and the tendency for downstream fining. More sophisticated methods and data would be necessary to predict cSDRs in watersheds with lower-gradient depositional reaches or to predict sediment transport on a storm-by-storm basis. Stream segments with reservoirs were assigned a cSDR of 0.05 because all but the finest particles would settle out and be trapped (Brune 1953). The proportion of sediment transported from a catchment to a given downstream water supply was calculated as the product of the connecting flowline cSDRs.

Water supply risk

We combined estimates of burn probability and fire effects to calculate baseline wildfire risk in US dollars per hectare to water supplies from pixels in catchment i as:

$$\begin{aligned} \textit{Risk} = BP_{25} \times \left(\mathrm{A}_{b,nt} - \mathrm{A}_{ub}\right) \times 2.1 \times \mathrm{hSDR} \\ \times \sum\nolimits_{k=1}^{N} C_k \prod\nolimits_{j=1}^{N} \mathrm{cSDR}_j \end{aligned} \tag{16}$$

where b and ub denote burned and unburned conditions; t and nt denote treatment and no treatment; A is annual soil loss (Mg ha^{-1}); coefficient 2.1 is the empirical adjustment factor to account for multiple years of elevated erosion; hSDR is the hillslope sediment delivery ratio; C_k is the sediment impact cost for the kth connected downstream water supply (USD Mg^{-1}); and cSDR_j is the channel sediment delivery ratio for the jth flowline segment connecting the source catchment i to water supply k. The risk reduction (USD ha^{-1}) from applying treatment t in catchment i is estimated by instead finding the difference between the burned not-treated conditions ($\mathrm{A}_{b,nt}$) and the burned treated conditions ($\mathrm{A}_{b,t}$):

$$\begin{aligned} \textit{Risk Reduction} = BP_{25} \times \left(\mathrm{A}_{b,nt} - \mathrm{A}_{b,t}\right) \times 2.1 \times \mathrm{hSDR} \\ \times \sum\nolimits_{k=1}^{N} C_k \prod\nolimits_{j=1}^{N} \mathrm{cSDR}_j \end{aligned} \tag{17}$$

Risk reduction is framed here as the positive benefit of treatment to be maximised in Eqn 1. As the annual soil loss for the burned treated scenario is always greater than or equal to the soil loss in the unburned scenario, the unburned scenario is ignored in Eqn 17. The risk reduction rate parameter ($RR_{i,t}$) in Eqn 1 is calculated as the mean risk reduction (USD ha^{-1}) for the feasible and effective pixels for treatment t in catchment i.

Treatment constraints

We evaluated the feasibility and cost of each treatment type with spatial data on land designations, roads and topography. Thinning is only feasible where there are forested fuels to modify (≥10% canopy cover) and mechanised equipment is permitted (i.e. excluding wilderness or upper-tier roadless areas). We assume that prescribed fire is feasible in any area after thinning, but before thinning, it must meet fire effects and safety criteria. We modelled fire behaviour with an additional FlamMap run under 30th percentile fuel moistures and 16.1 km h^{-1} winds at 6 m to approximate prescribed fire conditions. We assumed that any pixels with >30% crown fraction burned (Scott and Reinhardt 2001) would exceed the desired overstorey tree mortality. We also excluded prescribed fire from within 250 m of structures (mapped by Caggiano *et al.* 2016) and from forest types associated with infrequent, stand-replacing fire (i.e. 'wet forests'). Many factors influence the cost of thinning including site access, equipment operability, forest composition and structure, and the market value of timber or non-timber products. There is potential for merchantable timber extraction to offset some of the thinning costs, but we chose not to account for it here owing to local emphasis on fuel reduction prescriptions that retain larger trees of fire-resistant species (Agee and Skinner 2005; Reinhardt *et al.* 2008). Based on input from local forestry and logging professionals (B. Lebeda and M. Morgan, pers. comm.), we approximated thinning costs for mechanical harvesting equipment as functions of accessibility and operability using Eqn 18. We assumed that anywhere within 800 m of road and below 40% slope would cost 6200 USD ha^{-1} to thin, and that thinning costs would increase linearly from 6200 to 24 700 USD ha^{-1} as distance from roads (D) increased from 800 to 6400 m and as slope (S) increased from 40 to 200%, up to a maximum of 24 700 USD ha^{-1}.

$$Thinning\ Cost = \begin{cases} 6200; \mathrm{D} \leq 800\ and\ \mathrm{S} \leq 40 \\ 6200 + 3.3 \times (\mathrm{D} - 800) + 115.8 \times (\mathrm{S} - 40); \\ \quad \mathrm{D} > 800\ and\ \mathrm{S} > 40 \end{cases} \tag{18}$$

We estimated prescribed fire cost as 2500 USD ha^{-1} based on local experience (B. Karchut and J. White, pers. comm.). The thinning plus prescribed fire costs were calculated as the sum of the thinning costs and the prescribed fire costs.

Model parameterisation and testing

For each catchment and treatment type, we calculated the feasible and effective treatment area ($FE_{i,t}$), mean treatment risk reduction ($RR_{i,t}$), and mean treatment costs ($TC_{i,t}$). We formulated and solved the optimisation model using the lpSolve package in *R* (Berkelaar *et al.* 2015; R Core Team 2017), which uses the revised simplex method for continuous decision variables. We generated solutions for a large range of budget levels (10 to 500 million USD) to illustrate how metrics of risk reduction respond to increasing investment. In addition to percentage and absolute risk reduction in US dollars over the planning period, we present the treatment benefit : cost ratio ($\frac{risk\ reduction}{treatment\ cost}$) and return on investment ($\frac{(risk\ reduction - treatment\ cost)}{treatment\ cost} \times 100$).

Results

Model parameterisation

The study area-wide mean and maximum annual burn probabilities (Short *et al.* 2016) were 0.0028 and 0.0091 respectively. The 25-year planning period mean and maximum burn probabilities increase to 0.0659 and 0.2040 respectively, which corresponds to an expected area burned of 31 700 ha over the planning period. Under extreme fuel and fire weather conditions, 37.1% of the study area is predicted to burn as surface fire, 16.6% as passive crown fire and 36.5% as active crown fire, and the remaining 9.7% is non-burnable. Active crown fire was associated with dense forest conditions and steep slopes. For current conditions, the estimated increase in erosion during the first post-fire year was substantial (mean 31 Mg ha^{-1}; median 4.1 Mg ha^{-1}), but also highly variable across the watersheds (s.d. 61 Mg ha^{-1}; range 0–670 Mg ha^{-1}) owing to the combination of fire effects on cover and soil erodibility, and the large variations in the LS factor. Predicted unit area sediment yields decline after accounting for hillslope sediment delivery to the stream channels and the downstream transport of sediment to water supplies as illustrated for a subset of the study area in Fig. 5. The landscape-wide mean hSDR was 0.56 (range 0.26–1). The estimated increase in post-fire Year 1 sediment delivered to streams (mean 17 Mg ha^{-1}; median 2.3 Mg ha^{-1}; s.d. 34 Mg ha^{-1}) is ~44% lower than the increase in gross hillslope erosion. The decline in unit area sediment yield at water supplies varies with length of stream channels and the presence of dams. After accounting for hillslope and channel sediment transport, the average pixel in our study area is connected to 6.9 USD of water supply impact costs (range 0–37.5 USD).

Risk is concentrated in the densely forested, steep canyons of the lower BT and CLP rivers, and high-elevation forests that drain to nearby water supplies. Pixel-level estimates of wildfire risk to water supplies (Fig. 6) range from 0 to 3300 USD ha^{-1} over the 25-year planning period (mean 27 USD ha^{-1}; median 1.3 USD ha^{-1}). Note that the lower portion of the CLP watershed is mapped as low risk owing to recent fuels reduction from the 2012 High Park and Hewlett Gulch fires, even though it has a high connectivity to water supplies (Fig. 6). The total risk to water supplies is estimated at 12.8 million USD over the 25-year planning period assuming median rainfall erosivity.

Fuels reduction is constrained in our model to locations that can feasibly be treated, and where treatment is effective at modifying CFA. The presence of non-forest vegetation and land-management designations limit the area where thinning or combined thinning and prescribed fire treatments are feasible to 47% of the study area or just over 226 000 ha. Prescribed fire

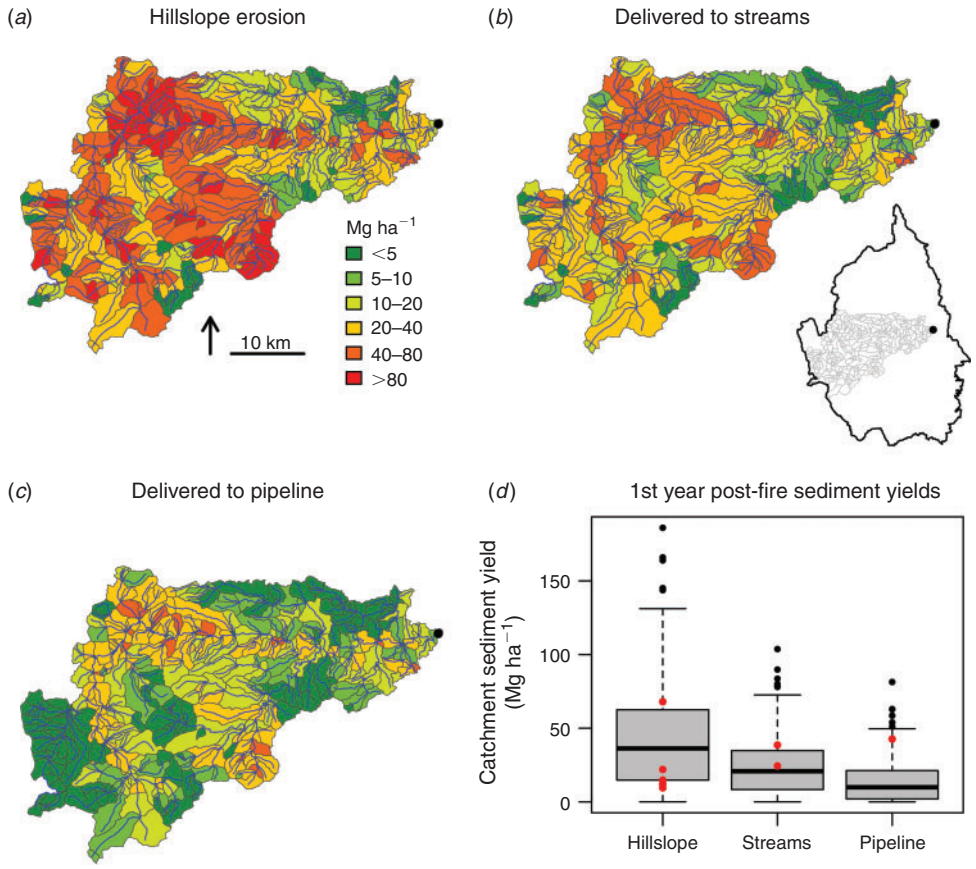

Fig. 5. Predicted first year mean post-fire sediment yields (Mg ha^{-1}) for each of the 435 catchments that contribute to a drinking water pipeline (a subset of the study area) for: (*a*) hillslope erosion; (*b*) sediment delivered to streams; and (*c*) sediment delivered to the pipeline. Catchment mean sediment yields decline from hillslope to whole watershed domains (*d*). Red dots in (*d*) are measured first-year mean post-fire sediment yields from Colorado field studies: hillslopes (Moody and Martin 2001; Wagenbrenner *et al.* 2006; Larsen *et al.* 2009; Robichaud *et al.* 2013*a*; Schmeer *et al.* 2018), small catchments (Robichaud *et al.* 2008, 2013*b*) and watershed (Moody and Martin 2001).

as the first-entry treatment is feasible on only 68 000 ha of the study area (14%), based on criteria for proximity to homes, crown fire behaviour and ecological setting.

Under extreme fuel and fire weather conditions, the thinning-only treatment is expected to reduce CFA on 115 000 ha of the feasible treatment area (51%) (Table 3). This is primarily from changing active crown fire to passive crown fire on 114 000 ha. Thinning alone only reduced active or passive crown fire to surface fire on less than 1% of the feasible treatment area owing to a combination of low initial canopy base heights and the increase in surface fire intensity from fuels added by thinning. The thinning-only treatment is predicted to intensify surface fire to crown fire on ~6800 ha of the feasible treatment area (3%), owing primarily to increased surface fuels and secondarily to reduced canopy wind sheltering. Thinning plus prescribed fire was slightly more effective than thinning alone; the combined treatment reduced CFA on 119 000 ha of the feasible treatment area (53%) (Table 3). Most of this change was due to modifying active crown fire to passive crown fire on 118 000 ha. Crown fire was reduced to surface fire behaviour on 610 ha and surface fire behaviour was only intensified to crown fire on 230 ha. Compared with thinning, prescribed fire was less effective at moderating CFA (8300 ha or 12% of the feasible treatment area) (Table 3), but it was the most effective treatment at reducing active and passive crown fire to surface fire (2500 ha) (Table 3) because of the reduced surface fire intensity.

Catchment-level mean risk reduction is highly variable across treatment type and location (Table 4; Fig. 7) owing to differences in treatment effects, erosion potential and connectivity to water supplies (Fig. 6). More than 70% of the 1827 catchments in the study area have some feasible and effective area to thin. Over half of the catchments include areas where prescribed fire can be scheduled safely and effectively, but in quantities smaller than are generally required to implement a prescribed fire (mean 8.5 ha) (Table 4). The mean risk reduction for catchments with feasible and effective area to treat was similar for the thinning-only and combined thinning and prescribed fire treatments (48.5–49.0 USD ha^{-1}), but lower for the prescribed fire treatment (31.9 USD ha^{-1}). Even though prescribed fire achieves less risk reduction, it is far cheaper than thinning, and this makes prescribed fire the most cost-effective treatment for these watersheds (Table 4). The combined

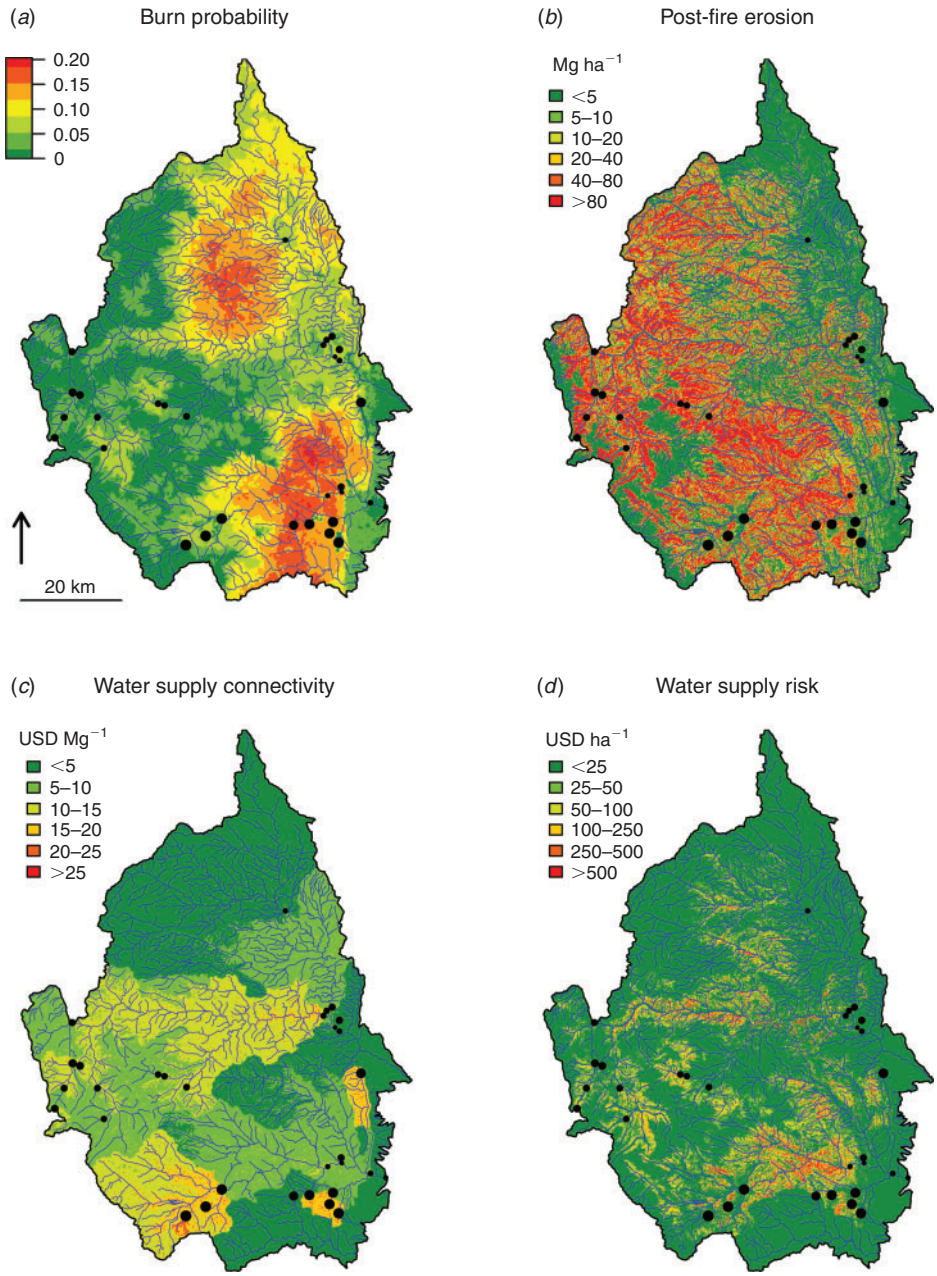

Fig. 6. Our integrated measure of water supply risk (*d*) describes the expected cost of wildfire impacts to water supplies over the planning period in US dollar per hectare by combining planning-period burn probability (*a*), post-fire increase in hillslope erosion over multiple years (*b*), and connectivity to downstream water supply impact costs (combination of hillslope and channel transport and water supply impact costs) (*c*).

thinning and prescribed fire treatment is the least cost-effective option because it has similar risk reduction as the thinning-only treatment and costs more (Table 4).

Optimisation model test case

We found that fuels reduction can reduce water supply risk by a maximum of 54% when there are no project size and budget limitations. However, assuming minimum treatment areas of 10 ha for thinning and 20 ha for prescribed fire, and that no more than 30% of the area can be treated in each catchment, fuels reduction treatments could reduce total water supply risk by approximately one third (Table 5). More than half of this risk reduction can be achieved by investing 100 million USD to treat 14 400 ha (3% of the study area), and 90% of this risk reduction can be addressed by spending 250 million USD to reduce fuels on 35 800 ha (7% of the study area). There is very low marginal benefit to investing more than 300 million USD (Table 5). At lower budget levels, fuel treatments should be concentrated along

Table 3. Fuel treatment effects on modelled fire behaviour

Effectiveness of fuel treatments at reducing crown fire activity (Scott and Reinhardt 2001) under extreme fuel and fire weather conditions for the feasible treatment area. All values reported are the predicted areas (ha) by crown fire activity. Treatment is considered effective if it reduces crown fire activity by one class

	Thinning			Thinning and prescribed fire			Prescribed fire		
Pretreatment	Surface	Passive	Active	Surface	Passive	Active	Surface	Passive	Active
Surface	28 539	6763	72	35 142	232	1	20 215	0	0
Passive	46	66 846	0	321	66 571	0	2137	31 471	0
Active	44	114 433	9352	291	118 348	5190	322	5841	8548
Total feasible			226 096			226 096			68 534
Total feasible and effective			114 523			118 960			8300

Table 4. Optimisation model parameters

Mean and range (in parentheses) of model parameters for catchments with feasible and effective area to treat. USD is US dollars

Treatment type	Catchments with feasible and effective area	Feasible and effective area (ha)	Risk reduction (USD ha^{-1})	Treatment cost (USD ha^{-1})	Benefit : cost ratio
Thinning only	1334	86.3 (0.1–1070)	48.5 (0–538)	6850 (6178–16 870)	0.0068 (0.0000–0.0622)
Thinning and Prescribed fire	1342	89.2 (0.1–1165)	49.0 (0–521)	9350 (8650–19 350)	0.0051 (0.0000–0.0475)
Prescribed fire	978	8.5 (0.1–182)	31.9 (0–434)	2471 (2471–2471)	0.0129 (0.0000–0.1757)

Table 5. Optimisation model performance metrics

Performance metrics for optimal fuel treatment plans for budgets of 50 to 500 million US dollars (USD) assuming a 10-ha minimum area for thinning, a 20-ha minimum area for prescribed fire, and no more than 30% of a catchment can be treated

		Budget (USD millions)									
		50	100	150	200	250	300	350	400	450	500
Risk reduction (%)		12.2	19.4	24.7	28.4	30.9	32.4	33.4	33.9	34.2	34.3
Risk reduction (USD millions) for percentiles of post-fire rainfall erosivity	5th	0.53	0.85	1.08	1.24	1.35	1.42	1.46	1.48	1.49	1.50
	25th	1.08	1.71	2.17	2.50	2.72	2.85	2.93	2.98	3.01	3.02
	50th	1.56	2.48	3.15	3.63	3.95	4.14	4.27	4.33	4.37	4.39
	75th	1.08	1.71	2.17	2.50	2.72	2.85	2.93	2.98	3.01	3.02
	95th	5.85	9.29	11.78	13.58	14.77	15.50	15.95	16.20	16.34	16.40
Benefit : cost ratio		0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01
Return on investment (%)		−96.87	−97.52	−97.90	−98.18	−98.42	−98.62	−98.78	−98.92	−99.03	−99.12
Catchments (no.)		87	161	251	340	432	513	582	639	695	746
Catchments × treatment type (no.)		101	200	328	461	607	736	819	885	950	991
Total treatment (ha)		7159	14 407	21 788	29 049	35 776	42 626	48 305	53 233	58 398	61 801
Thinning only (ha)		6668	13 254	20 116	26 618	31 844	37 479	38 970	37 967	36 989	30 259
Thinning and prescribed fire (ha)		71	190	356	865	2262	3502	7915	14218	20576	31 060
Prescribed fire only (ha)		421	963	1316	1565	1670	1644	1420	1047	832	481

the main stems of the CLP and BT rivers and near C-BT reservoirs (Fig. 8). As budget increases, fuel treatments expand to areas that are not as strongly connected to water supplies (Fig. 8).

The prescribed fire treatment is not often selected, despite its higher cost-effectiveness, because few catchments have >20 ha of feasible and effective area to treat with prescribed fire (Table 5). Hence, the thinning-only treatment is favoured at lower budget levels (Table 5). The model prioritises thinning on steep slopes because of the predicted high post-fire erosion rates despite the increased cost of thinning in these areas; the mean thinning cost for the 10 million USD budget was 8100 USD ha^{-1}, which is 31% higher than the base cost. As budget increases beyond 250 million USD, much of the marginal gain in risk reduction is made by converting thinning or prescribed fire treatments to the combined treatment (Table 5). The total estimated risk reduction from treatment is small compared with

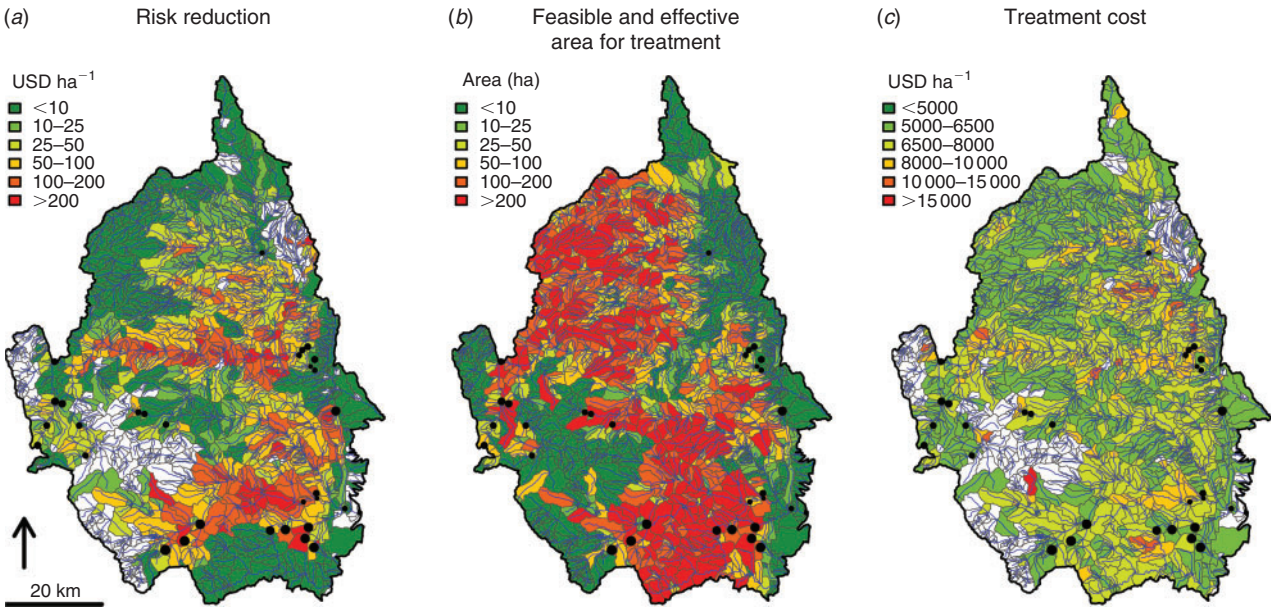

Fig. 7. Catchment-level statistics for the thinning-only treatment used to parameterise the optimisation model. Catchment mean risk reduction (*a*), and treatment cost (*c*) are calculated for the feasible and effective area to treat in each catchment (*b*).

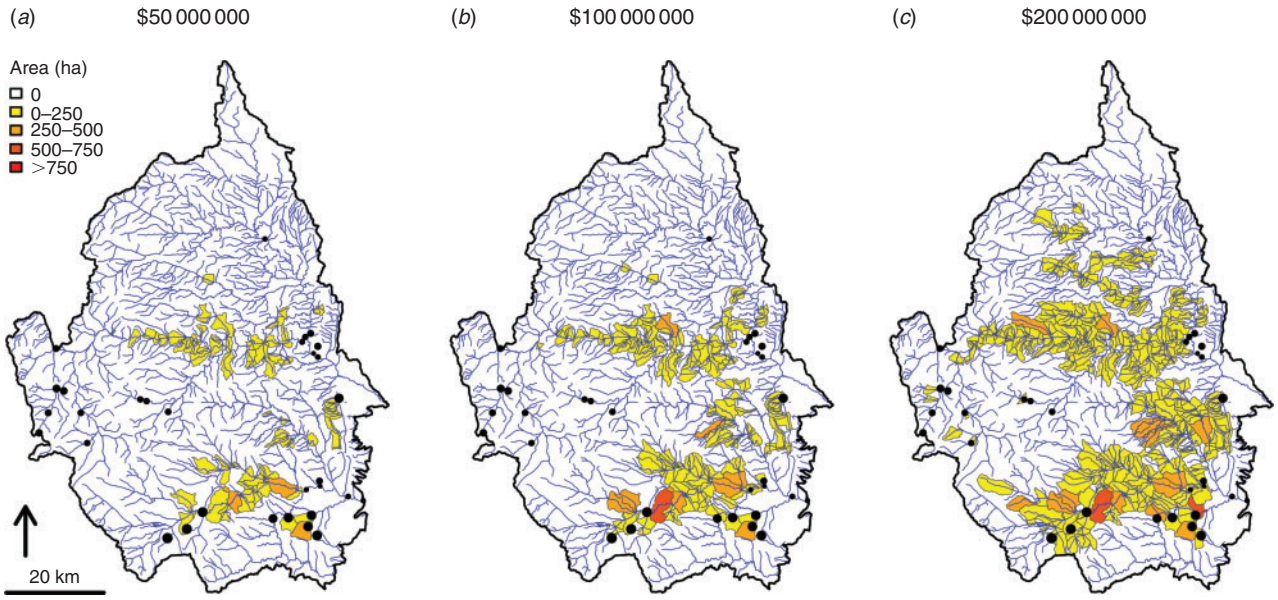

Fig. 8. Example optimal landscape fuel treatment plans for (*a*) 50 million (*b*) 100 million and (*c*) 200 million USD budgets using a 10-ha minimum area for thinning, a 20-ha minimum area for prescribed fire, and a maximum 30% treated area in each catchment. Areas are the sum of all treatments in each catchment.

the total cost of fuels reduction across all budget levels and percentiles of rainfall erosivity (Table 5).

Discussion

Combining quantitative measures of risk reduction with fuel treatment constraints facilitates fuel treatment targeting and realistic assessment of fuel treatment benefits. Our analysis extends common risk assessment methods (Scott *et al.* 2013) with a spatial topology and effects modelling framework (Fig. 1 and Fig. 3) that provides quantitative measures of risk for whole water systems (Fig. 6). These risk assessment methods should be useful for communities with large source watersheds and multiple water supplies. Our fuel treatment assessment and optimisation approach provides more information than a spatial wildfire risk assessment (e.g. Scott *et al.* 2013). By modelling fuel treatment effects on fire behaviour and water supply consequences, accomplishments can be reported in terms of avoided sediment (Mg) or risk reduction (USD), rather than area treated

(USDA Forest Service 2018). Our fuel treatment optimisation model demonstrates the potential to meaningfully reduce wildfire risk to water supplies by treating a small portion of the forested area (Table 5; Fig. 8). For example, in this study area, it was previously estimated that 190 000 ha of the CLP and BT require fuels reduction based on vegetation condition (Talberth *et al.* 2013), but we estimate that treating only 35 800 ha can address 90% of the feasible risk reduction (31% of total risk) assuming that no more than 30% of each catchment can be treated. Greater risk reduction is possible (54% of total) if we assume entire catchments can be thinned for water supply protection, but at much greater expense. Our analysis also demonstrates that it is more efficient to reduce fuels on erosion-prone steep slopes despite the higher cost of treatment. Fuel treatment targeting may be improved in similar landscapes by integrating fuel treatment feasibility and cost constraints into the prioritisation process. The availability of tools to assess baseline risk and fuel treatment benefits (Fig. 6; Table 5) should help groups engaged in fuels reduction for water supply protection define clear risk reduction goals and treatment priorities (Ozment *et al.* 2016).

We estimate wildfire risk to water supplies in the CLP and BT at 12.8 million USD over the next 25 years based on median rainfall erosivity, which is approximately half of the ~26 million USD cost Denver Water incurred from the Buffalo Creek and Hayman fires (Jones *et al.* 2017). This difference can be attributed to the much higher than median rainfall at Buffalo Creek that caused massive hillslope and channel erosion (Moody and Martin 2001) and the lower values assigned to water supply sediment impacts in the CLP and BT. The mean sediment impact cost in the present study was 18.1 USD Mg^{-1}, which is much lower than the 62.5 USD Mg^{-1} Denver Water paid to dredge Strontia Springs after the Buffalo Creek and Hayman Fires (Jones *et al.* 2017). The three municipal water providers we studied all have multisource systems, which provides flexibility to cope with wildfire impacts (Oropeza and Heath 2013). Communities with single-source water systems are likely to value wildfire-related sediment impacts more highly than we do here.

Our results suggest the avoided costs to water supplies from fuels reduction are less than the cost of treating fuels, which is consistent with a similar study of the Mokelumne Watershed in the Sierra Nevada of California (Buckley *et al.* 2014; Elliot *et al.* 2016). Our estimated rates of return for fuel treatment (Table 5) are similar in magnitude but slightly higher than the 1 million USD avoided sediment impacts to water supplies for 68 million USD of fuels reduction reported by Buckley *et al.* (2014). Our higher returns could be due to more efficient prioritisation, higher-value water supplies, or differences in risk assessment methods. The similarity in our results, despite differences between our sites and assessment methods, suggests it may be challenging to demonstrate a positive return on investment from proactively managing forest fuels to protect water supplies from post-fire sediment. Fuel treatments are only predicted to yield a positive return on investment from avoided sediment when per-unit sediment impacts are expensive and assuming that fuel treatments will be exposed to both extreme wildfire and extreme rainfall (Jones *et al.* 2017), which may be rare events in some watersheds.

It should be recognised that although our methods integrate key components of wildfire risk to water supplies, some compromises and assumptions were required to make the assessment tractable. Our measure of water supply risk is based on the likelihood of fuel treatment encountering wildfire over 25 years using modelled burn probability (Short *et al.* 2016) calibrated to historical rates of burning (Finney *et al.* 2011). Increasing fire frequency, however, has the potential to magnify wildfire risk to water supplies (Sankey *et al.* 2017) and therefore increase the value of proactive fuels reduction. Additionally, our narrow focus on sediment impacts likely underestimates wildfire risk to water supplies and undervalues the full suite of fuel treatment benefits. For example, we did not account for potential reductions in post-fire watershed rehabilitation spending, or avoided costs related to non-sediment water quality degradation. We also did not account for the potential benefit of fuel treatments reducing burn probability. A similar study in Oregon suggests a large fuel treatment program may reduce annual area burned by up to 25% within treated areas, but by less than 10% across a large landscape. We chose not to quantify these effects owing to the computational demands of burn probability modelling and uncertainty in whether potentially greater grass and shrub production in thinned forests could increase burn probability (Reinhardt *et al.* 2008).

In the present study, we did not account for the sediment generated from increased erosion from the fuel treatments or the associated increases in traffic, road maintenance or road building. The highest-priority locations for fuel treatments are steep, erosion-prone slopes that are close to main stream channels, meaning that any increase in erosion is likely be transmitted downslope into the stream and then to the water supplies. A small increase in erosion over the no-treatment scenario (~3%) was predicted from similar fuel treatments in California (Elliot *et al.* 2016). In Colorado, thinning treatments retained close to 80% surface cover (Libohova 2004), which should minimise increases in erosion from the treatments themselves (Larsen *et al.* 2009), but it is possible that heavy equipment use on steep slopes will cause greater surface disturbance and erosion. Prescribed fire could increase erosion but limiting the extent and patch size of areas burned at high and moderate burn severity should result in little or no increases in erosion and hillslope transport to streams (Benavides-Solorio and MacDonald 2005). Much larger increases in sediment production would be expected from increasing traffic on unpaved roads (Sosa-Pérez and MacDonald 2017), grading existing roads or building new roads (Libohova 2004). We did not account for new road construction here because we assumed thinning operations would use the existing road network and costs would increase with skidding distance (Eqn 18). Treatment-related sediment may be important to consider if it has the potential to exacerbate chronic sediment issues, such as reservoir sedimentation, but it may be of minor importance if acute sediment impacts following wildfire are the primary concern.

The high cost of forest thinning is often a major barrier to wildfire risk reduction and forest restoration in the western USA (North *et al.* 2015). This is especially true in our study watersheds owing to challenging terrain and the limited market for small-diameter materials. It may be possible to offset some of the treatment costs by harvesting large trees, but harvesting

larger and older trees is often controversial (e.g. Sánchez Meador *et al.* 2015) and can be counter to fuel treatment objectives (Agee and Skinner 2005; Reinhardt *et al.* 2008). Despite higher treatment costs, we found it is more efficient to thin forests on erosion-prone steep slopes. Our analysis also shows that prescribed fire is the most-cost effective and least-feasible treatment in these watersheds (Table 4). In the absence of local data, we based our prescribed fire effects (Table 1) on research from more productive forests with larger trees (Stephens and Moghaddas 2005). This may underestimate prescribed fire effects on canopy fuels in the shorter-statured forests of the Colorado Front Range. Prescribed fire feasibility would also increase if managers accept the potential for more extreme fire behaviour in remote areas, or where there are barriers to fire spread protecting highly valued resources or assets. More accurate definition of prescribed fire constraints would help to identify where limited investments in thinning could expand the application of prescribed fire or managed wildfire for resource benefit.

Model limitations and research needs

Linked fire–erosion–sediment transport models can provide quantitative fire effects measures, but it is important to recognise the uncertainties from linking models (Elliot *et al.* 2016; Jones *et al.* 2017), the imperfect predictive performance of erosion models (Larsen and MacDonald 2007) and the high variability in sediment transport (Wagenbrenner and Robichaud 2014). Our use of CFA as a proxy for fire severity limited our ability to resolve fuel treatment effects. More precise methods for simulating fuel treatments and predicting fire behaviour could better differentiate treatment effects, especially for combined thinning and prescribed fire treatment (Martinson and Omi 2013). Previous studies accomplished the link between fire and erosion using predicted fire behaviour (Elliot *et al.* 2016; Jones *et al.* 2017) or more detailed ecological models (Miller *et al.* 2011; Sidman *et al.* 2016). Confidence in these methods would improve with more understanding of the first-order fire effects on soils in relation to fire intensity, heat per unit area and residence time (Moody *et al.* 2013; Shakesby *et al.* 2016).

Our hillslope erosion estimates were comparable with field-measured values, with the notable exception of some very high predicted values for very steep slopes (Fig. 5). This issue may be addressed by process-based erosion models such as WEPP or KINEROS (e.g. Elliot *et al.* 2016; Miller *et al.* 2016; Sidman *et al.* 2016; Jones *et al.* 2017). The precision of GIS RUSLE could be improved for erosion prediction in steep mountain topography with higher-resolution elevation data and alternative flow-routeing algorithms to avoid the long flow paths mapped by the D8 algorithm on near-planar slopes. Current methods to calculate the LS factor also assign high erosion rates to areas of convergent flow, which may be appropriate (Winchell *et al.* 2008), but should be validated with field data from forests. It is also possible that RUSLE correctly predicts high erosion potential on steep slopes, but sediment yields should be adjusted to reflect sediment supply limitations due to poorly developed soils. Data to validate erosion and sediment transport models beyond the hillslope scale are needed to test the accuracy of these approaches and inform model improvements. We provided only a cursory analysis of post-fire rainfall because of its high spatial and temporal variability and therefore low utility for spatially characterising risk. Ideally, a full accounting of risk would consider joint probabilities of fire occurrence, severity and post-fire rainfall conditions over several years of recovery (e.g. Jones *et al.* 2014).

We also did not discount avoided sediment impacts to net present value. Assuming an equal probability of burning for each year over the 25-year planning period and a 3% interest rate, discounting would reduce our risk reduction estimates by ~30%. For practical reasons, we used burn probability to represent the spatial and temporal variability in wildfire occurrence (Scott *et al.* 2013), which limits our ability to quantify wildfire consequences that are tied to fire and rainfall event magnitudes, such as exceeding turbidity thresholds for water treatment (Oropeza and Heath 2013; Hohner *et al.* 2017). Simulation-based risk analysis methods (Thompson *et al.* 2016; Haas *et al.* 2017) could be used to better quantify the fuels reduction effects on fire event consequences and probabilities for exceeding thresholds of impact.

Management implications and future directions

Spatial optimisation of fuel treatments can improve the efficiency of fuels reduction for water supply protection. However, fuel treatment is not expected to produce a positive return on investment when only considering avoided sediment impacts to water supplies (present study; Buckley *et al.* 2014; Elliot *et al.* 2016). Wildfire risk assessment is an important first step to appraise risk and develop risk reduction goals. Evaluating fuel treatment effects can inform whether fuels reduction should be part of a risk mitigation strategy and where in the watershed it will be most effective. Other assessments have suggested that most of the economic benefit of fuel treatment is from reduced suppression costs and avoided damage to homes and infrastructure (Talberth *et al.* 2013; Thompson *et al.* 2013*c*; Buckley *et al.* 2014). Water providers are often interested in these and other co-benefits of fuels reduction (Jones *et al.* 2017). In many cases, public agencies will match the investments made by water providers to achieve these other benefits (Ozment *et al.* 2016), which improves the cost-effectiveness of fuel treatment from the water provider perspective. Identifying where water supply protection goals align with other ecosystem restoration, risk reduction and fire management objectives may provide opportunities to further leverage funding. Ideally, fuel treatment contributes to landscape conditions that allow more natural or prescribed fires to maintain and expand the footprint of low-fuel conditions. Efforts to identify where limited investments in forest thinning will support the use of prescribed or managed fire may be more cost-effective than using it alone as an area-wide treatment. Coordination among forest and fire managers is needed to understand how and where fuels reduction can facilitate more beneficial fire on the landscape.

Conclusions

Our study suggests that combining fuel treatment effectiveness measures and constraints in an optimisation framework can improve fuel treatment targeting for water supply protection. Moreover, the model facilitates program-level assessments of potential risk reduction and fuel treatment costs, which can help

interested stakeholders frame risk reduction goals and evaluate the efficacy of fuels reduction compared with alternative risk reduction strategies. Although there are uncertainties in the model assumptions and data used to evaluate the risk reduction to water supplies from fuel treatments, the results show that the risk reduction benefits are much smaller than the cost of treatment in our two study watersheds in Colorado. This raises questions about the economic efficiency of area-wide fuel treatment to reduce wildfire risk to water supplies and points to the need to both expand more cost-effective fuel treatment methods and identify where water supply protection priorities overlap with other wildfire risk reduction and ecological restoration objectives.

Conflicts of interest

The authors declare no conflicts of interest.

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