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VIII. Deliverables Cross-Walk

Proposed	Delivered	Status
Data transfer interfaces between MAGIS, FlamMap and FVS-FFE that automate and integrate model information.	OptFuels application interfaces that include windows data entry forms, program procedures, and a recommended method for using FVS-ready data for landscape-level vegetation and fuels simulation.	Prototypes ready 2008. See Integrated DSS entry below.
Heuristic optimizer that integrates resource issues/economics with fire behavior projections for various treatment options.	C++ executable. Requires multiprocessor machine for reasonably timely results. Prototype FIREMAGIS.exe	1. First version integrated with OptFuels October, 2009. 2. Solver is functional Feb. 2010. 3. In Progress: testing with different data sets.
Integrated decision support system (DSS) with enhanced solution display to optimize fuel management schedules with enhanced GIS-based solution displays for MTT results.	Decision support system that integrates GIS, FVS-FFE, and FlamMap as a single user-driven application (OptFuels). Generates optimal feasible schedule of fuel treatments. Outputs GIS maps and files of solutions. Outputs FlamMap FMP file to allow user to run MTT on solution landscape files.	Complete (beta) version with working interfaces and procedures. Solutions can be analyzed with MTT and ArcGIS. In progress: solution reports and procedures for GIS statistics.
Test models using data from National Forest(s) with input from local management for resource objectives and constraints.	Test models from Bitterroot National Forest analyses: Willow-Gird and Trapper-Bunkhouse.	1. Trapper-Bunkhouse, September 2008. 2. Willow-Gird, May 2009. 3. Maps posted on JFSP website.
Workshops with field managers: 1. Gather feedback on proposed system 2. Present system to potential users	1. 'FIREMAGIS' workshop held September 2008. 2. Workshop scheduled April 2010.	1. Powerpoint presentation on JFSP website.
JFSP reports	Annual and final reports.	Completed, posted on JFSP website.
Publications and Presentations 1. Development. 2. Effects of budget constraints.	1. OptFuels: Optimizing Placement of Fire and Non-fire Fuel Treatments over Time at Landscape Scales.	1. Paper presented at AFE 4 th International Congress on Fire Ecology & Management. Savannah, GA Nov 30- Dec 4, 2009.

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	2. Developing a Decision Support System to Optimize Spatial and Temporal Fuel Treatments at a Landscape Scale. 3. OptFuels: A decision support system to optimize spatial and temporal fuel treatments. 4. Effects of budget constraints on optimal hazardous fuel reduction treatment scheduling using fire behavior modeling.	2. Paper presented at Council on Forest Engineering, Kings Beach, CA June 15-18 2009. 3. Presented at the 13th Symposium on Systems Analysis in Forest Resources, Charleston, SC May 26-29, 2009. 4. In progress.
DSS Technology transfer: Website and User Documentation with active tutorials. DSS Distribution System for Software Delivery: Installation package and software delivery system (ftp and website for downloads and updates).	1. Project website: www.fs.fed.us/rm/human-dimensions/optfuels 2. Draft user guide and tutorial: www.fs.fed.us/rm/human-dimensions/optfuels/OptFuelsUsersGuide.pdf	1. Project Website live. 2. In progress: Userguide (draft manual posted), context-sensitive help, tutorials, installer.
Other Presentations / Posters.	1. Spatial and Temporal Optimization of Fuel Treatments. 2. OptFuels: Optimizing Placement of Fire and Non-fire Fuel Treatments over Time at Landscape Scales. 3. Fire-MAGIS: A Decision Support System to Optimize Spatial and Temporal Fuel Treatments at Landscape Scales. 4. Optimizing Spatial and Temporal Treatments to Maintain Effective Fire and Non-fire Fuels Treatments at Landscape Scales.	1. Poster presented at the 5th Biennial Lake Tahoe Basin Science Conference, Incline Village, NV, March 16-17, 2010. 2. Poster presented at AFE 4th International Congress on Fire Ecology & Management. Savannah, GA Nov 30- Dec 4, 2009. 3. Poster presented at IUFRO All-D3 Conference, Sapporo Japan, June 15-20, 2008. 4. Poster presented at International Mountain Logging and 13th Pacific Northwest Skyline Symposium, Corvallis OR April 1-6 2007.

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	5. Optimizing Spatial and Temporal Treatments to Maintain Effective Fire and Non-fire Fuels Treatments at Landscape Scales	5. Poster presented at 2 nd Fire Behavior and Fuels Conference, Destin, FL March 26-30, 2007
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EXHIBIT F

Effects of fuel spatial distribution on wildland fire behaviour

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Abstract. The distribution of fuels is recognised as a key driver of wildland fire behaviour. However, our understanding of how fuel density heterogeneity affects fire behaviour is limited because of the challenges associated with experiments that isolate fuel heterogeneity from other factors. Advances in fire behaviour modelling and computational resources provide a means to explore fire behaviour responses to fuel heterogeneity. Using an ensemble approach to simulate fire behaviour in a coupled fire–atmosphere model, we systematically tested how fuel density fidelity and heterogeneity shape effective wind characteristics that ultimately affect fire behaviour. Results showed that with increased fuel density fidelity and heterogeneity, fire spread and area burned decreased owing to a combination of fuel discontinuities and increased fine-scale turbulent wind structures that blocked forward fire spread. However, at large characteristic length scales of spatial fuel density, the fire spread and area burned increased because local fuel discontinuity decreased, and wind entrainment into the forest canopy maintained near-surface wind speeds that drove forward fire spread. These results demonstrate the importance of incorporating high-resolution fuel fidelity and heterogeneity information to capture effective wind conditions that improve fire behaviour forecasts.

Keywords: fire behaviour modelling, fuel classification, fuel representation, wind response.

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Introduction

It is exceedingly difficult to know *a priori* if a wildland fire will extinguish, or spread and contribute to the annual 36 to 46 million km² burned globally (Doerr and Santin 2016). Nevertheless, this knowledge is critical for forecasting if a wildland fire will meet management targets or for guiding management response to fires that endanger lives and property. A combination of environmental factors – including wind, topography, fuel moisture, and the amount and arrangement of fuel – determine wildland fire behaviour. For example, the spatial distribution of fuel heterogeneity, which determines the arrangement of combustible material and local wind flows, significantly influences fire behaviour (Turner and Romme 1994; Finney 2001; Knapp and Keeley 2006; Parsons *et al.* 2017). Simulated wind conditions, coupled to fire interacting with heterogeneous forest canopies, show that fire behaviour is affected by fuel structure (Pimont *et al.* 2011; Linn *et al.* 2013; Hoffman *et al.* 2015; Parsons *et al.* 2017; Ziegler *et al.* 2017). However, studies that systematically characterise the sensitivity of fire behaviour to fuel heterogeneity are

absent owing to poorly described fuel conditions and computational or experimental costs. Therefore, the response of fire behaviour to fuel arrangement remains poorly quantified, which limits estimates of fire outcomes.

Over the past two decades, a growing breadth of fire scenarios – ranging from prescribed fires in marginal conditions to high-intensity wildfires – and the increasing availability of computational resources have motivated the development of coupled fire–atmosphere models, such as WFDS (Mell *et al.* 2007, 2009; Bova *et al.* 2016), FIRESTAR3D (Frangieh *et al.* 2018; Morvan *et al.* 2018), FIRETEC (Linn 1997; Linn *et al.* 2002) and QUIC-Fire (Linn *et al.* 2020). These models resolve wind fields that are consistent with local heterogeneous vegetation structure and respond to dynamic two-way feedbacks between the fire and surrounding winds that compare well with observations (Linn and Cunningham 2005; Linn *et al.* 2012; Hoffman *et al.* 2016). By simulating wind flows and explicitly accounting for shear stress through canopy structures, including intermittent gusts and lulls that result from gaps between groups of trees (Pimont *et al.* 2009), fire

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behaviour simulations respond to the aerodynamic influences of canopy structure and the spatial heterogeneity of vegetation and buoyant heat from combustion. Although many of these models are too computationally expensive for operational use, they allow a fully three-dimensional description of the forest. The development of this class of models now lets us test how sensitive simulated fire behaviour is to representation of fuel and the characterisations of fuel heterogeneity, especially for low-intensity fires that are more sensitive to fuel arrangement compared with high-intensity fires (Clements *et al.* 2016).

Discontinuities in the horizontal distribution of canopy fuels associated with large-scale heterogeneities create wind patterns (Dupont and Brunet 2007) that influence fire behaviour. Forest structure affects the fire environment by determining: (1) the distribution of combustible material; (2) the ambient flow patterns through and around vegetation (Gao and Shaw 1989; Finnigan 2000; Pimont *et al.* 2011); and (3) the response of winds to the heat released during the fire (Kiefer *et al.* 2018). Canopy heterogeneity increases the spatial and temporal variation in the wind field within and just above the canopy, with the intermittent sweeping of fast-moving air down into the canopy and the ejection of slow-moving air upward out of the canopy (Kiefer *et al.* 2016; Kiefer *et al.* 2018; Moon *et al.* 2019). The aggregated effects of this turbulence alter the mean wind shear above (Dupont and Brunet 2008), within and below the canopy. Likewise, the distribution of fuels influences the spatial patterns of winds that can be drawn in by the fire and fire-influenced winds that feed back to fire behaviour (Kiefer *et al.* 2018).

Variability in wind conditions associated with boundary-layer turbulence and wind–canopy interaction is recognised as a chief contributor to uncertainty in fire behaviour (Burrows *et al.* 2000; Sun *et al.* 2009; Linn *et al.* 2012; Pinto *et al.* 2016; Benali *et al.* 2017). Atmospheric turbulence is amplified when winds interact with fire (Clements *et al.* 2008), increasing uncertainties in fire behaviour simulations, especially under marginal fire conditions (Hiers *et al.* 2020) when fire-influenced winds are significantly stronger than ambient winds. This complicates the ability to measure how forest heterogeneity interacts with fire-influenced winds to affect fire behaviour.

Given the influence of canopy structure on ambient and fire-induced winds, it is essential to explicitly account for the effects of canopy structure when exploring the interaction between forest structure and fire behaviour (Hilton *et al.* 2015). Nevertheless, the effects of forest heterogeneity on the variability of fire behaviour have not been quantified adequately (Parsons *et al.* 2017) because few studies systematically account for increasing levels of fuel variability. Therefore, a generalised understanding of how spatial fuel characterisation determines fire behaviour is lacking. By identifying how fuel heterogeneity influences fire behaviour and describing essential aspects of fuel heterogeneity, simulated uncertainty and fire behaviour variability can be constrained.

To determine the influence of vegetation structure on fire behaviour, an analysis of ensembles of simulations is required to avoid confounding mean behaviour with the influences of site and moment-specific conditions (Parsons *et al.* 2017). Fire behaviour at a specific location in time and space is a function of the site and moment-specific environmental conditions, including the local arrangement of fuels and timing of gusts

relative to the fire's arrival at that location. The absence of precise knowledge of fuel locations or relative timing of fires and wind events limits predictability (Pimont *et al.* 2017). Ensembles of vegetation scenarios with the same macro-scale characteristics (e.g. canopy bulk density) but different fine-scale characteristics (e.g. the position of individual trees) can help (1) determine the sensitivity of fire behaviour to fine-scale fuel characteristics, and (2) quantify the uncertainty associated with fire behaviour forecasts. By performing ensemble simulations with a physics-based model of combined dynamic winds and fire behaviour, we can quantify both the mean and variability in fire behaviour associated with macro-scale fuel heterogeneity. Likewise, an ensemble approach provides a measure of fire behaviour uncertainty within constrained conditions (Pinto *et al.* 2016) that can inform fuel management planning and risk assessment frameworks for operational use (Ager *et al.* 2011; Finney *et al.* 2011). Increasingly, probabilistic ensemble methods have also been shown to elicit fundamental behaviour within complex fire models that account for non-linear processes (Cruz and Alexander 2017). To discern fire behaviour sensitivity to details of fuel heterogeneity, ensembles of multiple fuel beds that have the same domain fuel load and spatial characterisation of the variance of fuel density are required. Here, we investigated the sensitivity of fire behaviour simulations in FIRETEC to spatial characterisation of fuel arrangement. Virtual canopies with the same macro-scale characteristics but different degrees of detail in representation were developed to perform ensemble fire behaviour simulations.

Methodology

We used FIRETEC, a mechanistic fire–atmosphere model, to investigate how the representation and heterogeneity of fuel influence simulated fire behaviour. We generated ensembles of virtual forest canopies based on field measurements from a 50 × 20-m ponderosa pine (*Pinus ponderosa*)-dominated plot near Flagstaff, AZ, with 860 trees ha^{−1}, a mean diameter at breast height (DBH) of 23 cm and a mean tree height of 14 m (Linn *et al.* 2005). Each ensemble features identical macro-scale characteristics, including domain average and vertical profiles of fuel density (0.083 kg m^{−3}) (Fig. 1, plot (a)), average tree height, and average height to live crown, but with different variance and spatial characterisation of fuel conditions. We conducted a total of 101 simulations, including 20 replicates each of five different heterogeneous fuel distributions, and an unreplicated simulation with a homogeneous fuel distribution (Average Fuel). We explored the spectrum of fuel fidelity starting with the low-fidelity homogeneous or Average Fuel case. The five heterogeneous fuel scenarios represent a stepwise increase in fuel fidelity and length scales of fuel heterogeneity representation. They are: (1) Average Tree, with one representative tree randomly replicated across the domain (no difference between trees); (2) Forest Data, with variable trees, whose attributes match field data, randomly placed across the domain; (3) 15-m Gaps, with the same fuel fidelity as Forest Data, but with trees aggregated to create 15-m gaps; (4) 30-m Gaps, same as Forest Data, with trees aggregated to create 30-m gaps, and (5) 45-m Gaps, same as Forest Data, with trees aggregated to create 45-m gaps. In each simulation, the total fuel load was held constant, and only the

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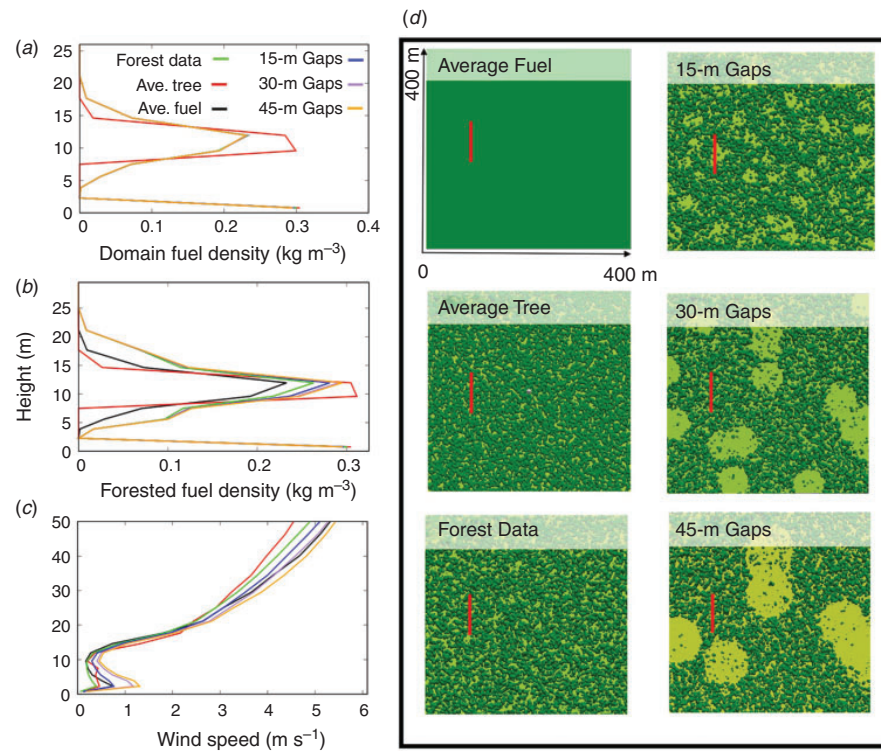


Fig. 1. (a) Domain-average vertical fuel density profiles for each ensemble; note that all ensembles except Ave. Tree overlap. (b) Vertical fuel density profiles averaged over areas with canopy fuel densities above zero. Note that excluding areas where vertical fuel density equalled zero resulted in a gradation of fuel density with increased fuel variance. Domain fuel density equalled 0.083 kg m^{-3} for all ensembles, and variation of canopy fuel density plotted was due to differences in tree density for the areas with trees. (c) Ensemble-average u wind (streamwise velocity) profiles to 50 m above the surface before ignition. (d) Example fuel domains for each of the six ensembles. Red lines denote the fire ignition locations.

Table 1. Domain fuel load characteristics

Representation class (Ensemble)	Fuel density variance	Fuel density correlation length (m)
Average Fuel	0	0
Average Tree (1)	0.188	1
Forest Data (2)	0.299	2
15-m Gaps (3)	0.359	10
30-m Gaps (4)	0.364	27
45-m Gaps (5)	0.377	40

arrangement of the trees was altered. The 20 replicates were developed by rerandomising tree and gap locations. All simulations were performed in 400×400 -m domains with 2-m horizontal discretisation to a height of 600 m. Domain fuel density was defined as the total mass of fuel within the $160\,000\text{-m}^2$ domain between the ground and 22.9 m, top of the highest cell containing fuel. We established a gradient of fuel density variability between the ensembles, starting with $0 (\text{kg m}^{-3})^2$ for the Average Fuel ensemble and increasing to $0.377 (\text{kg m}^{-3})^2$ for the

45-m Gap ensemble (Table 1). Likewise, there was a gradient of increasing lengths at which deviations from the local fuel load were no longer similar (correlation lengths).

We developed a different 3D fuel density arrangement for each replicate within each ensemble using values for tree height, crown radius and height to live crown obtained from data. For the Forest Data ensemble, the distribution of fine fuel in the canopy was parameterised following the methods outlined by Linn *et al.* (2005), where sampled trees and their dimensions were randomly placed throughout the domain to maintain observed stem density and forest characteristics. We developed the Average Tree virtual forest realisations by first estimating the mean tree height, height to live crown and crown circumference, and then randomly populating the domain with trees that had these properties. Note that populating the domain with a single-tree representation resulted in slightly different vertical profiles of fuel density (Fig. 1a). To develop the Average Fuel realisation, we computed the vertical distribution of fuel by horizontally averaging every vertical layer in the Forest Data domains. This vertical distribution was then applied to every x and y location to establish a horizontally homogeneous forest with the same vertical distribution of fuel density as for the

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Forest Data cases. Because there was no spatial variation in the Average Fuel realisation, only one ensemble member was used. For the 15-, 30- and 45-m Gap ensembles, we randomly selected locations for gap creation. All trees within the gap were then moved to a new random location, which might be placed back in the gaps, thus ensuring that the overall fuel load and canopy density was maintained among ensembles. This approach effectively decreased the fuel density within the designated patches and increased the fuel density in other areas (Fig. 1b), which mimics the structure found in forests with natural disturbances (Lindenmayer and Franklin 2002; Mitchell *et al.* 2006).

We parameterised surface fuels assuming that grass dominates in the spaces between trees, and litter accumulates and diminishes grass loads beneath trees. We used a grass fuel density of 0.35 kg m^{-3} , which had a height of 0.7 m, and a litter fuel density of 0.5 kg m^{-3} , which had a maximum litter depth of 10 cm under dense trees. The spatial distribution of grass and litter contributed to the overall domain fuel density variance and spatial gradients of fuel density variance. As described in Linn *et al.* (2005), the total fuel loads in surface cells included contributions from grass, litter, and short trees that reached into the lowest computational cell. The aggregated fuel properties of the combined surface fuels (e.g. moisture and height) were determined via a mass-weighted average. We observed no difference in domain surface fuel density between ensembles (Fig. 1a; all lines overlap below 2 m).

Fire simulations

To represent wind conditions characteristic of a given ensemble, turbulent structures need to develop in response to the simulated forest structure from an initial inflow boundary condition, which generally requires simulations to include a long fetch area. To reduce the size of the computational domain, we used the methodology described in Pimont *et al.* (2020). A large-scale pressure gradient force and cyclic boundary conditions, where winds exiting the domain are cycled back as inflow into the domain, create the long fetch necessary for turbulence to adjust to the ensemble fuel structure. This results in turbulent structures evolving within the model domain to be spun up and used as inflow boundary conditions during the fire simulation. We developed ensemble-specific wind fields using a single representative fuel arrangement for each ensemble. A 3-m s^{-1} streamwise wind speed (u) was specified at 25 m above the ground, ~ 10 m above the canopy that accompanied an initial log profile wind speed with height. This fairly low wind speed was chosen to represent marginal fire spread conditions. The winds and turbulence were spun up in this manner for 500 s, at which time the mean vertical velocity profile and the turbulence profiles ceased to change with time. Using the cyclic boundary condition mode, we simulated turbulent winds for each ensemble type for an additional 20 min as forcing conditions for the combustion simulations.

Each realisation within a given ensemble used the same representative forcing conditions but resulted in different wind profiles, as determined by the specific drag imparted by the characteristic spatial fuel arrangement of that ensemble (Fig. 1). These forcing conditions were applied for an additional 400 s before the time of ignition so that the flow field could adjust to the specific vegetation distribution. Ignition in each simulation

was achieved by bringing surface and canopy fuels up to combustion temperatures (1000 K) for 3 s in a 100-m-long and 4-m-deep rectangular area located 100 m from the upwind domain boundary. The idealised ignition method is intended to ensure each realisation starts with a similar region of combustion. Not including the model spin up, each realisation required 64 processors and 16 h of wall-clock time to simulate combustion, resulting in 103 524 CPU hours for all combustion simulations. Spinning up wind fields for all ensembles required an additional 12 288 CPU hours.

Fire and wind behaviour metrics

For each ensemble and realisation, we calculated the forward rate of fire spread, heat release per unit area and the total area burned. We calculated the spread distance for each fire to be the farthest distance of the fire front from the ignition line along the streamwise wind direction (u) and plotted it against time to evaluate the forward rate of fire spread. Heat release per unit area is the total amount of energy released by combustion per second divided by the area of the fire, and therefore has units of kilowatts per metre squared. The area burned was estimated as the total area of the domain where combustion (i.e. loss of fuel mass) occurred projected onto a 2D plane. We quantified domain wind conditions in terms of turbulence kinetic energy (TKE), which is a measure of the energy associated with fluctuations in the wind field shear stress. TKE was calculated by summing the variances of the directional wind component:

$$\text{TKE} = \frac{1}{2} ((u'u') + (v'v') + (w'w')) \quad (1)$$

where:

$$\begin{aligned} u'u' &= \frac{1}{t} \int_0^t (u_{(t,i,j)} - \bar{u}_{(i,j)})^2 dt \\ v'v' &= \frac{1}{t} \int_0^t (v_{(t,i,j)} - \bar{v}_{(i,j)})^2 dt \\ w'w' &= \frac{1}{t} \int_0^t (w_{(t,i,j)} - \bar{w}_{(i,j)})^2 dt \end{aligned} \quad (2)$$

Here, u is the streamwise horizontal wind component, v is the cross-stream horizontal wind component, w is the vertical wind component, i and j are the indices of specific cells, and t is the time index.

Results and discussion

The Average Fuel simulation had the greatest forward spread, heat release rate per unit area and area burned (Fig. 2). The Average Tree ensemble with randomly placed trees slowed the forward spread and decreased fire intensity compared with the Average Fuel simulation. Increasing the level of detail in the representation of fuels resulted in added variations in fuel density, such as small gaps between trees that caused the fire to slow and reduced heat per unit area. Likewise,

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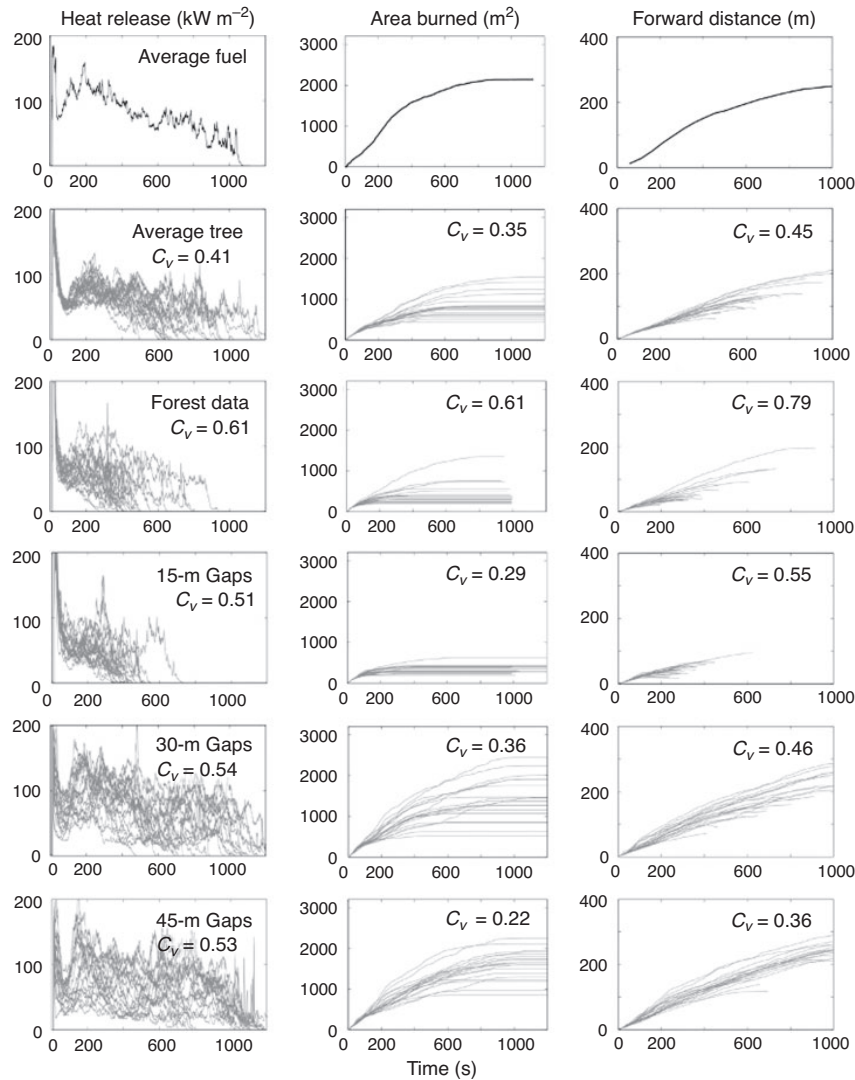


Fig. 2. Time series of fire intensity (left), area burned (centre), and forward progress of fire (right) highlight variability in fire metrics for all ensembles except for Average Fuel, which only has one ensemble member. The coefficient of variation, $C_v = \frac{\sigma}{\bar{X}}$ (σ is the standard deviation and $\bar{X}$ is the mean), is also provided for each ensemble.

increasing the variation of sizes and shapes of trees to that of the Forest Data and 15-m Gap ensembles further reduced heat released, rate of spread and area burned. Conversely, increasing local canopy density and the length scale of sparse forest gaps from the 15-m to the 30- and 45-m ensembles resulted in simulated fire behaviour metrics to rebound compared with the simulated results of the Average Tree, Forest Data and 15-m Gap ensembles. The increase in fire behaviour metrics for the 30- and 45-m Gap ensembles demonstrates that increasing variability in spatial fuel density does not necessarily act to slow fire progression and that fire behaviour is a result of complex interactions with fuel structure.

Ensemble results (Fig. 2) show a range of fire outcomes within each characteristic fuel representation, except for the Average Fuel simulation, which did not have any replicates. The range in fire behaviour outcomes for each ensemble was determined by the variation between details of specific fuel representations, fuel arrangement for given realisations and the associated wind variability. Interestingly, the range in fire behaviour metrics did not increase along the gradient of fuel density variability because the Forest Data and the 15-m Gap ensembles generally did not propagate fire and extinguished quickly. However, when scaled by the mean fire behaviour, the coefficient of variability for the Forest Data remained high.

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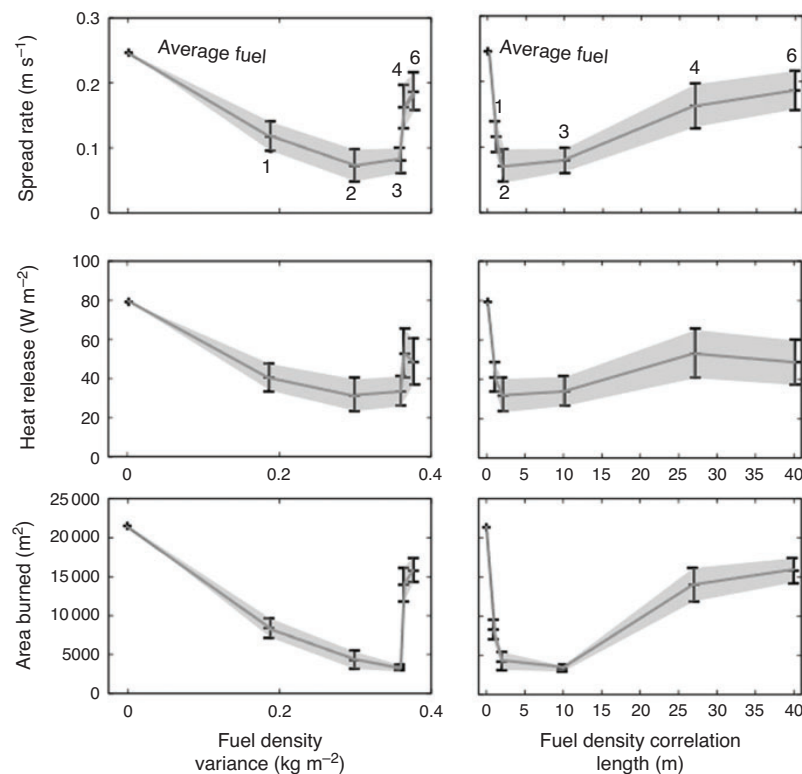
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Fig. 3. Mean and the 95th confidence interval of spread rate, heat release rate, and area burned for each ensemble plotted against variation in fuel density and correlation length of fuel density. Numbered ensembles are cross-referenced in Table 1.

Furthermore, one Forest Data realisation carried 200 m, which contributed to the observed variability in that ensemble (Fig. 2). This suggested that while there is a high probability that fires in the Forest Data ensemble will not spread under the conditions simulated, there is also the possibility that some fires will act outside the ensemble characteristic. Similarly, the large fuel density correlation lengths in the large-gap ensembles also contributed to variability in fire size and behaviour, similar to what Parsons *et al.* (2017) observed.

Emergent fire behaviour from characteristic fuel variability

Differences between ensembles indicated that both the representation and heterogeneity of fuel density influenced fire behaviour. How fuel arrangement characteristics influenced probable fire behaviour in these marginal conditions was shown by plotting summarised fire behaviour metrics for each ensemble against the domain variance of fuel density and the correlation length of that variability (Fig. 3). As fuel density variability increased, all fire behaviour metrics (forward spread, heat released and area burned) decreased linearly for correlation lengths less than 10 m. However, as the correlation length of fuel density increased beyond 10 m, the fire behaviour metrics rebounded (Fig. 3). In the 30- and 45-m Gap ensembles, which correspond to correlation lengths of 27 and 40 m respectively, all fire behaviour metrics increased compared with the other

ensembles except for the Average Fuel case. The 45-m Gap ensemble had slightly greater spread rates and area burned than the 30-m Gap ensemble, whereas the 30-m Gap ensemble had a slightly greater heat release. However, these changes were also associated with an increased variance for both the 30- and 45-m Gap ensembles, and distinguishing ensemble trends from each other was difficult.

These results have three implications for simulating fires in a forest with heterogeneous fuels using process-based modelling: (1) there can be significant differences associated with representing the canopy and surface fuels as a homogeneous layer for ecosystems that naturally include gaps between trees; (2) the variability between sizes and shapes of trees in the forest can have significant impacts on fire behaviour by slowing spread; and (3) the length scales of heterogeneity in fuel density also influenced fire behaviour, where length scales greater than 10 m increased rate of spread and area burned. The sensitivity of fire behaviour to fuel fidelity and variability highlighted in these results suggests the need for increased fuel description detail. Historically, fuels were characterised using stand-scale spatially averaged descriptors (i.e. canopy bulk density, canopy base height), often without considering the within-stand variability (Hoffman *et al.* 2016). However, rapidly evolving remote sensing and machine learning techniques can now characterise three-dimensional fuel structure, including tree-scale spatial

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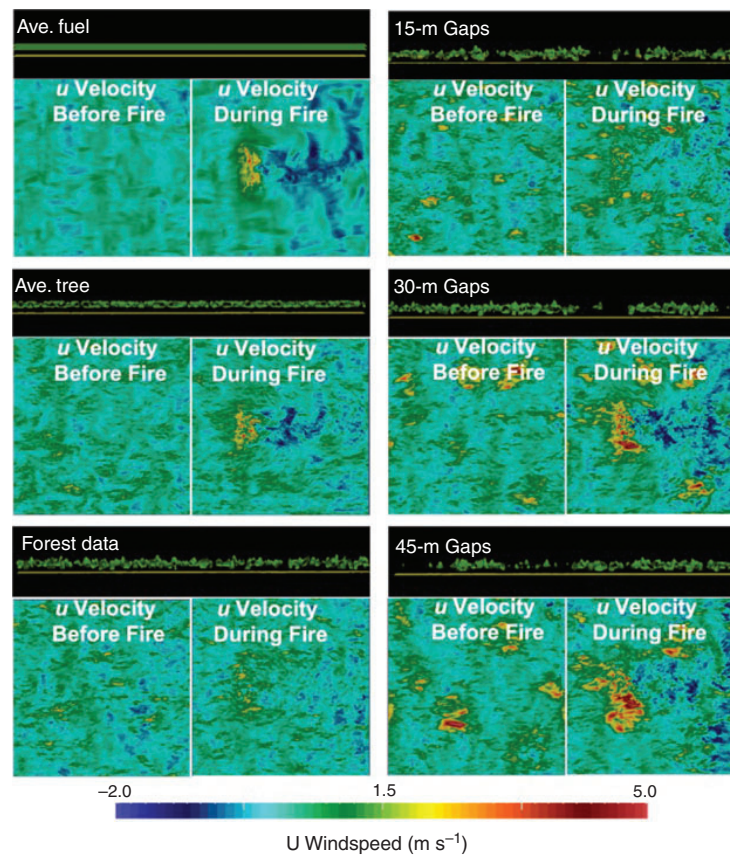


Fig. 4. Horizontal fuel profiles from a sample realisation of each ensemble, a u velocity snapshot at mid-canopy height (11 m) before ignition and after ignition showing the interaction of wind flow with the fire. Note the disaggregated u velocities in the Forest Data and 15-m Gaps ensembles.

heterogeneity (Liao *et al.* 2018; Massetti *et al.* 2019; Narine *et al.* 2019) and three-dimensional below-canopy fuel density (Hudak *et al.* 2020). Furthermore, the ability to quantify fuel structure and model physically based fire dynamics motivates an in-depth understanding of the three-dimensional wind and fuel interactions that influence fire behaviour. Combining three-dimensional wind and fuel interactions with quickly assessed remote sensing and machine learning techniques could increase the application and accuracy of data-driven wildfire models (Coen and Schroeder 2013; Coen *et al.* 2013).

Influence of changing the level of detail in fuels descriptions

The Average Fuel realisation had the least amount of fuel detail, where the horizontal fuel mass was spread evenly, creating a continuous layer of low-density fuel rather than individual trees. Conversely, when representing individual trees, the same amount of canopy mass was concentrated into localised areas – ‘trees’ – leaving gaps in the canopy. Similarly, surface fuel also shifted to denser litter under trees and less dense grass in spaces between trees. Gaps between trees acted as barriers to crown fire spread, which required stronger and more consistent local winds

to bridge the gaps. Additionally, the representation of individual trees and litter, in which the fuel density was higher than in the homogenised Average Fuel, slowed fire spread because it took longer to consume fuels of higher densities and push forward spread, behaviour previously observed by Pimont *et al.* (2006). Areas with higher fuel densities also released more heat, resulting in a stronger local vertical motion, which, coupled with longer combustion residence time, resulted in longer periods of updrafts that impeded the forward propagation due to winds in the along-stream direction.

Canopy structure impacted winds because randomly arranged trees imposed variable aerodynamic drag. It is not surprising that winds would be slower within or right behind dense vegetation compared with lower-density vegetation. Although there were gaps in the Average Tree canopy, those gaps were not large enough for the wind to efficiently penetrate and reestablish, and thus the average wind speeds within the canopy were lower (Fig. 1). The lower wind speed within the canopy combined with canopy gaps and higher localised fuel densities of trees all worked to slow or stop canopy fire spread because the weak winds could not push the simulated fire across

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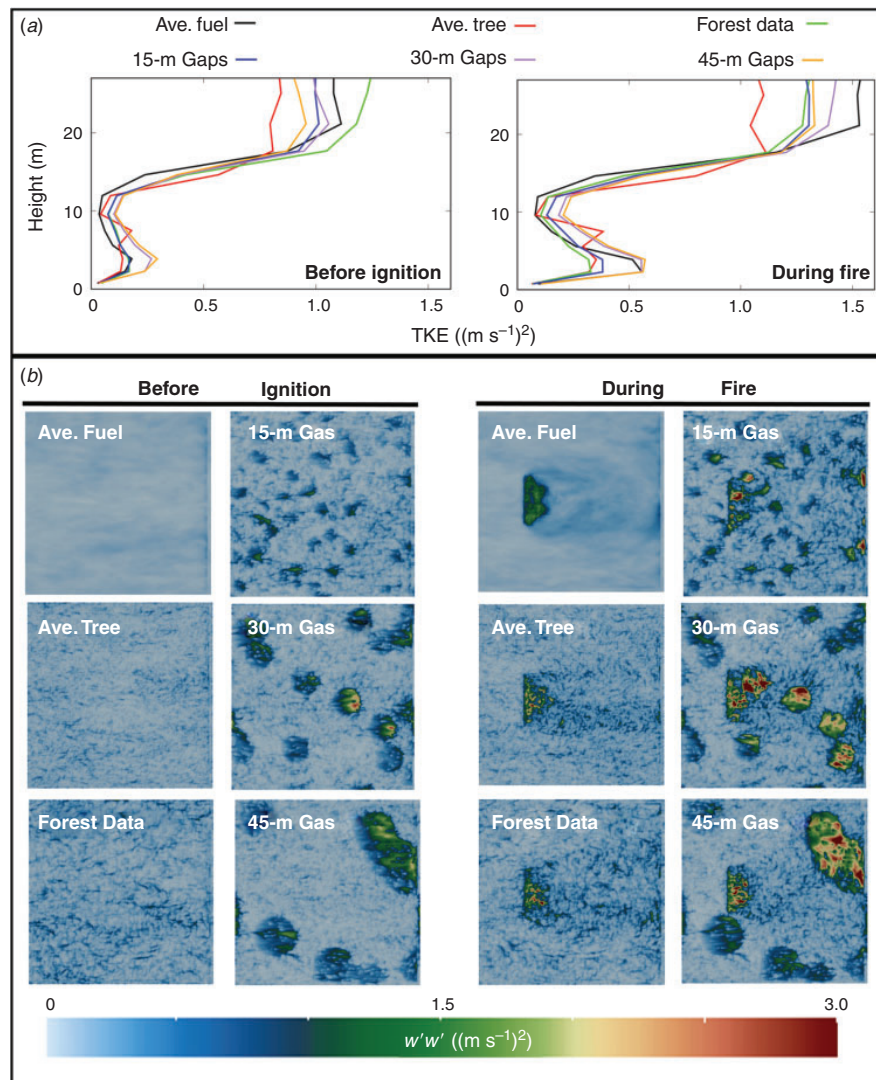
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Fig. 5. Average turbulent kinetic energy (TKE) for the 2.5 min before the time of ignition is plotted on the left in panel (a) and the average TKE for the 2.5 min after ignition on the right of panel (a). Panel (b) shows the average $w'w'$ magnitude for the 2.5 min before ignition (left) compared with the 2.5 min following ignition (right) at the mean canopy height of 10 m for a sample realisation from each ensemble.

the gaps and the buoyancy-induced flow was less likely to lean enough to the side to ignite a neighbouring tree.

Describing the variation among the trees

When considering differences between the Forest Data and Average Tree ensembles, the additional representation of fuel fidelity and therefore variation among trees resulted in a further decrease in fire spread, heat release per unit area and area burned. Using heterogeneous tree sizes and shapes meant trees were interacting with the wind field over a larger vertical extent than an averaged canopy or as a characteristic tree. This essentially broke up the larger-scale wind patterns into tree and

gap-scale patterns. The level of explicit detail related to the canopy structure influenced simulated winds and turbulence; similarly to Boudreault *et al.* (2014), greater canopy representation resulted in a higher level of fine-scale turbulence (Fig. 4). For example, the presence of low hanging branches or smaller trees in the forest data ensemble disrupted dominant winds, especially near the surface, resulting in the lowest subcanopy wind speeds (Fig. 1b). Low wind speeds below the canopy hindered both surface and crown fire spread. Interestingly, complex canopy-driven disruptions to dominant wind flow were noticeable without fire as well as with fire when buoyant wind dynamics caused high-speed horizontal winds to feed the fire

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from multiple directions (Fig. 4). These findings contrast with earlier studies that reported little change in overall turbulent kinetic energy associated with small-scale heterogeneity because vertical shear instabilities typically dominated (Patton 1997; Pimont *et al.* 2011). Our results suggest that even if the fine-scale turbulence was only a marginal contribution to the total kinetic energy budget, the turbulent features associated with small-scale heterogeneity can impact fire behaviour through their influence on both instantaneous local flows and reaction rates.

Influences of fuel density heterogeneity

The wind and fire behaviour also responded to a heterogeneous density of canopy fuel, suggesting that including canopy fuel heterogeneity in forest inventory databases or fuel class descriptions may help fire behaviour forecasts. The increased continuity of canopy fuel in densely forested regions and the increased surface and canopy wind speeds generated by the large gaps resulted in increased forward spread and area burned. The small distance between adjacent trees in aggregated canopies reduced the barriers to active crown fire spread. Likewise, surface fuel continuity increased with less-dense and faster-burning grasses. In addition, as canopy gap size increased, winds could penetrate through the canopy, resulting in increased wind velocity and fire spread.

Our results show that large openings in the canopy allow large-scale wind entrainment below the canopy, similarly to Dupont *et al.* (2011) and Pimont *et al.* (2011), and push the fire front along despite the increased fuel heterogeneity. To visualise how these openings allowed wind turbulence to pass vertically through the canopy, we examined the magnitude of the vertical variance of velocity ($w'w'$) 2.5 min before the fire was ignited and 2.5 min after ignition (Fig. 5). Using $w'w'$ allowed us to visualise the persistence of positive and negative vertical fluctuations from the mean and to identify areas of strong variations. The areas of large $w'w'$ corresponded to large canopy openings. Moreover, there was a larger increase of $w'w'$ and TKE during the fire (Fig. 5) for the 30- and 45-m Gap ensembles. Corresponding increases in $u'u$ and $v'v'$ (not shown) accompanied increases in $w'w'$. Large gaps in the canopy acted to increase wind entrainment, shear stress above the canopy shown as increased windspeed in Fig. 1c, and therefore TKE before and especially during combustion, thus allowing larger and consistent wind structures to interact with the fire (Fig. 5). This ability to move air in and out of the openings and an increase in the cross-stream wind turbulence ($v'v'$) also helped to maintain a larger fire line width (Hilton *et al.* 2015).

The non-monotonic relationship between correlation length of fuel variability and fire behaviour metrics, which rebounded at large length scales, illustrated that below a certain gap size, changes to canopy and subcanopy winds were not strong enough to change fire behaviour. Studies of wind interaction with forest canopies suggest that for winds to re-equilibrate to the absence of trees, a length of ~ 22 to 30 times the average canopy height is needed (Lee 2000; Pimont *et al.* 2018). To induce canopy and subcanopy turbulent wind structures, a length of 1 to 5 times the canopy height appears to be necessary (Pimont *et al.* 2011; Parsons *et al.* 2017). At 1.8 to 2.6 times the average canopy height, the 30- and 45-m Gap ensembles resulted in the canopy

and subcanopy wind turbulence structures that influenced fire behaviour. In contrast, the ratio between gap length and canopy height for the 15-m Gap ensemble was not enough for the canopy and subcanopy turbulent winds to develop.

We note that we have focused on a ponderosa pine forest with circular canopy gaps of different sizes under low-velocity wind conditions, which demonstrated the dominant role that forest canopy heterogeneity has on effective wind conditions driving fire behaviour. However, many different forest types and conditions will likely impart unique signatures on fire behaviour such as the level of surface fuel homogenisation. A supplementary analysis (see supplementary material) comparing a homogenised surface fuel configuration with our heterogeneous grass and litter surface fuel conditions demonstrates a strong influence of surface fuel conditions. Yet for our simulations, surface fuel homogeneity or heterogeneity does not significantly affect the relationship between fire behaviour metrics and fuel density variability or the length scales of that variability. We therefore hypothesise that fuel variability and the spatial length scales of that variability will influence fire behaviour in predictable ways. For example, greater wind velocities associated with more extreme burning conditions would dampen the effects of spatial variability on fire behaviour (e.g. Sieg *et al.* 2017). In contrast, increased canopy height could strengthen the relationship. Additionally, the overall domain canopy density could play a role in the strength of this relationship, where lower forest densities could weaken the effects of spatial fuel variability on fire behaviour.

Conclusions

We demonstrated that fuel variability and spatial characterisation of fuel density influenced simulated fire behaviour. Greater detail in fuel representation resulted in increasingly fine-scale wind discontinuities, which reduced fire spread and area burned. Likewise, when introducing variability in tree size and shape, the strength of fire behaviour metrics decreased. Spatial scales of fuel variability were also instrumental in the interaction of wind and fuel variability in determining fire spread. We observed a non-monotonic relationship between correlation length of fuel variability and fire metrics, all of which decreased with increasing correlation length up to 10 m but increased with correlation lengths above 10 m. Wind entrainment associated with large, sparse canopy patches resulted in both mean and localised wind speeds and faster fire spread. Furthermore, the turbulent wind conditions in large openings resulted in a disproportional increase in TKE and crosswinds that maintain fire line width.

The use of ensembles with equally probable spatial fuel distributions to characterise fire behaviour was necessary given the range of outcomes. Although mean behaviour for each ensemble was identified, significant overlap existed among individual realisations from different ensembles, highlighting the limitation of drawing conclusions from a single model realisation. Nevertheless, this research clearly shows how both the level of detail used to represent fuels and the inherent aggregation in canopy fuels influenced potential fire behaviour. Fuel characterisation that moves beyond spatially averaged descriptions to include increased spatial fidelity and effective wind description associated with characteristic fuel heterogeneity will better constrain fire behaviour uncertainty.

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Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgements

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EXHIBIT G



OPEN

Effects of canopy midstory management and fuel moisture on wildfire behavior

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Increasing trends in wildfire severity can partly be attributed to fire exclusion in the past century which led to higher fuel accumulation. Mechanical thinning and prescribed burns are effective techniques to manage fuel loads and to establish a higher degree of control over future fire risk, while restoring fire prone landscapes to their natural states of succession. However, given the complexity of interactions between fine scale fuel heterogeneity and wind, it is difficult to assess the success of thinning operations and prescribed burns. The present work addresses this issue systematically by simulating a simple fire line and propagating through a vegetative environment where the midstory has been cleared in different degrees, leading to a canopy with almost no midstory, another with a sparse midstory and another with a dense midstory. The simulations are conducted for these three canopies under two different conditions, where the fuel moisture is high and where it is low. These six sets of simulations show widely different fire behavior, in terms of fire intensity, spread rate and consumption. To understand the physical mechanisms that lead to these differences, detailed analyses are conducted to look at wind patterns, mean flow and turbulent fluxes of momentum and energy. The analyses also lead to improved understanding of processes leading to high intensity crowning behavior in presence of a dense midstory. Moreover, this work highlights the importance of considering fine scale fuel heterogeneity, seasonality, wind effects and the associated fire-canopy-atmosphere interactions while considering prescribed burns and forest management operations.

Increasing wildfire impacts has been documented over the past decades^{1,2} and is projected to increase under climate change in the United States (US) and other parts of the world^{1–8}. Apart from the changing patterns of precipitation, vapor pressure deficit and longer drought periods^{7,9}, an increasing trend of human habitation at the wildland-urban interface (WUI) has rendered the problem of wildfire management particularly complex. The WUI is the fastest growing land-use type in the US¹⁰ and also poses significant wildfire threat in other countries such as Portugal. In the western US, about 50% of residential households are situated at the WUI, and flammable vegetation can come into close contact with infrastructure. This situation enhances the impact of wildfires, particularly with fast moving wildfires that escape efforts at containment during initial attack¹¹.

Successful suppression of small fires, called initial attack, is critical to limiting fire size, but successful suppression is increasingly difficult in the growing WUI. Mechanical thinning and prescribed burns are offered as effective techniques to decrease fuel loads and limit fire spread into communities^{12,13}. However, given the complexity of interactions between fine scale fuel heterogeneity and wind, it has been difficult to assess the success of such management operations. Thinning forests may decrease fire intensity but also increase rates of spread during critical phases of initial attack under certain conditions^{14–18}. Under extreme wind events such as those experienced in Paradise, California during the Camp Fire in 2018¹⁹ or the south eastern Australian fires in 2019²⁰, fire behaviour in fuel treatments can be affected by fire-atmosphere interactions, affecting fire suppression outcomes.

The main factors that control the rapid expansion of small wildfires are the response times of fire crew, size of fire upon initiation of suppression action²¹, and weather condition for that day. The removal of midstory and understory vegetation is targeted by managers to reduce wildfire intensity and decrease the probability of surface fire transitions to crown fire^{22–25}. Thus, fuel treatment strategies focus on reduction of surface fuels, increasing the height to the live crown, decreasing crown density and a species-selective approach¹². However, in order to assess the impact of fuel reduction treatments on fire behavior outcomes, one must consider the types of fuels,

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such as dead and live fuels, litter, ladder (midstory) fuels and canopy fuels associated with larger trees and their effects on fire behavior under different conditions of moisture levels²⁶.

The reduction of midstory and understory vegetation does not drive fire behavior in isolation. Depending upon the seasonality and fuel conditions, midstory vegetation can increase wind drag lowering wind speeds or increase fuel moisture, which each can slow fire spread or reduce intensity. Thus, to evaluate the efficacy of fuel treatments, fuel structure alone is insufficient to understand how treatments will alter future wildfire spread and suppression success^{18,27–39}. To this effect, Bessie and Johnson⁴⁰ determined that local weather conditions, especially factors governing fuel moisture and wind speed are stronger indicators to determine fire behavior in vegetative fuel beds compared to stand age or species composition^{41,42}. Keyes and Varner⁴³ recognized that higher wind speeds and turbulence in the sub canopy after thinning treatment might lead to higher mid-flame wind speeds, enhanced rates of spread and erratic fire behavior. Varner and Keyes²⁶ highlighted the importance of variations of fuel moisture and wind adjustment factors post fuel treatment in influencing fire spread and intensity. Moon et al.⁴⁴ studied sub canopy wind variations under a variety of fuel structures and called for further research into fire behavior under fuel treatment scenarios which incorporates the changes in wind among other factors post treatment. A broader discussion into sub-canopy changes under fuel treatment and associated fire behavior is beyond the scope of the current paper and the interested reader is referred to Banerjee¹⁸ for a detailed review.

Beer⁴⁵ identified several mechanisms through which a fire propagates within a fuel bed. He also discussed the potential influence of coherent structures such as sweeps and ejections in a vegetation canopy where a surface fire burns the understory but the canopy crown remains unburnt. The fluctuations in vertical wind velocity generated by the fire can interact with these motions and help disperse heat to the unburnt fuel elements downstream of the flame sheet. Moreover, Cheney et al.⁴⁶ determined that while wind and dead moisture are important for grass fires, fuel load is the primary determinant of fire intensity. On the other hand, closed canopy forests with a higher moisture content and lower wind speeds can lead to lower intensity and slow moving fires⁴⁷. Additionally, changing stand structure by thinning can lead to reduced torching and crowning potential^{48,49}. Contreras et al.⁵⁰ used light detection and ranging (LiDAR) mapped forest structure data to characterize the role of vegetation connectivity and thinning operations (that reduce connectivity) in the context of crown fire potential. White et al.⁵¹ and Davies et al.⁵² determined that the flammability of surface fuels are also important in governing fire severity. The type of ignition is another factor that sets up the initial condition for fire propagation. Keeley and Syphard⁵³ identified the major wildfires in California from 2003 to 2018 and deduced that the fire regimes can be either identified as fuel dominated or wind dominated. In either case, the complex fire-fuel-atmosphere interaction is of critical importance.

Fuel moisture patterns in humid environments are more complex than previously assumed⁵⁴, and environmental conditions during a wildfire event may have non-linear treatment effectiveness outcomes. Finney et al.⁵⁵ identified the importance of studying turbulent flows associated with fuel structures and fuel moisture, especially how they contribute to buoyancy production and flow instabilities, but as yet, these complex coupled fire-atmospheric dynamics have not been applied to the question of fuel treatment effectiveness on initial attack success.

Computational fluid dynamic (CFD) modeling approaches are capable of representing the non-linear feedback between changes in forest structure, complex in stand flows, and fire behavior outcomes^{56–64}. Pimont et al.⁶⁵ used FIRETEC to study the effect of different fuel treatments in the landscape on fire behavior. Linn et al.⁶⁶ used FIRETEC to model wind fields and fire propagation following bark beetle outbreaks. Kiefer et al.⁶⁷ studied the detailed budget of turbulent kinetic energy during a low intensity fire and investigated the sensitivity of mean and turbulent flows to canopy density as well as atmospheric stability using the ARPS-CANOPY model. Another series of studies^{68–72} conducted detailed turbulence measurements during grass fires and surface understory fires using high frequency micrometeorological measurements from the FIREFLUX campaigns and two New Jersey Pine Barrens fire experiments.

However, there remains uncertainty regarding the complicated fire–atmosphere interaction in the canopy sub layer in presence of midstory vegetation of different densities, which governs fire spread in treated vs. untreated fuels. In this work, simulations using FIRETEC are used to address the following questions:

- What are the driving factors governing fire behavior under different levels of midstory management and fuel moisture?
- What are important factors leading to torching and crowning?
- How to characterize turbulent transport of momentum and energy to explain fundamental differences in fire behavior?

To answer these questions, specifically six sets of simulations are conducted. The cases are described in more detail in the methods section. The simulation cases are called dry no midstory (DN), dry sparse midstory (DS), dry dense midstory (DD), moist no midstory (MN), moist sparse midstory (MS) and moist dense midstory (MD), respectively. For brevity, these abbreviated forms will be used for further discussion. It is also important to note that the vegetation phenology in this study is driven by seasonality rather than atmospheric conditions.

Results

Burnt area. Figure 1 shows the burnt area after 520 s of fire propagation. Since the initial and boundary conditions are same for all the simulations, the differences in fire spread are entirely due to differences in canopy structure among the different cases. For the dry scenario, the DN case and the DD case have burnt areas of similar sizes, although the burn scar shapes are slightly different. The DS case has a smaller and thinner burn area. For the moist scenario, the MN case has the largest burn area. The size of the burn area is smaller for the MS and smallest for the MD case. Figure 1 highlights a crucial factor—namely the competing influences of fuel avail-

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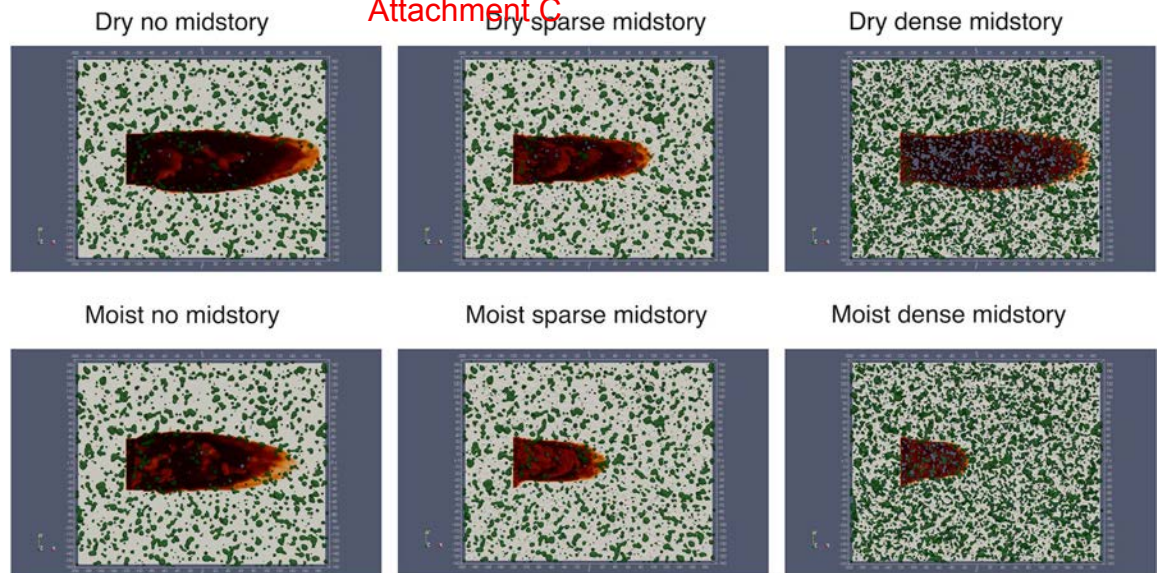


Figure 1. Burnt area after 520 s for different cases. Green depicts midstory vegetation, the light yellow shade depicts the ground surface covered with grass and litter and the dark color depicts burned area.

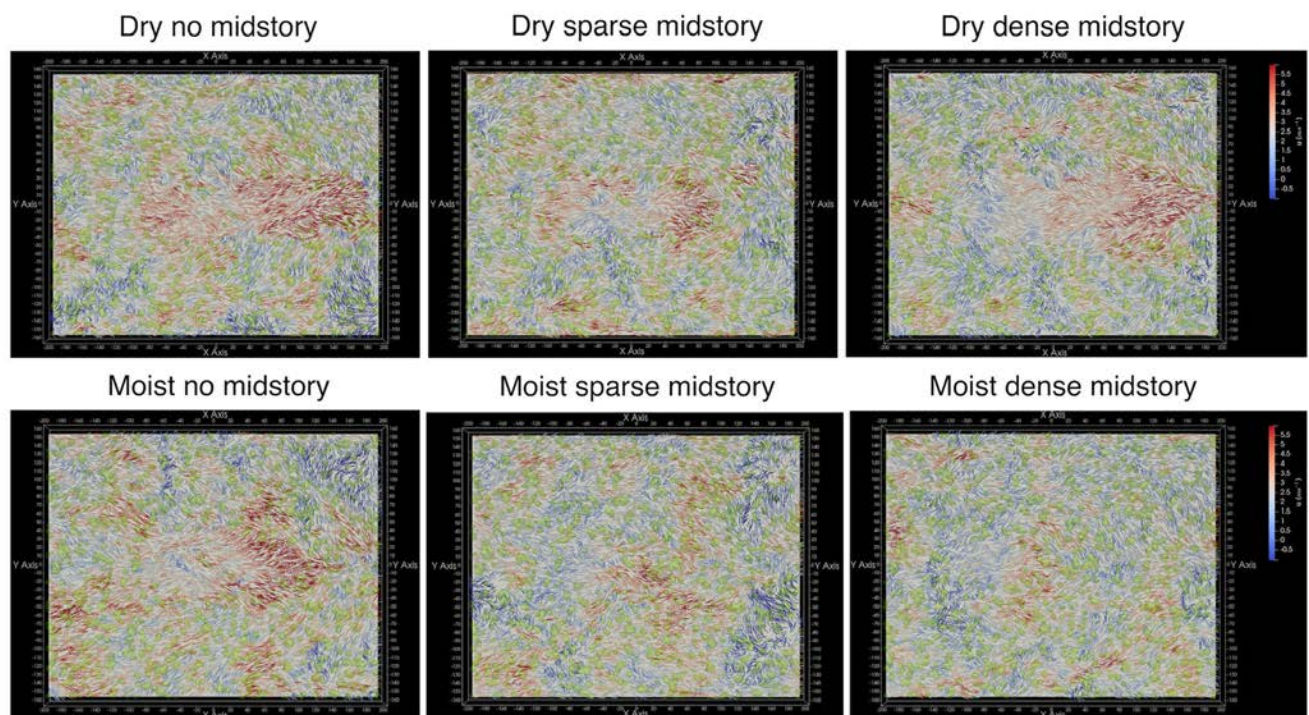


Figure 2. Sub canopy wind field ($x - y$ plane at 7 m height) with arrows colored by instantaneous streamwise velocity component (u) after 520 s for the six scenarios.

ability, fuel moisture and wind effects. Under dry conditions, the availability of dry fuels in the DD case creates a strong head fire. However, the DN case is characterized by a stronger wind field inside the canopy due to lower vegetative drag. This indicates that there is likely a threshold effect, where either the fuel availability or the wind effects dominate. The DS case falls in the intermediate regime, and consequently has a smaller burn scar. Under moist conditions, the higher fuel moisture dampens the effect of fuel availability on fire propagation, and thus the wind effect dominates. This fact is highlighted in Fig. 2, which plots the horizontal ($x - y$) wind field at 7 m height, with velocity vectors colored by the streamwise velocity component (u). As observed, the no midstory case has higher wind speeds compared to the other cases due to lower vegetative drag. A more quantitative understanding of the role of turbulence will be discussed in a subsequent section.

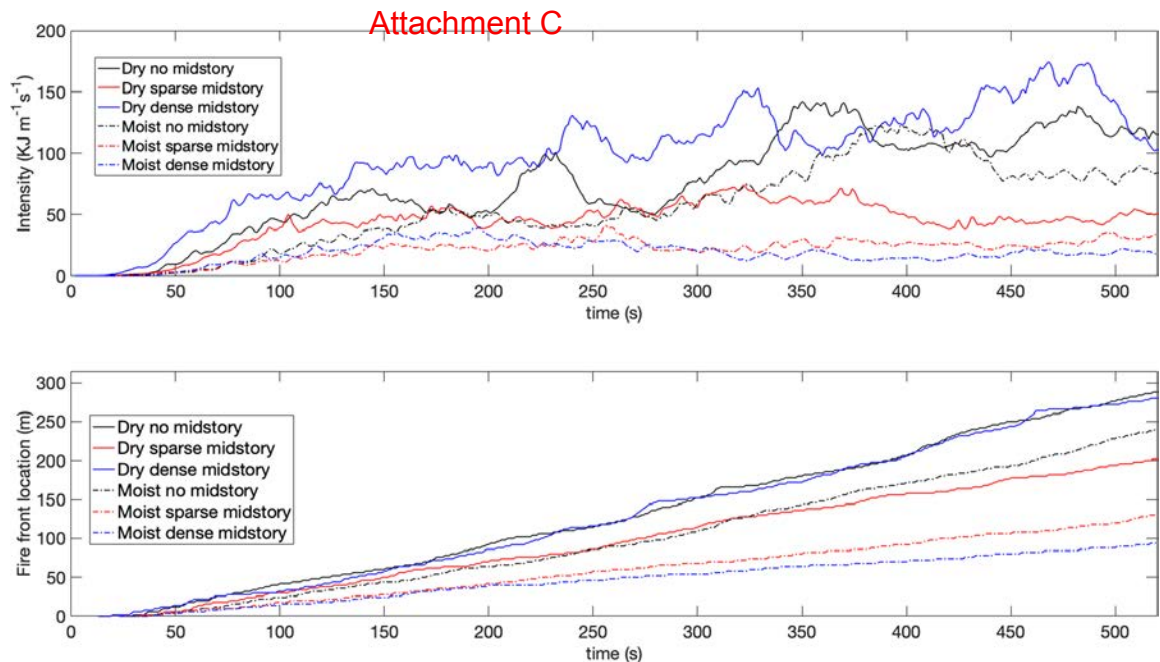


Figure 3. Burning intensity (top) and fire front location with respect to time (bottom) for different cases. The black lines indicate non midstory cases, the red lines indicate the sparse midstory cases and the blue lines indicate the dense midstory cases. The solid lines indicate dry scenarios and the dash dotted lines indicate moist scenarios.

Fire intensity, fire spread and fuel consumption. Figure 3 shows burning intensity (top panel) and the location of the fire front (bottom panel) with respect to time. As observed, the DD case has the highest intensity because of elevated fuel availability among all cases. Interestingly the DN case burns more intensely compared to the DS case, highlighting the critical interaction between fuel availability and wind effects. The moist cases generally showed reduced fire intensity than the dry cases as expected. The differences among the fire intensities observed within the moist cases are smaller than those among the dry cases. This implies the absence of any critical behavior feedback for the moist cases with respect to the competition between wind effects and fuel availability and the dominance of wind effects for the moist scenarios.

Interestingly the fire front propagation spread rate follows the trend of the intensities. However the difference between the cases do not follow the trend in differences of fire intensity. The DN and DD cases have similar spread rates and these two cases show the fastest fire front propagation, although the DN case is slightly faster. The reason for this behavior is likely the same—one dominated by dry fuel availability and the other by strong winds. The effect of the wind prevails for the moist cases as well and the MN case is faster than the MS and MD cases. To summarize, it can be stated that fire intensity is strongly governed by fuel availability and fire propagation speed is governed by wind effects. However, fuel moisture significantly reduces both fire intensity and rate of spread. This is partly because fire induces its own wind environment as well. However, under drier scenarios the effect of vegetative drag becomes more evident.

Figure 4 shows the consumption of canopy overstory fuels (top panels) and canopy midstory and understory fuels (bottom panels) after 520 s. The left panels show the actual amount of fuel remaining over time in metric tons (kg multiplied by 1000) for the entire domain (12.8 ha), the middle panels show the percentage consumption and the right panels show the rate of consumption per second. Any vegetation below 5 m height is considered midstory and understory vegetation. Note that all cases start with the same amount of overstory fuel (35 metric tons). As the leftmost bottom panel shows, the dense midstory cases have about 35 metric tons of midstory and understory fuels, although the moist case has slightly more fuel, as expected, since the deciduous midstory seasonally loses leaf biomass. The sparse midstory case has about 27 metric tons midstory and understory fuels in the moist season and about 26 metric tons in the dry season. The no midstory case has about 22 metric tons of understory fuels, and that amount does not vary in the dry and moist seasons.

A few observations can be made from Fig. 4:

- **Net consumption** The net consumption for the overstory is highest for the DD case, about 40%. The DN case has a similar consumption rate—about 30%. Interestingly, both the dry dense and DN cases have about 45% consumption for the mid and understory fuels. This indicates that while crowning happens for both these cases, driven by the dry fuels and higher winds, the presence of midstory and understory fuels influence how much overstory fuel the crown fire consumes. Moreover, the MN case has about 25% consumption for the overstory fuel and 35% consumption for the mid and understory fuels. The fact that the MN case has more consumption than the DS case is also highlights that wind effects can dominate over moisture effects.

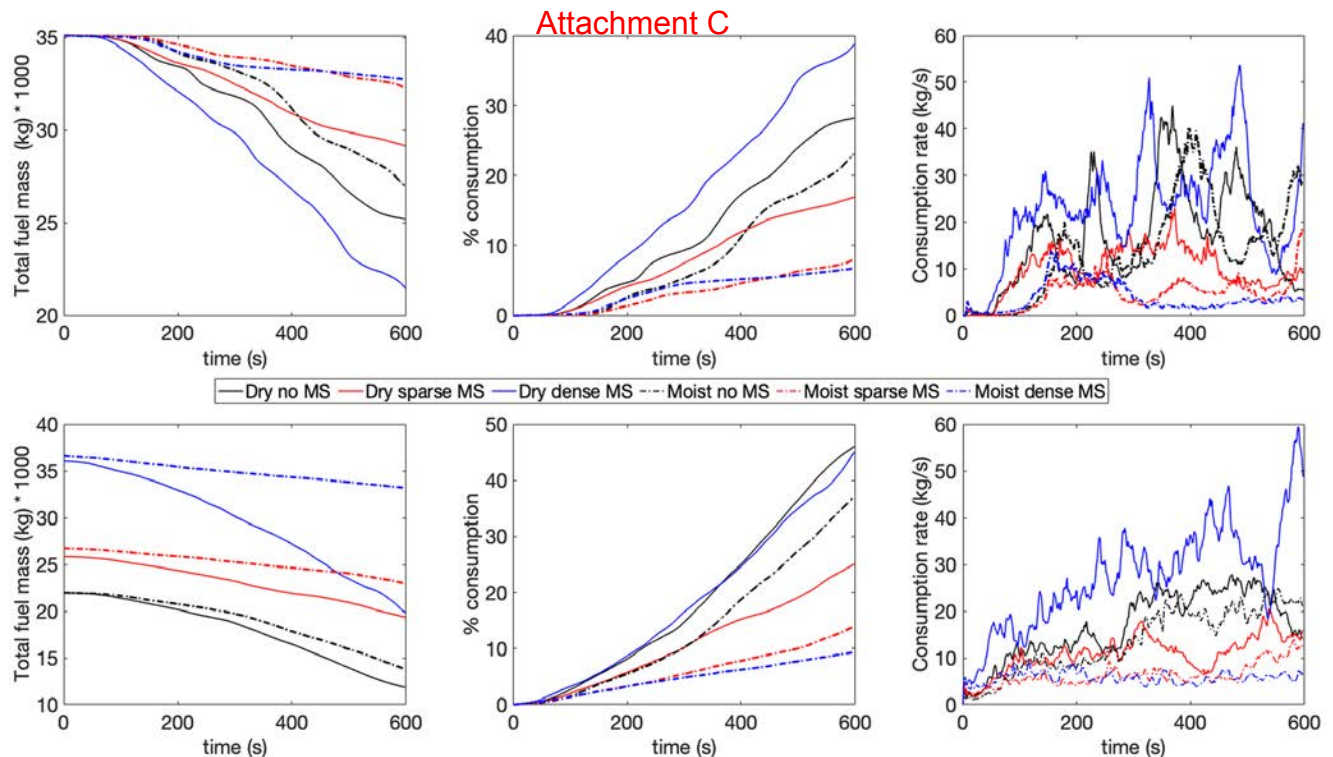


Figure 4. Actual fuel amount remaining over time (left), percentage consumption (middle) and rate of consumption (right) of fuel elements with respect to time for different cases. Line styles are same as Fig. 3. The top row shows the quantities for the overstory and the bottom row for the midstory and understory combined.

- Difference based on fuel moisture** The dry fuels are always consumed more than moist fuels, as expected, both for overstory and understory vegetation. The difference between dry and moist scenarios is most prominent for the dense midstory cases—about 35% more overstory and about 40% more mid and understory fuels are consumed in the dry condition compared to the moist condition, highlighting the importance of fuel moisture and seasonality in fire behavior. This difference is strikingly lower for the no midstory cases—about 5% for both overstory and mid/understory fuels. This indicates that when wind effects are more prominent, seasonal changes in moisture are less important. For the sparse midstory cases, this difference is about 10% for both overstory and mid/understory fuels, highlighting the fact that fire behavior is partially dominated by both wind and moisture effects.
- Rate of consumption** The rate of consumption with respect to time closely follows the trends of actual consumption. However it is important to note that the rate curve is not uniform and is highly variable in time. This non uniformity is more conspicuous for the overstory fuel compared to the midstory and understory fuels. This is due to the complex nature of the turbulence and combustion phenomena across a strongly heterogeneous canopy fuel complex.

To understand the role of turbulence inside the canopy in more detail, virtual sensors were placed at different locations on the domain, so turbulent statistics could be calculated. In section, time series of such turbulence statistics are presented.

Characterization of wind and turbulence. Figure 5a shows 1 min moving average means of several quantities at 3 m height at the domain center. Figure 5b shows the same at 7 m and Fig. 5c shows the same for 15 m height. These three locations are chosen so the variations in turbulent quantities and fluxes can be shown with time as the fire approaches the domain and with height so the dynamics inside the canopy can be probed in a much more detailed and quantitative way. Several observations can be made from Fig. 5a–c:

- Mean streamwise velocity (U)** Because of higher vegetative drag, the U velocities are higher for the cases with no midstory and sparse midstory compared to the dense midstory case before the fire reaches the center of the domain. The DD case also records negative U velocities at 3m height before the fire starts influencing the velocity field. The velocities for all cases are centered around $1\text{--}3\text{ ms}^{-1}$ before the influence of the fire, with the dense midstory cases (dry and moist) recording the lowest U velocities. Once the fire starts influencing the velocity field, the U velocities for the six different cases diverge widely. Still, the no midstory cases report the highest U velocities—about $6\text{--}8\text{ ms}^{-1}$. However, when the fire reaches the domain center, the DN case records a strong U velocity even at 7 m height (7 ms^{-1}). This is likely due to also the loss of vegetation due to burning, which reduces the drag force when the fire passes a particular region. The DN case also records

Attachment C

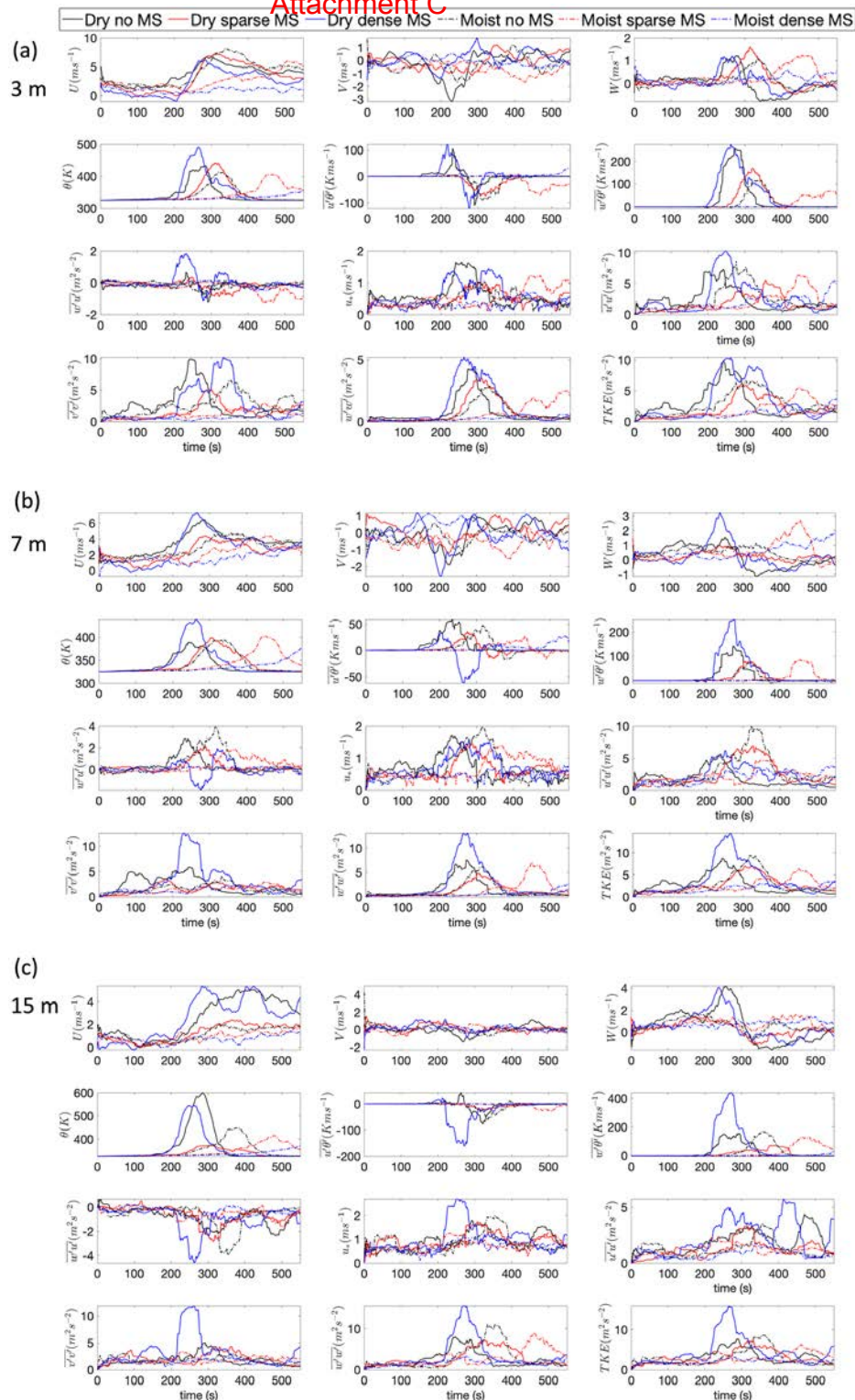


Figure 5. Moving average of turbulence statistics at (a) 3 m height, (b) 7 m height and (c) 15 m height at the domain center. Line styles are same as Fig. 3. U is the mean streamwise velocity, V is the mean cross stream velocity, W is the mean vertical velocity, θ is potential temperature, $u'\theta'$ and $w'\theta'$ are sensible heat flux along the streamwise (u) and vertical (w) directions (the primed quantities are fluctuations from the mean). $w'u'$ is the vertical momentum flux, $u'u'$, $v'v'$ and $w'w'$ are velocity variances in u , v and w directions respectively. TKE is turbulent kinetic energy and defined by one half of the summation of $u'u'$, $v'v'$ and $w'w'$.

Attachment C

strong U velocities at 7 m height, both before and during the fire front passage. At 15 m, the high canopy drag results in lower velocities for all the cases except for the DD case and the DN case. The high velocity for the DD case is partly due to loss of fuel by burning and partly due to high turbulence due to buoyancy. Note that U is generally higher for all cases the canopy mid-story and understory compared to the canopy crown region where the drag is much higher.

- **Mean cross stream velocity (V)** Although the inflow boundary conditions prescribe a zero V component, it becomes finite as the flow field is influenced by the fire. Before the fire influences the domain, the V velocities are centered around zero. However they start to diverge as the fire gains strength. As noticed in Fig. 2, there is a significant cross flow component as the cold wind wraps around the fire and entrains the burnt area behind the top flank of the fire. This V component also experiences drag and thus the no midstory case has the highest (-3 ms^{-1}) V velocity at 3 m height. Interestingly, the DD case also picks up a strong V component, probably influenced by cold air entrainment due to high intensity burning. At 7 m height, the finite V component still persists. However, at 15 m, the V velocity component is almost zero, due to the strong drag effects of the vegetation crown.
- **Mean vertical velocity (W)** At 3 m height, the cases with no and sparse midstory has strong vertical updrafts ($1.5\text{--}2 \text{ ms}^{-1}$). This can be attributed to lower drag forces, as dry and moist scenarios for these two cases record similar W components as well. Interestingly, the DD has strong updrafts but the MN case does not. This indicates that the buoyancy generated due to intense burning of dry fuels is responsible for the updrafts. Note that the strong updrafts are followed by downdrafts (order of 0.5 ms^{-1}), as the cold air entrains the burnt area behind the fire front. At 7 m, the DD case reports even higher updrafts (3 ms^{-1}) and a stronger downdraft (-1 ms^{-1}) after the fire front moves past the virtual sensor. This is likely due to the presence of dense dry midstory which burns vigorously, and supported by the fact that under moist conditions, the dense midstory case has lowest W components. This effect is dominated by stronger drag forces. Interestingly, the sparse moist midstory case also has strong updrafts (2.5 ms^{-1}), likely due the nonlinear combination of drag and buoyancy effects. At the crown level (15 m height), both the dry dense and DN cases record strong updrafts (4 ms^{-1}), due to effects described previously.
- **Potential temperature (θ)** at 3 m height, the air temperature reaches the highest level (500 K) for the DD case. The no midstory and sparse midstory cases reach slightly lower temperature (about 375 K). The dry cases reach higher temperatures than the moist cases, as expected. The only exception is the MS case (about 300 K). This also explains the previous observations regarding the high updrafts for the dry midstory cases. At 7 m height, the difference among the cases become more prominent. The DD case reaches a peak temperature of about 450 K and the other cases reaches around 400 K when the fire reaches the sensor. At the crown level of 15 m, the dry dense and DN cases reach high temperatures of about 550–600 K. The other cases still record about 400 K.
- **Streamwise sensible heat flux ($\overline{u'\theta'}$)** This term can also be called the kinematic advective heat flux along the streamwise (x) direction and is a measure of horizontal heat transfer along the mean flow direction at any level. A positive heat flux should indicate advective heating of the fuel elements in the direction of the fire spread. This is why the peaks for $\overline{u'\theta'}$ occur before the spike in temperature as the fire approaches the sensor. The DD case records the highest $\overline{u'\theta'}$ at 3 m height (about 110 K ms^{-1}), followed by the DN case. After the fire passes, the $\overline{u'\theta'}$ becomes negative, indicating that the fuel elements are cooling down. At 7 m height, the DN case records more advective heating compared to the DD case. However, the magnitude of $\overline{u'\theta'}$ is lower at 7 m, about 50 K ms^{-1} for the DN case. This can be attributed to higher amount of fuel availability at this level. Interestingly, the moist cases record $\overline{u'\theta'}$ of a similar order of magnitude. This indicates that advective heating at the midstory level in the model is dominated by wind and drag, not moisture. At the crown height of 15 m, the heating effects are even smaller than the midstory and understory levels. However, there is strong cooling effect, probably attributed to the crowning behavior at this level.
- **Vertical sensible heat flux ($\overline{w'\theta'}$)** A positive value of $\overline{w'\theta'}$ represents an upward flux of warm air due to buoyancy and should be interpreted as a measure of the strength of the buoyant flame dynamics. The presence of a fire generates buoyancy driven turbulence, which should result in a strongly positive $\overline{w'\theta'}$. The dry cases register higher values of vertical sensible heat flux compared to the moist cases. At 3 m, both the DD and DN cases record similar $\overline{w'\theta'}$, about 250 K ms^{-1} . The DS case records about 175 K ms^{-1} . At 7 m, the trends remain similar, although the DD case $\overline{w'\theta'}$ values (about 250 K ms^{-1}) are nearly twice as large as the the DN case. This behavior is an indicator of laddering as the fire climbs up towards the crown. The MN case has lower $\overline{w'\theta'}$ at 7 m height (about 70 K ms^{-1}) which indicates that the sensible heat flux is definitely impacted strongly by fuel moisture. However, the dry sparse and moist sparse cases record similar $\overline{w'\theta'}$ at 7 m, which means that under sparse conditions, moisture effects are less prominent. At the crown height of 15 m, the DD case records a much stronger $\overline{w'\theta'}$ of about 400 K ms^{-1} , while the other cases remain similar to the 7 m level. This increasing $\overline{w'\theta'}$ with height for the DD case is an indicator of crown fire behavior.
- **Vertical momentum flux ($\overline{w'u'}$)** The parameter $\overline{w'u'}$ represents the vertical flux of horizontal momentum and its value should be negative inside the vegetation canopy in regular atmospheric boundary layer flow as the canopy absorbs momentum from the flow and acts as a momentum sink. The value of $\overline{w'u'}$ should also change as the canopy is consumed by the fire, which changes canopy drag. However, as the presence of fire create a strong buoyancy driven updraft, it can create a positive momentum flux in the canopy sublayer. At the 3 m height, all the cases record negative $\overline{w'u'}$. However, as the fire passes the virtual sensor, the DD case records a strong positive $\overline{w'u'}$. However, as the fire passes the sensor, cool air rushes in a negative $\overline{w'u'}$ is recorded because of strong drag effects. The DN case also shows a similar behavior although the peak values are much lower. At 7 m height, the no midstory and sparse midstory cases, (both dry and moist) records strong positive $\overline{w'u'}$. Higher drag at this level reduces $\overline{w'u'}$ for the DD case. Interestingly, at 7 m level, the burning of midstory fuels still generate upward fluxes of momentum. At the 15 m level, the upward flux of

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momentum is small, indicating that the crown region absorbs the locally generated upward momentum flux and the fire does not 'leak' additional momentum into the atmospheric surface layer above the canopy. Moreover, at the crown height of 15 m, the canopy also absorbs momentum from the overlying air mass perturbed by the fire and the DD case absorbs most of it even when the fire is burning strongly. Another interesting fact is that the momentum flux is not very sensitive to moisture effects.

- **Friction velocity (u_*):** The friction velocity is computed as

$$u_* = (\overline{u'w'^2} + \overline{v'w'^2})^{1/4}, \quad (1)$$

where v' denotes cross stream velocity fluctuations and u_* represents the net magnitude of wind shear stress at a particular height. In regular atmospheric turbulence, u_* can range between 0.1 ms^{-1} to 0.5 ms^{-1} . At the 3 m height, u_* is indeed at that range for all cases, until the fire enhances the magnitude of the turbulence locally. This increase of u_* is observed for all cases during fire front propagation, which is associated with strong vertical motions close to the flame associated with a 'chimney effect'⁶⁹, resulting in higher turbulent stress. At 3 m height, the DN case records u_* around 1.6 ms^{-1} as the fire passes the sensor. The DD case records a slightly lower u_* but of similar order of magnitude during fire passage. The sparse cases also report a u_* about 1.2 ms^{-1} . At 7 m level, u_* is higher for all the cases, while the no midstory cases reach magnitudes around 2 ms^{-1} . The amount of moisture does not have much impact in the magnitude of shear stress and potentially is more strongly driven by the amount of fuel present and at the rate fuel is removed by fire. u_* returns to pre-fire magnitudes after the fire passes, in spite of ongoing smoldering. Interestingly, at crown height, the DD case has the highest magnitude of u_* (around 2.6 ms^{-1}), likely due to buoyancy generated turbulence during the fire. Before and after the fire passage, the dense midstory case has much lower magnitudes of u_* .

- **Turbulent kinetic energy (TKE):** The turbulent kinetic energy is computed as

$$TKE = \frac{1}{2} (\overline{u'u'^2} + \overline{v'v'^2} + \overline{w'w'^2}), \quad (2)$$

where u' , v' and w' are fluctuations from the 1 min moving averaged mean. Figure 5 shows the individual components of TKE as well as the net TKE for the three heights and for the six different cases. At 3 m height, before the fire, the DN case has higher magnitudes of TKE, about $2.5 \text{ m}^2\text{s}^{-2}$, while the DD case has slightly lower TKE close to the surface. This indicates the effect of fuel drag. As the fire passes, the TKE for all cases increases significantly, from 0.5 – $2.5 \text{ m}^2\text{s}^{-2}$ to about $10 \text{ m}^2\text{s}^{-2}$. The DD case records the highest TKE in this range. Interestingly, this TKE rise has two components. First, the large rise is contributed by $\overline{u'u'}$, during intense burning between 200 and 300 s. Next, a strong rise is recorded for $\overline{v'v'}$, between 300 and 400 s, which leads to the net TKE peak that lasts between 200 and 400 s. This rise is associated with strong crosswind flows that wrap around the fire. The $\overline{w'w'}$ component shows the contribution from buoyancy driven turbulence, which is vertical in direction. The DD case records the highest $\overline{w'w'}$ as well due to most intense burning, followed by the DN and DS cases. The moist cases record lower $\overline{w'w'}$ which is expected, as the intensity of burning is less. However, the patterns of $\overline{u'u'}$ and $\overline{v'v'}$ are more complicated as they are dependent of vegetative drag and how fuel is removed with burning, which also dictates the nature of the wind as it rushes to the upstream of the fire flank as the fire passes the area. The net TKE contains all these combined effects. After fire front passage, TKE values return to their pre-fire-front-passage values. Another interesting observation is that even during fire front passage, the relative contributions of $\overline{u'u'}$, $\overline{v'v'}$ and $\overline{w'w'}$ remain similar, i.e. $\overline{w'w'} \approx 0.5\overline{u'u'}$ and $TKE \approx \overline{u'u'} \approx \overline{v'v'}$ in terms of magnitude, which is also observed in regular atmospheric turbulence⁷³. At 7 m height, the net TKE follows similar patterns, although the DD case records about $15 \text{ m}^2\text{s}^{-2}$ during fire passage, while the DN case is still at $10 \text{ m}^2\text{s}^{-2}$. This contribution is mainly due to buoyancy effects and cross stream velocity components, as the $\overline{w'w'}$ increases significantly at this height, about $15 \text{ m}^2\text{s}^{-2}$, due to higher fuel availability. At this height, the contribution to TKE from $\overline{u'u'}$ is rather small, because of higher fuel drag. The no midstory and sparse midstory cases have higher $\overline{u'u'}$ at this height. At the crown height of 15 m, the trends are similar to the midstory level. Another point to note here that the level of vertical turbulence can also set the boundary conditions for spotting potential, which can launch firebrands aloft. These embers and other burning particles can get transported by the turbulent wind aloft the canopy sub layer and create spot fires ahead of the fire front.

- **Isotropy** Another factor associated with TKE is isotropy. Figure 6 shows the time variation of $\overline{w'w'}/(2 * TKE)$ for all 6 cases, for the three heights 3 m, 7 m and 15 m. For isotropic turbulence, this value should be $0.33^{71,74}$. If this value is < 0.33 , it indicates that the horizontal component of the TKE ($\overline{u'u'} + \overline{v'v'}$) strongly dominates over the vertical component $\overline{w'w'}$. Before the fire front passage, all cases exhibit strong anisotropy, however, the anisotropy is stronger (further away from 0.33) close to the ground surface and is more isotropic at crown height. During fire front passage, the strong buoyancy effects enhance $\overline{w'w'}$ and increases isotropy for all cases and all levels, especially for the DD case.

There are few instances in the literature that have reported fine-scale turbulent quantities in such detail as discussed above, especially in the context of wildfires spreading in a vegetative environment. However, Clements et al.⁶⁹ had conducted field experiments (FIREFLUX) which collected high frequency turbulent data on a micro-meteorological tower at four heights (2 m, 10 m, 28 m, 42 m) in the path of a grass fire. This allowed the authors to examine mean and turbulent quantities before, during and after fire front propagation. Clements et al.⁶⁹ used 1 min moving averages to look at the evolution of flow statistics as the fire passed the tower, which is the strategy used in this work as well. They observed friction velocities (u_*) in the range of 2.5 – 3 ms^{-1} at 2 m height and 3 – 3.5 ms^{-1} during fire front passage. The u_* observed in this study has a similar order of magnitude.

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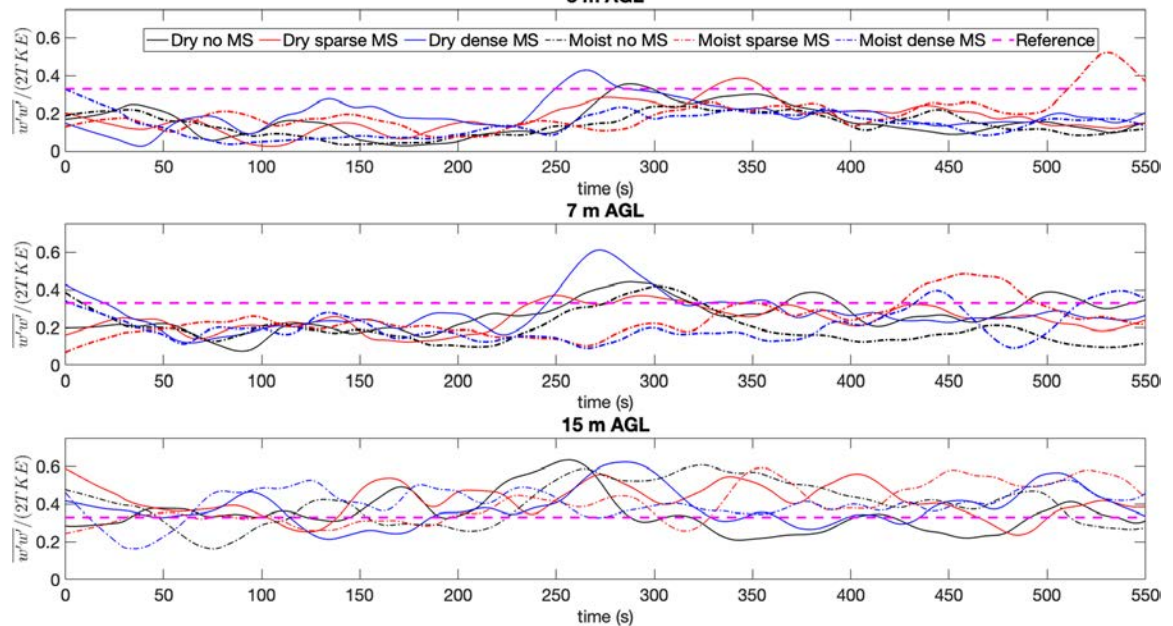


Figure 6. Time variation of 1 min averaged values of $\overline{w'w'}/(2 * TKE)$ showing turbulent anisotropy. Line styles are same as Fig. 3. Dashed magenta line shows the value of 0.33 for isotropic turbulence.

Moreover, they observed TKE in the range of $6\text{--}12 \text{ m}^2\text{s}^{-2}$ which is also the range observed in this study. Heilman et al.⁷⁴ reported peak TKE values of $5\text{--}20 \text{ m}^2\text{s}^{-2}$ during two burns at the New Jersey Pine Barrens (forest environment). Heilman et al.⁷¹ reported similar trends of turbulence anisotropy (0.10–0.20) during these burn operations. The buoyancy flux, defined as $B_f = g/\theta * w'\theta'$ are also on the order of $0.5\text{--}1 \text{ m}^2\text{s}^{-3}$ similar to the magnitudes reported by⁶⁹. However, the difference between fuel characteristics (grass in the case of⁶⁹, forest vegetation in this case) precludes further one to one comparisons.

Discussion

In this work, we investigated the drivers of wildfire spread following linear ignition in the context of active fuel reduction treatments. We further examined how clearing midstory vegetation alters fire behavior through changes in canopy drag and the interdependence on fuel moisture. A line ignition was used to investigate the fundamental processes in fire behavior, with the application of these simulations addressing potential fire size on initial attack success. Simulations in this study were conducted using HIGRAD/FIRETEC to observe bulk fire behavior indicators such as fire intensity, fire spread rate and fuel consumption.

The generally expected trend was found with the DD case, which produced the highest fire intensity. Interestingly, under dry conditions, the gradual lowering of midstory density did not yield monotonically decreasing trends of fire intensity. Up to a level of midstory thinning, termed sparse midstory in this study, the fire intensity and rate of spread were reduced. However, under the DN case, where most of the midstory and understory vegetation was thinned, the wind speed and turbulence levels were enhanced such that the rate of spread increased and was often higher than the DD case. More interestingly, the fire intensity actually increased compared to the DS case with the absence of midstory but lower than the DD case. The enhanced wind speed, turbulence and the resulting augmented sensible heat flux were partly responsible for this behavior, which is seemingly counter intuitive as the DS case was characterized by more fuels.

This behavior further highlight the trade off between fuel availability and wind effects. Under the DN case, the wind effects dominated as the canopy drag was low. Under the DD case, the fuel effect dominated as there is simply too much dry fuel. In the sparse case where both the fuel effects and wind effects were moderated, both fire spread and fire intensity were reduced. This trade off offers another perspective on the practice of fuel treatments with prescribed fires. Under dry conditions, both no thinning and excessive thinning can lead to high amount of fuel consumption. Whereas a moderate degree of thinning can lead to lowered consumption for both overstory and understory vegetation. Hence burn managers might consider this trade-off on consumption as well as the consequences on fire intensity and rate of spread when conducting cost-benefit analyses of a prescribed fire.

Under seasonably moist conditions, these trade-offs were absent and wind effects dominated the fire, with the fire being slower and less intense with higher fuel moisture. Higher winds drove the fire faster under moist conditions. To understand the physical mechanisms behind this behavior, detailed analyses were conducted by collecting data on virtual towers at different locations. Time series of flow quantities such as mean velocities, potential temperature and turbulent statistics such as sensible advective and buoyant turbulent heat fluxes, turbulent stress (momentum flux), friction velocity (a measure of shear stress) and turbulent kinetic energy and its components were plotted at the domain center, at three different heights, close to the surface, at midstory height and at crown height.

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These emergent picture of the consequences of nonlinear fire atmosphere interaction in the fine scales on fire behavior is also consistent with new insights coming out the analyses of a large number of recent fires in California⁵³, which were identified to be either fuel dominated or wind dominated. Consequences of long term fire suppression policy, silvicultural practices, grazing and timber harvesting practices can alter the fire regime in either directions. For the fuel driven fires, altering fuels can offer bottom up controls as hypothesized by Keeley and Syphard⁵³ and clearly demonstrated in this work. It is also important to recognize that when extreme synoptic scale wind events (such as Santa Ana winds) dominate fire behavior, fuel treatments are hardly a limiting factor and those cases are beyond the scope of the current manuscript. However, mastication and thinning operations can establish a higher degree of control even on fires on shrub type ecosystems under lower wind events^{75,76}. Future research will attempt to establish the limits of these top down and bottom up controls on wildland and prescribed fires, as well as their interaction with complex terrain.

Nevertheless, a physical understanding of canopy-fire atmosphere in such detail as explored in this work can help burn managers design treatments to alter fire behavior. Moreover, the patterns of fire spread within treatment zones during initial attack will depend heavily on interacting factors of canopy-induced winds, fuels moisture, and loading. The suite of conditions under which desired fire behavior can increase suppression success can only be fully understood in the context of complex feedbacks. The details provided in the current analyses offers an unprecedented level of insight into mechanisms that govern momentum and energy exchange in the the complex heterogeneous canopy environment, which are relevant for fire behavior assessments. Moreover, the analyses also shed light on the potential indicators of high intensity crowning behavior. To conclude, this work highlights the importance of accounting for the effects of vegetation management, fine-scale vegetation heterogeneity, winds, and turbulence on fire behavior when conducting prescribed burn operations and the success of initial attacks on wildland fires.

Methods

Fuel data. The fuel data were collected at the Eglin Air Force Base in Florida. Based on tree inventory data, three major species of trees were present, namely longleaf pines (*Pinus palustris*), common persimmon (*Diospyros virginiana* L.) and turkey oaks (*Quercus cerris*). Further details about the fuel data collection methods are described in⁷⁷. The average tree canopy density (fine fuel) was 0.3 kg m^{-3} for longleaf pines and persimmons. For turkey oaks, this value was 0.4 kg m^{-3} . The density of grass was 1.573 kg m^{-3} , with an average grass height of 0.5 m. The average litter height was 0.1 m and the litter load was 5.0 kg m^{-3} . Moreover, the density of grass was reduced and the litter density was increased below the trees due to canopy shading, using an exponential attenuation factor 5.0. Under the moist condition, the nominal fuel moisture was 133% for longleaf pines, 170% for persimmons, 200% for turkey oaks and 8% for grass and litter. The nominal fuel size was 0.0005 m for longleaf pines and persimmons and 0.0002 m for turkey oaks. Note that the persimmons and the turkey oaks usually comprised the midstory. In the dry season, the moisture for the turkey oaks were 15% and the persimmons were killed (omitted from the fuel complex in the model). Tree data were collected in three stages of management—‘no midstory’ where there are only 408 pines per hectares (1 hectare is equal to 10,000 square meters), ‘well managed or sparse midstory’ where there are 408 pines, 551 persimmons and 44 turkey oaks per hectare; ‘unmanaged or dense midstory’ where there are 408 pines, 551 persimmons and 983 turkey oaks per hectare. The average height for the longleaf pines was 18 m and the average height for the midstory vegetation was about 11 m. It is also important to note that the fuel loading values (2.0–2.5 metric tons per hectare for midstory + understory) and 2.7–3.0 metric tons per hectare for overstory) are consistent with those observed both in the US Southeast (Longleaf and Loblolly pines)⁷⁸ and the Southwest (Ponderosa pine and mixed conifer stands)⁷⁹. So the observations in this work are deemed to reflect a wide range of conditions. Another important point to note is that the moist or dry conditions in fuel moisture are entirely driven by seasonality and not by other management efforts.

Since the purpose of these simulations was to isolate the effects of midstory fuel management on wildland fire behavior, surface fuel conditions were held unchanged. Varying the surface fuel moisture would impose additional variations in fire behavior unrelated to treatment evaluations—and it would further complicate the interpretation of the results. In addition, whether this level of midstory fuel treatment would be sufficient to make the surface fuel drier is not clear and the literature poses contrasting evidences. Whitehead et al.¹⁵ noted that forest thinning might lead to enhanced solar radiation, wind speed and near-surface temperature but did not find any significant changes in relative humidity or surface fuel moisture. Kalias and Kent¹⁷ lists several studies which reported fuel treatment effects on fuel moisture and fire behavior. Banerjee¹⁸ also offers a detailed review on this topic and summarizes these contrasting evidences. Some field experimental studies such as Bigelow and North⁸⁰, Faiella and Bailey⁸¹ and Estes et al.⁸² have reported no appreciable changes in the surface fuel moisture post thinning. Bigelow and North⁸⁰ argued that micrometeorological changes in the sub canopy environment post thinning can counter each other. An increase in wind speed after thinning could increase the turbulence driven mixing of the air above and below the canopy sub layer, thereby not allowing air temperature to increase or surface fuel moisture to decrease. On the other hand, some other studies such as Pook and Gill⁸³, Weatherspoon et al.⁸⁴ and Countryman⁸⁵ noted that thinning could lead to a drier surface fuel layer, which could enhance fire intensity. Given these uncertainties, it is unclear at this stage if changes in the midstory fuel (without removing the entire crown) would lead to any appreciable changes in the surface fuel moisture. While more research is needed to address this topic, the surface fuel properties were held fixed in this study while the midstory fuel was varied across the six simulation cases in this study based on available data.

Model description. Simulations are conducted using the HIGRAD/FIRETEC code developed at Los Alamos National Laboratory^{86–88}. FIRETEC is a large-eddy simulation (LES) tool that can resolve atmospheric tur-

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bulence over three dimensional heterogeneous fuel distributions at spatial resolutions on the order of 2 m and can capture the spread, intensity and extent of burn area under different ignition conditions. FIRETEC simulates the movement of a wildfire by accounting for a few processes, such as the convective heating of fuel elements in front of a flame, the entrainment of cold air from the surroundings atmosphere, radiative heating and cooling of fuels and the drag experienced by the wind over vegetation canopy. The combustion of solids, which leads to chemical products and heat, is handled using a single compartment model without regards to chemical composition of the fuels. More specifically, it includes an evolution equation for the density of dry fuel as well as the density of water separately. A budget equation for the internal energy of the fuel that includes radiation, advection and energy exchange due to chemical reactions and evaporation of water tracks the temperature of the solid fuel elements. The evolution of the density and momentum of the gas phase are governed by the mass and momentum budgets of a fully compressible Navier Stokes equation. There is another budget equation for the internal energy of the gas phase which results in the potential temperature of the gas phase. It includes turbulent advection, turbulent diffusion as well as radiation effects and the energy exchange with the burning solids. Last but not the least, an advection diffusion equation tracks the evolution of oxygen. It is important to note that fine scale (below 2 m) processes are treated as sub grid scale processes. The sub grid scale variations of temperature, velocity and fine scale fuel features are parameterized.

Simulations. Each simulation is conducted over a 400 m by 320 m (12.8 ha) domain with a grid resolution of 2 m by 2 m. The vertical extent of the domain is 550 m. The vertical grid resolution is non uniform and uses a grid stretching function in order to accommodate more grid points close to the surface within the vegetation canopy. There are 49 grid points in the vertical direction, 12 of which are within the canopy layer. The average grid spacing within the canopy layer is 1.8 m. The time step of each simulation is 0.02 s. Each simulation is spun up with a wind run for 3100 s (about 52 min) so that sufficient turbulence is generated and the wind field develops a steady state. Periodic boundary conditions are used on both sides of the domain. 80 processors are used in parallel for each set of simulations. An inlet wind profile with a value of 8 ms^{-1} at 30 m above ground level (AGL) is prescribed, which adjusts to the vegetation for the corresponding simulation during the wind run and follows a logarithmic profile above the zero plane displacement height. A free slip boundary condition is used at the top of the domain. The fire simulations start after the wind runs, with an ignition line, 4 m wide, 80 m long and offset by 80 m from the left edge of the domain along the wind direction (x axis) and centered perpendicular to the wind direction (y axis). Note that line ignitions are standard while investigating fundamental aspects of wildland fire behavior both in terms of experiments and simulations^{46,87}. The target temperature of ignition is 1000 K and a ramp rate of 350 K s^{-1} is used. Each fire simulation is run for 600 s (10 min).

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Author contributions

T.B. planned and designed the project, conducted the analysis and wrote the paper. R.L. and K.H. collected the fuel data used in the paper. K.H., S.G. and W.H. provided comments and suggestions.

Competing interests

The authors declare no competing interests. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

Additional information **Attachment C**

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EXHIBIT H

Deconstructing the King megafire

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Abstract. Hypotheses that megafires, very large, high-impact fires, are caused by either climate effects such as drought or fuel accumulation due to fire exclusion with accompanying changes to forest structure have long been alleged and guided policy, but their physical basis remains untested. Here, unique airborne observations and microscale simulations using a coupled weather–wildland-fire-behavior model allowed a recent megafire, the King Fire, to be deconstructed and the relative impacts of forest structure, fuel load, weather, and drought on fire size, behavior, and duration to be separated. Simulations reproduced observed details including the arrival at an inclined canyon, a 25-km run, and later slower growth and features. Analysis revealed that fire-induced winds that equaled or exceeded ambient winds and fine-scale airflow undetected by surface weather networks were primarily responsible for the fire’s rapid growth and size. Sensitivity tests varied fuel moisture and amount across wide ranges and showed that both drought and fuel accumulation effects were secondary, limited to sloped terrain where they compounded each other, and, in this case, unable to significantly impact the final extent. Compared to standard data, fuel models derived solely from remote sensing of vegetation type and forest structure improved simulated fire progression, notably in disturbed areas, and the distribution of burn severity. These results point to self-reinforcing internal dynamics rather than external forces as a means of generating this and possibly other outlier fire events. Hence, extreme fires need not arise from extreme fire environment conditions. Kinematic models used in operations do not capture fire-induced winds and dynamic feedbacks so can underestimate megafire events. The outcomes provided a nuanced view of weather, forest structure, fuel accumulation, and drought impacts on landscape-scale fire behavior—roles that can be misconstrued using correlational analyses between area burned and macroscale climate data or other exogenous factors. A practical outcome is that fuel treatments should be focused on sloped terrain, where factors multiply, for highest impact.

Key words: coupled atmosphere–fire model; fire behavior; fire model; LiDAR; multiple plumes; numerical weather prediction; pyrocumulus; wildfire; wildland fire.

INTRODUCTION

Wildfire is a major force in the western United States and globally and has the potential to reshape forested landscapes into new and possibly novel configurations (Bond and Keeley 2005, Turner 2010). For years, concern has been rising that long-term fire exclusion (Keane et al. 2002) and, increasingly, climate change may be changing fire behavior and increasing the risk of very large, severe fires (Westerling et al. 2006, Williams 2013), yielding a new category of wildfires, “megafires,” that are becoming more common in the western United States and perhaps worldwide. The term became widespread in 2002 when five western U.S. states experienced their worst fires on record (Williams 2013), the magnitude and impacts of which stood out even in regions frequented by fire. The term has since been applied to describe outbreaks of large, intense fires in other fire-prone locations such as Australia (Bartlett et al. 2007), Canada (Stocks et al. 2003), Greece (Dimitrakopoulos et al. 2011), and Europe overall (Tedim et al. 2014). Criteria identifying a megafire vary; fires may be notable in terms of size, severity, cost, resources required, or human, economic, or environmental impacts.

Analysis of historical data suggests that climatic factors have become more favorable for wildfires in general (Westerling et al. 2006, Barbero et al. 2014, Dennison et al. 2014, Stavros et al. 2014), and very large fires in particular (Dennison et al. 2014), increasing their frequency and extent (Dennison et al. 2014) over recent decades in some regions. Though still an infrequent event—only a small percentage of fires exceed 100 ha in size—very large fires have a disproportionate impact on overall area burned (Littell et al. 2009), 80–96% of which is due to the largest 1% of fires (Strauss et al. 1989). The hypotheses that megafires in general, or individual megafires in particular, are directly attributable to either climate change effects such as drought or long-term fuel accumulation due to fire exclusion with accompanying changes to forest structure have been widely asserted but are not directly experimentally testable; most evidence supporting either thesis is correlational, integrated over broad scales, and circumstantial. The climate hypothesis (Dale et al. 2001, Flannigan et al. 2009) has generated debate amid the broader climate change controversy while the “century of suppression” hypothesis (Williams 2013) has led to second-guessing of well-intentioned and strongly supported fire management programs and intense criticism of land management agencies. The debate has raged with significant consequences on forest policy issues, conservation, healthy forest initiatives, and public passion. The debate in the United States is paralleled by debates elsewhere in countries with fire-prone ecosystems.

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Similarly, debates have contested the relative importance of climate-scale factors such as drought vs. day-to-day weather in creating very large fires (Abatzoglou and Kolden 2011, Riley et al. 2013). Fire growth is episodic, and even during sustained drought, most growth occurs on a small proportion of days—not always consecutive—during a wildfire’s active period (Wang et al. 2014). Anecdotal firefighter reports from recent megafires describe unprecedented fire behavior that could not be reproduced with standard fire behavior modeling systems. Further complicating understanding, observational data on megafires, which may behave differently than less extreme events (Alvarado et al. 1998, Pyne 2015), have been limited. Reproducibility that is possible with repeatable laboratory experiments and more common occurrences is often not possible when the subject is an extreme or unusual unplanned natural event. Thus, broad regional statistical analyses have been recommended (Schoennagel et al. 2004), either time series or spatial correlations, to draw out the causal factors. Inferences about the atmospheric factors causing these events, for example, have relied upon statistical correlations between megafire occurrence and macroscale monthly weather data (Bowman et al. 2017) and been specified to speculate on the cause of individual megafires or megafires in general. Brotak and Reifsnnyder (1977) identify synoptic conditions associated with large fires, chiefly strong prefrontal surface winds preceding a trough, while Peterson et al. (2015a) draw similar conclusions in the context of the Rim Fire, concluding strong prefrontal surface winds aligned with terrain drove some periods of extreme fire spread. Similarly, studies have used statistical analyses to identify environmental factors related to observed degrees of severity, such as the severity of previous burns and topographic slope (Harris and Taylor 2017) and, for the Rim Fire, the influence of forest structure, fire history, topographic, and weather conditions (Lydersen et al. 2014). The latter study indicated that on days characterized by strong plume activity, severity was moderate to severe regardless of forest conditions. While these approaches identify general associations, they may overlook important factors for which data are not available. Thus, the mechanisms causing the emergence of one of these rare events are still not well understood and have not yet been scrutinized with complementary methods such as physically based process studies, either observational studies or contemporary dynamic models that simulate fire behavior—methods that, of necessity, examine individual events.

This study decomposes the factors leading to the size, behavior, and duration of a megafire of a type increasingly common in the United States and similar to fires in Mediterranean Europe, Australia, Canada, and Israel. The 2014 King Fire, which occurred in California’s northern Sierra Nevada mountains, stood out due to its size, rapid spread, and severity. It provides a unique opportunity for hypothesis testing and separation of the effects of climate, short-term weather, and forest condition because airborne remote sensing provided preburn forest structure and vegetation type data, thermal imagery during the fire, and quantitative characterization of impacts to vegetation postfire. Before the King Fire, in the summer of 2014, NASA’s preHypIRI preparatory program (Lee et al. 2015) imaged the entire region containing the fire with high-resolution airborne spectroscopic and thermal sensors. Additionally, much of

the area was surveyed with LiDAR by the U.S. Department of Agriculture Forest Service, providing direct information on forest structure. Thermal imagery was acquired during active burning, and comprehensive LiDAR, thermal, and spectroscopic data were acquired over the burn scar shortly after the fire. These data sets, taken together, allow fire behavior during the event to be related to prior forest structure and field condition, enable energy release during the fire to be estimated from contemporaneous thermal imagery, and further constrain modeled fire behavior by comprehensively surveying residual forest structure postburn. By combining these data with a fully mechanistic coupled atmosphere–wildland–fire model, we could estimate the separate effects of the antecedent drought, fuel, forest structure, topography, and weather on a single fire. By doing so, we could connect cause and effect as in a process study and uncover the dependency of fire behavior on these contributing factors in a way that is currently unique and a countercheck to conclusions garnered from the previously mentioned broad statistical analyses. This more clearly refines how climate change impacts might be distributed locally and how climate change, disturbances, and land management practices might cumulatively shape future fires. While the King Fire is only a single example and inherently unreplicable and this data set is unique and likely to remain so until and unless spectroscopic and LiDAR coverage becomes ubiquitous, this study provides a paradigm for interpreting the factors that lead to extreme fires.

We seek to disentangle the influence of weather, fuels, and climate factors on the King Fire and provide insights into megafire behavior. We ask (1) Does current understanding, as encapsulated in a state-of-the-art modeling system, explain the megafire’s behavior? (2) Does better representing the spatial variability of forest structure, derived solely from airborne remote sensing observations of pre- and postfire forest structure and composition, improve simulation and understanding of fire behavior and effects? We examine attributable factors to answer (3) What role did fire-induced winds play in its rapid growth? (4) Did drought contribute to the fire’s rapid growth and extent? (5) How would this fire have behaved if fuel had not accumulated? This uniquely observed case study provided an opportunity to gain insight that can inform science and wildfire management more generally, as well as raising hypotheses that can be tested in other settings. Because, while these factors may have differing importance in other fires occurring in different terrain, forest type, and weather, the physical relationships presented in this study, as well as identification of the conditions under which drought and fuel load can and cannot affect fire behavior, are ubiquitous. This work suggests how megafire behavior may be better interpreted, predicted, and mitigated.

Study context

During the study period, a trough of low pressure was approaching the California coast, preceded by weak southwesterly surface winds, where they generally ascended the west slopes of the Sierra Nevada Mountain Range. The King Fire was ignited at 18:37 (all times Pacific Daylight Time [PDT], Coordinated Universal Time [UTC] –7 h) on 13 September 2014 near Pollock Pines, California, USA (ignition location

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38.782° N, 120.604° W). It spread during a severe drought (Griffin and Anchukaitis 2014) in the central Sierra Nevada mountain range in complex terrain covered by mixed conifer forests (shown in Appendix S1: Fig. S1), which generates complex fuel beds shaped by drought, land management practices (e.g., forest cultivation and harvesting, fire suppression, and fuel mitigation), and burn scars from numerous prior fires. The King fire grew 7 km to the northeast through the evening of 16 September as nearby surface weather stations recorded weak-to-moderate south-southwesterly winds (Fig. 1a) upon which weak diurnal circulations (e.g., 0–3 m/s at Bald Mountain) and gusts of 2–10 m/s were superimposed (Fig. 1b). From 21:49 on 16 September, when the fire was mapped by the National Infrared Operations (NIROPs) airborne imager, until 13:06 on 17 September, when satellite active fire detection data from the Visible and Infrared Imaging Radiometer Suite (VIIRS; Schroeder et al. 2014) detected the fire entering the Rubicon Canyon, the fire traveled north over rolling hills. In an afternoon run that was unanticipated in light of weak-to-moderate ambient winds, the fire grew over 16,200 ha

(40,000 acres), racing approximately 25 km to the northeast over the next 11 h, an average spread rate of 2.3 km/h, following the canyon to its crest at Hell Hole Reservoir, where growth stalled. Operational fire behavior models largely failed to capture this run, instead predicting slower expansion similar to previous days (J. A. Fites-Kaufman, *personal observations*). Beginning at 16:00 on 17 September, humidity increased and area winds weakened and changed to easterlies, redirecting and slowing growth (Fig. 1c). Progression was mapped nightly by NIROPs (Fig. 1d) and twice daily (early afternoon and midnight) by VIIRS. The fire was contained at 39,545 ha (97,717 acres) on 10 October.

Based on how the fire environment (fuel properties and moisture content, terrain slope, and weather, notably wind) affects fire behavior, primary factors that could have shaped this event are winds, which may have included fire-induced winds; the Rubicon Canyon's inclined, concave shape; and fuel properties including amount, vegetation type and structure, and fuel moisture content. Appendix S1 reviews key dependencies. In summary, (1) fire spread rate is only weakly

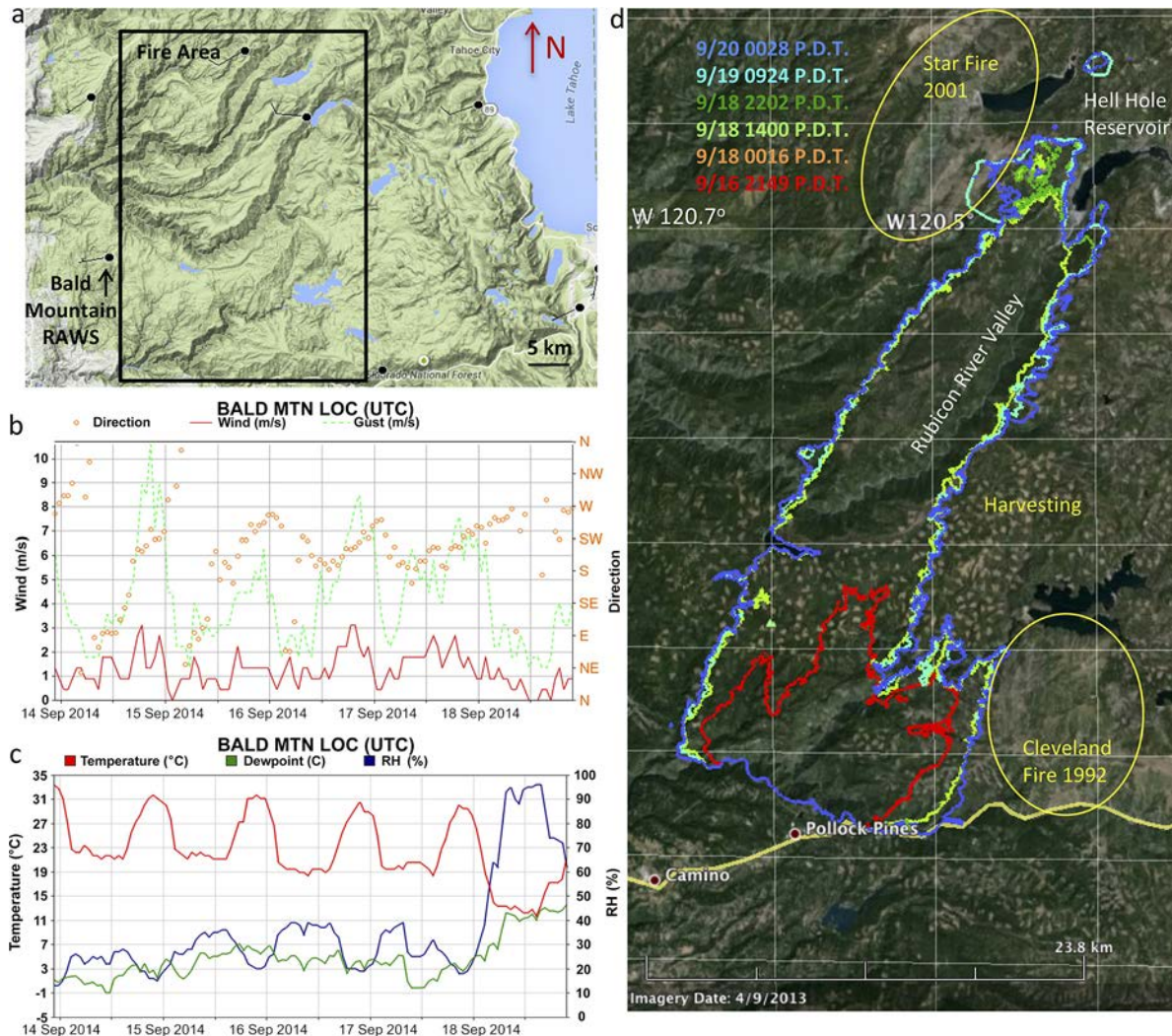


FIG. 1. Overview of the King Fire (California, USA) environment and progression. (a) Weather station wind data near the King Fire at 14:00 17 September. The boxed area is shown in (d). (b) Winds at Bald Mountain weather station. Wind directions are N, north; NW, northwest; W, west; SW, southwest; S, south; SE, southeast; E, east; NE, northeast. (c) Temperature and humidity at the Bald Mountain weather station. (d) NIROPs airborne fire mapping data collected during periods 1 and 2. Yellow annotations indicate disturbance areas.

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influenced by fuel load, (2) spread rate is directly influenced by the dead fuel moisture content, which responds rapidly to weather changes, rather than the fuel moisture content of live canopy fuels, which reflects longer term conditions such as drought, and (3) spread rate is indirectly sensitive to conditions that cause faster heat release on inclined terrain through production of an along-slope component of fire-induced winds.

MATERIALS AND METHODS

Model description

The CAWFE modeling system (derived from coupled atmosphere–wildland–fire environment) integrates a numerical weather prediction (NWP) model (Clark and Hall 1991, Clark et al. 1996, 1997) designed for simulations in complex terrain with a wildland fire behavior module (Clark et al. 2004, Coen 2005, 2013). Fig. 2 shows a schematic of the system. Gridded atmospheric states from model analyses (distributed by the National Oceanic and Atmospheric Administration) are used to initialize and update the boundary conditions of the outermost of several interactive, nested modeling domains (analyses *available online*).⁵ Regional weather is simulated at horizontal grid spacing of tens of kilometers while horizontal and vertical grid refinement allows simulations to telescope into tens to hundreds of meters near the fire.

CAWFE operates at resolutions that are extremely fine for weather models yet too coarse to resolve combustion. Instead, the fire module parameterizes fire processes with semiempirical relationships. A semiempirical spread rate formula (Rothermel 1972) is used to parameterize surface fire spread in terms of terrain, fuel properties, and wind at the fire line, although in CAWFE, the latter includes fire-induced winds. Another relationship (Albini 1994) estimates the rate at which fuels of various sizes are consumed once passed by the flaming front. The model calculates the sensible (thermal) and latent (water vapor) heat releases and the smoke particulate release via an emission factor. The surface fire heats and dries the tree canopy, if present. If the remaining heat flux exceeds a threshold (Van Wagner 1977), a crown fire is ignited and travels through the canopy at a semiempirically determined rate (Rothermel 1991), consumes the tree biomass, and releases more sensible and latent heat. A simple radiation treatment distributes sensible and latent heat fluxes and particulates from the fire into the lower atmosphere. The NWP model and fire module are coupled such that heat and water vapor fluxes from the fire alter the atmospheric state, notably producing fire winds, and the evolving atmospheric state affects fire behavior.

CAWFE's fire behavior module is similar to the standard fire behavior models used as operational tools. However, key differences are that CAWFE simulates three-dimensional airflow at fine resolution (hundreds of meters) as it varies in time and space over the fire, capturing intricate mountain airflows, whereas standard fire models project fire extent by ingesting weather data (either a single time or a time series) from a single weather station that may be kilometers from the

fire or, more recently, a coarse surface weather-gridded forecast product. In addition, CAWFE is a dynamic modeling system that allows two-way feedback between the weather and the fire, allowing the heat released by the fire to alter the atmospheric state, which, in turn, directs the fire. These “fire-induced winds” (discussed in Appendix S1: Section “Winds”) may greatly exceed background winds. CAWFE has been applied to wildland fires that span a wide range of terrain, weather, and fuel conditions (e.g., a windstorm in the Colorado Front Range [Coen and Schroeder 2015], solar heating-driven mountain valley circulations [Coen 2005], a southern California Santa Ana [Coen and Riggan 2014], and a thunderstorm gust front in the desert southwest [Coen and Schroeder 2017]). The weather model has been applied and validated over 30 yr to simulate many meteorological phenomena, including precipitation formation, terrain-induced turbulence, and windstorms. CAWFE simulations of over 15 fire events have been tested against in situ measurements and incident team maps, fires mapped by airborne infrared instruments, and VIIRS satellite active fire detection data (Coen and Schroeder 2013, 2015, 2017, Coen and Riggan 2014).

Experimental design

The objectives of the study were to reproduce the unfolding of the King megafire and then analyze sensitivity experiments to disentangle how factors contributed to its exceptional and unanticipated behavior. The factors include terrain-shaped airflows, fire-induced winds, drought as it affects fire behavior, fuel accumulation as it affects fuel loads, and forest structure as revealed in a separate study by analyses of airborne remote sensing measurements.

CAWFE was applied to two periods during the King Fire, separated because model error growth precludes a single fine-scale simulation from retaining sufficient skill throughout the entire event. First, a four-nested-domain simulation (finest atmospheric spatial resolution, 370 m; fuel grids, 74.1 m) modeled the period 17:00 16 September to 19:45 18 September, initializing a fire in progress using the 21:49 16 September NIROPs airborne fire mapping data.

In the second period, a five-nested domain simulation (finest atmospheric spatial resolution, 185 m; fuel grids, 37.0 m) spanned 21:00 18 September to 20:51 19 September, during which time the fire was initialized in progress with the 01:03 19 September VIIRS active fire detection data (Schroeder et al. 2014). National Centers for Environmental Prediction (NCEP) Final Operational Global Analysis-gridded atmospheric data were used to initialize the atmospheric state and provide boundary conditions to a Weather Research and Forecasting (WRF) Model (Skamarock et al. 2005) simulation. WRF dynamically downscaled the analyses to provide initial conditions and hourly lateral boundary gradients of atmospheric state variables for the outermost domain (10-km horizontal grid resolution) of CAWFE simulations. Inner CAWFE domains were refined to 3.33, 1.11, 0.370, and (for period 2) 0.185 km. Simulations ingested fuel data categorized into fuel models, a stylized categorical classification of fuel type, amount, and physical arrangement, using the 13-category Albini (1976) classification system as restated by Anderson (1982). Based on weather station data, dead fuel moisture content was set 5% and 12% for periods 1 and 2,

⁵ <http://nomads.ncdc.noaa.gov>

CAWFE® Modeling System

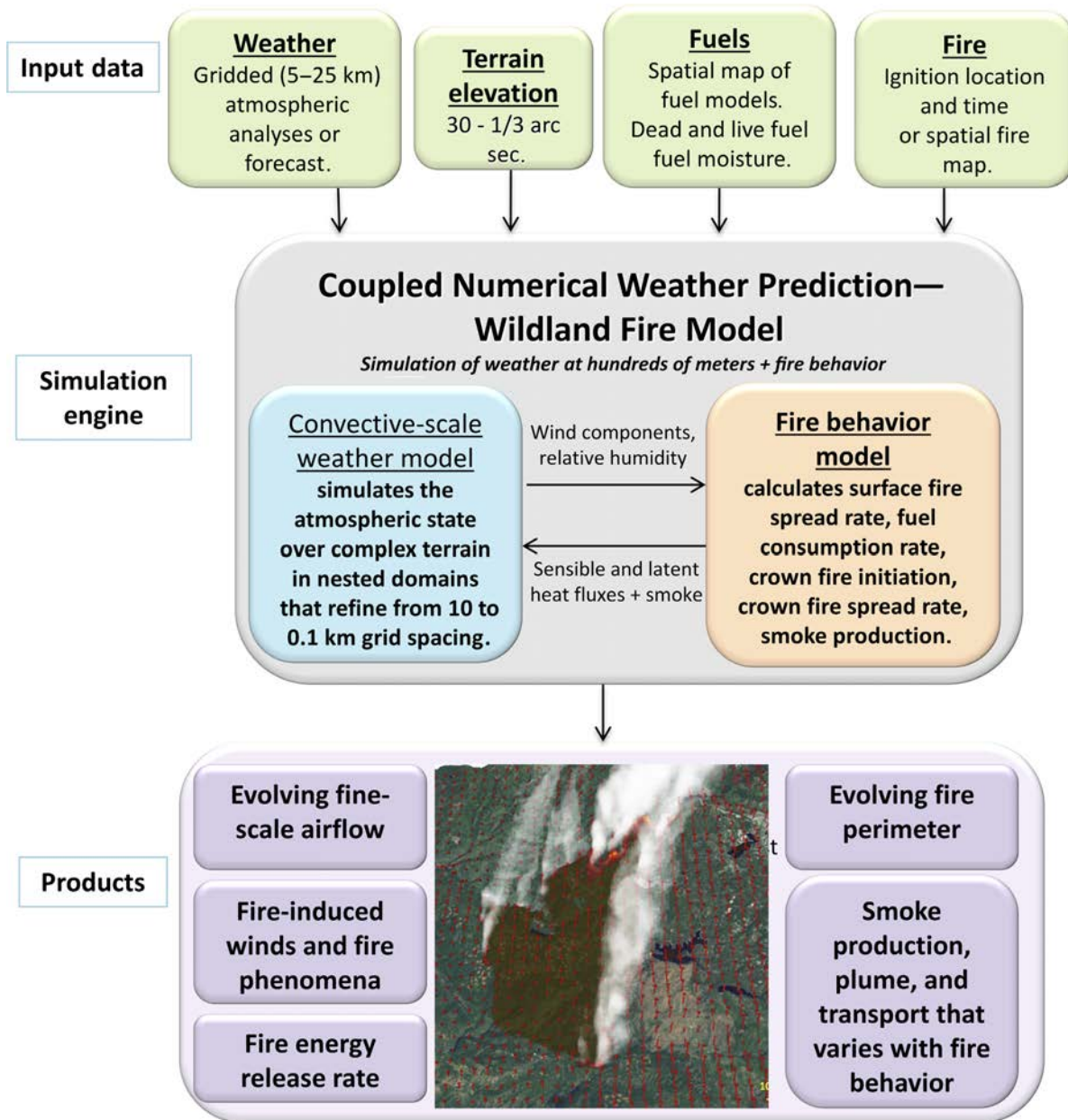


FIG. 2. Overview of the CAWFE modeling system.

respectively, each experiencing a diurnal increase and decrease of 1% (data available online).⁶ Sensitivity experiments to test the effect of drought during period 1 varied the dead fuel moisture content (DFMC) from the measured 5% to its historical low (3%) and high (8%) and the live fuel moisture content (LFMC) from 120% in the control experiment to 90% and 150%, values that bracket the natural range from extreme drought to spring moisture values. Experiments to test the effect of fuel accumulation simultaneously halved the fuel load and depth, thus keeping the packing ratio constant, to represent preaccumulation surface fuel load. Other tests

varied the canopy fuel load from the control experiment value of 1.11 to 3.33 kg/m². This was the most direct approach to test fuel accumulation; other effects on forest structure such as the accumulation of ladder fuels may also have occurred but are much more difficult to credibly implement and test.

Fuel data

Fuel models establish properties needed for the fire module algorithms including fuel load, fuel bed depth, surface area to volume ratio, and moisture of extinction. Two sources provided data mapping how fuel models varied in space. The

⁶<http://mesowest.utah.edu>

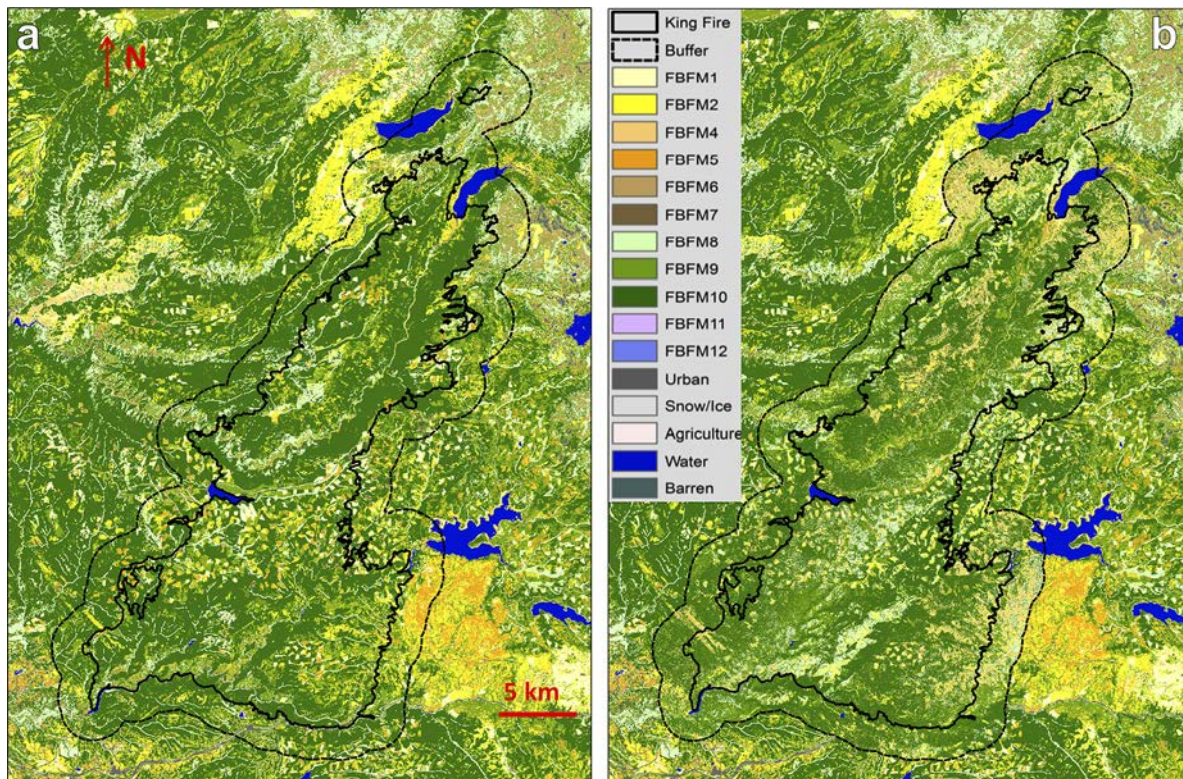


FIG. 3. Spatial variability in fuel models from LANDFIRE and remote sensing data. Fuel models classified according to the Anderson 13-category Fire Behavior Fuel Models (FBFM) system (Anderson 1982; FBFM1-FBFM3 are types of grasses, FBFM4-FBFM7 are shrubs, FBFM8-FBFM10 are forest litter from light to heavy, and FBFM11-FBFM13 are slash piles) from (a) LANDFIRE and (b) MapFUELS data (both reproduced from Stavros et al. (2018)). The heavy solid line indicates the King fire outline, and the thin black line indicates the area over which the analysis for defining MapFUELS fuel models was performed.

control experiment used 2012 fuel model data from the Landscape Fire and Resource Management Planning Tools Project (LANDFIRE) database available from the U.S. Department of Agriculture Forest Service and U.S. Department of Interior (Fig. 3a; data *available online*).⁷ An alternative method (Stavros et al. 2018) called MapFUELS established maps of these fuel models using only remote sensing observations from the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) to create a dominant vegetation map and clusters of structural metrics (Fig. 3b) from the Airborne Snow Observatory (ASO) light detection and ranging (LiDAR; Painter et al. 2016). MapFUELS data were derived from pre- and postfire airborne data (Stavros et al. 2016) and evaluated against forest inventory analysis field data. That analysis covered actual fire area plus a 2-km buffer. Differences were most apparent in areas varying from a natural state such as in dense plantation, harvested and replanted areas, and areas in transition such as the 1992 Cleveland burn scar in the southeast and the 2001 Star Fire west of Hell Hole Reservoir (Fig. 4). For both sources, data were resampled to model fuel cells (5×5 cells are within each atmospheric grid cell) using nearest-neighbor resampling. Standard fuel loads and other properties from (Anderson 1982) were used. In simulations using data from both sources, where a forest fuel type was indicated, the canopy fuel load uses the control experiment value of 1.11 kg/m^2 .

⁷ <http://www.landfire.gov>

RESULTS

Fire progression

We simulated two periods during the King Fire with the CAWFE coupled weather-wildland-fire model. Period 1 spanned 17:00 16 September to 19:45 18 September. During this time, the CAWFE simulation reproduced notable features of the fire event (Appendix S1: Video S1). These included weak-to-moderate southerly winds (Fig. 4a), multiple heading regions along the fire front (Appendix S1: Fig. S2), each pulling a section of the fire up a draw through fire-induced winds and creating a distinct smoke plume, the fire entering the Rubicon Canyon at approximately 13:00 (Fig. 4b), and the fire's 25 km run up canyon on the afternoon of 17 September (Fig. 4c) to Hell Hole Reservoir where growth diminished due to reaching the canyon's top, rockier terrain, and weaker ambient winds (Fig. 4d). VIIRS data (Fig. 5a) supported this sequence of events but indicated the flanks' simulated lateral growth was overestimated (Fig. 5b). This variance from actual outcomes may have occurred because the model neglected fire suppression, which was heavily applied to the western flank south of the Rubicon Canyon, because of deficiencies in identifying forest structure in prior disturbances (later discussed in *Sensitivity to spatial distribution of fuel models*), and inherent model error. Within the Rubicon Canyon, a narrow band of wind (Fig. 4b, c) channeled by the upward, concave valley shape contributed to the run. The heat released by the fire

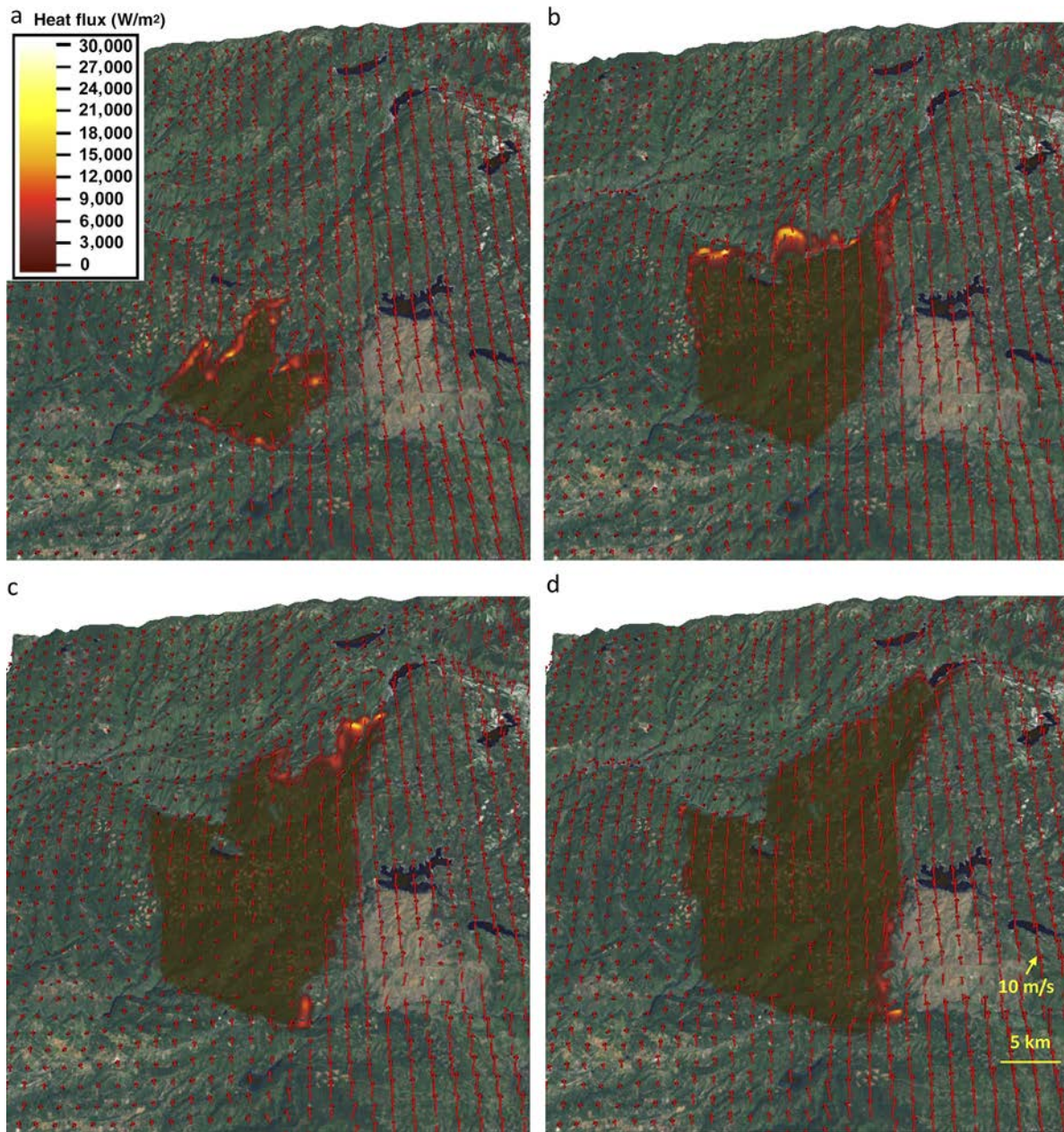


FIG. 4. Snapshots throughout the control simulation of the King Fire. Simulated total heat flux in domain 4 (colored according to key at right) with wind vectors (every fourth grid point) near the surface, at (a) 22:00 on 16 September, (b) 13:00 on 17 September, (c) 18:00 on 17 September, and (d) 23:00 on 17 September.

created a single, strong, downwind-leaning plume that drew air faster over the fire front, further accelerating the fire (later discussed in *Fire-induced winds*).

A pyrocumulus cloud was produced in the simulation for under 1 h at approximately 19:00 on 18 September (Appendix S1: Fig. S3), as the leading edge of the fire was approaching the top of the canyon. It occurred near the base of a moist layer that extended from 3 to 6 km above ground level. The fire plume increased the ambient relative humidity of approximately 60% at that height to saturation, forming trace amounts of cloud and rainwater. As the amount of liquid produced was small and this occurred late in the fire's run, it contributed little to simulated fire growth.

During period 2, from 21:00 on 18 September to 20:51 on 19 September, the fire was less active and spread slowly under moist easterlies. It crept outward along its flanks with active burning at the northern edge toward the west and higher intensity burning within 0.3 to 1 km wide lobes that were aligned with small drainages. These lobes lay under fire-produced convective cells that drew the fire up the drainages, which served as topographic "chimneys." The simulation (Fig. 6a) contained features seen in concurrent high spatial resolution (35-m pixel) thermal infrared data from MASTER (Moderate Resolution Imaging Spectroradiometer [MODIS]/Advanced Spaceborne Thermal Emission and Reflection Radiometer [ASTER] airborne prototype; Hook et al. 2001; Fig. 6b).

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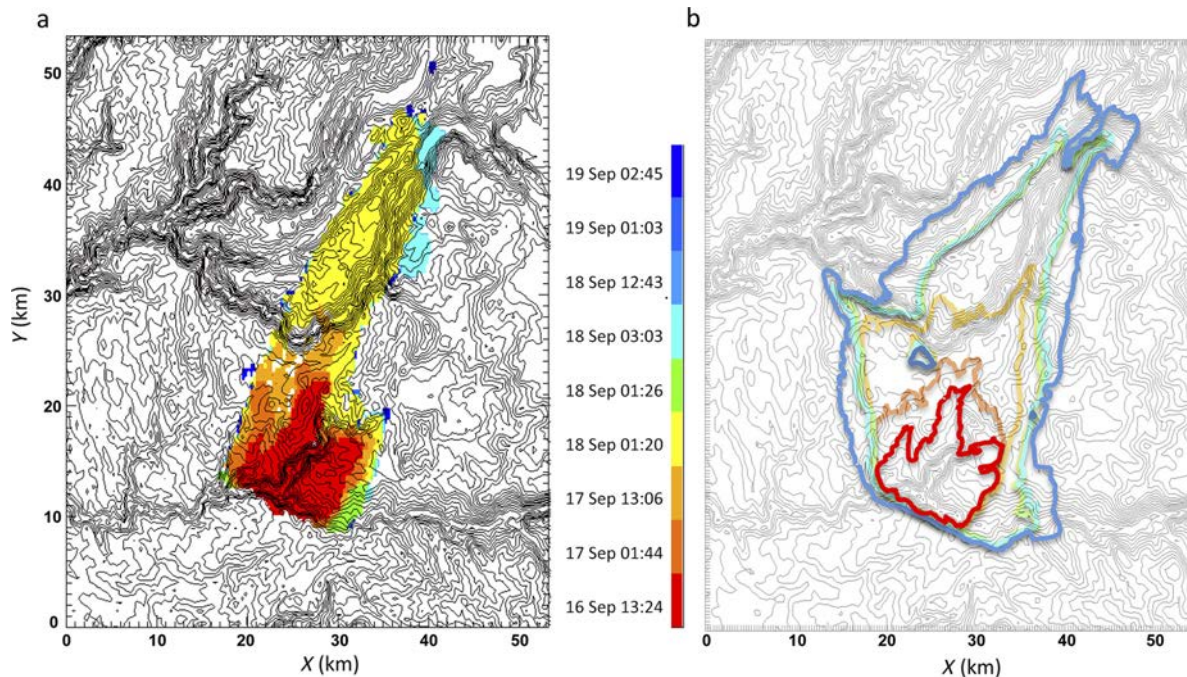


FIG. 5. Observed and simulated fire progression. (a) NIROPs extent used to initialize fire in progress (red) (21:49 on 16 September) and later VIIRS fire detections through 02:45 on 19 September. NIROPs data are distributed by the National Interagency Fire Center (<https://ftp.nifc.gov>). (b) Simulated fire extents at VIIRS detection times to 12:43 on 18 September, plotted with corresponding colors. Historical active fire detection data are distributed by the USDA Forest Service Active Fire Mapping Program (<https://fsapps.nwcg.gov/afm/>).

Fire-induced winds

Fire-induced winds were calculated using the difference between the west-east, south-north, and vertical wind components in the control simulation and corresponding fields in a simulation without a fire. At 22:00 on 16 September, as the fire drew itself up drainages in the rolling hills south of the Rubicon Canyon, the horizontal component of the fire-induced winds was 0–11.1 m/s, (Fig. 7a) on the order of the ambient winds, and the impact on the vertical wind component was –3.4 to 8.7 m/s (Fig. 7b). These perturbations appear as individual updraft plumes along the fire line, compensating downdrafts and inflow into the plumes, and outflow accelerated downwind to the north-northeast. Fire-induced winds were arranged differently at 16:20 on 17 September as the fire raced up canyon, when the horizontal winds in the fire's leading edges, those driving it up canyon, reached 12–13.7 m/s (Fig. 7c) and fire-induced vertical winds, located primarily in the plume leading the fire, ranged from –5.1 to 14.5 m/s (Fig. 7d), both exceeding ambient winds.

Sensitivity to drought

The control simulation used the 10 h DFMC at the Bald Mountain Remote Automated Weather Station (RAWS), which was measured at its historical average of 5% during the fire, similar to other nearby stations. The 10 h DFMC reflected the response of smaller fuel elements that spread a fire front to varying weather. Concurrently, exceptionally low moisture content was measured in larger dead fuel elements that respond over longer timescales that reflect the drought but these do not influence spread rate. Sensitivity experiments

varied the DFMC using the historical low and high extremes of 3% and 8%, respectively. Fires in all three simulations traveled rolling hills to reach the Rubicon Canyon in the early morning of 18 September. The simulated fire for the observed DFMC arrived in 12 h at 17:00, while simulations with historical high (low) DFMC experiments arrived at the same time (1 h earlier), respectively (Fig. 8). Both the control and historical high DFMC simulations took 6.3 h to cross the Rubicon Canyon and begin their runs, while the historically low DFMC simulation crossed and began to climb at once. After each simulated fire began to climb, the race up canyon of experiments with 8%, 5%, and 3% DFMC took 16.7, 15.0, and 11.7 h, respectively. Faster moving simulated fires reached waypoints sooner but did not lead to a larger ultimate fire extent, the growth of which was restricted by rocky terrain at the top and slowed by deteriorating weather conditions as winds changed direction and weakened, humidity increased, and rain occurred over the area.

LFMC had the potential to influence fire behavior. Energy rising from a surface fire is used to heat and dry the canopy, and if the remaining energy flux exceeds a threshold, the canopy ignited. Thus, the barrier to igniting canopies with higher LFMC is higher. Contrarily, once ignited, the latent heat flux is higher, per kilogram fuel consumed, for higher LFMC, as water vapor contributes to the air's buoyancy, fueling stronger fire-induced winds, although the canopy fuel consumed may be lower. The difference in evolving fire extent or rate of spread, as expressed through CAWFE simulations, between experiments with LFMC of 90%, 120%, and 150%, effectively the natural range of values, was negligible (not shown). Differences in fire effects such as burn severity were not tested.

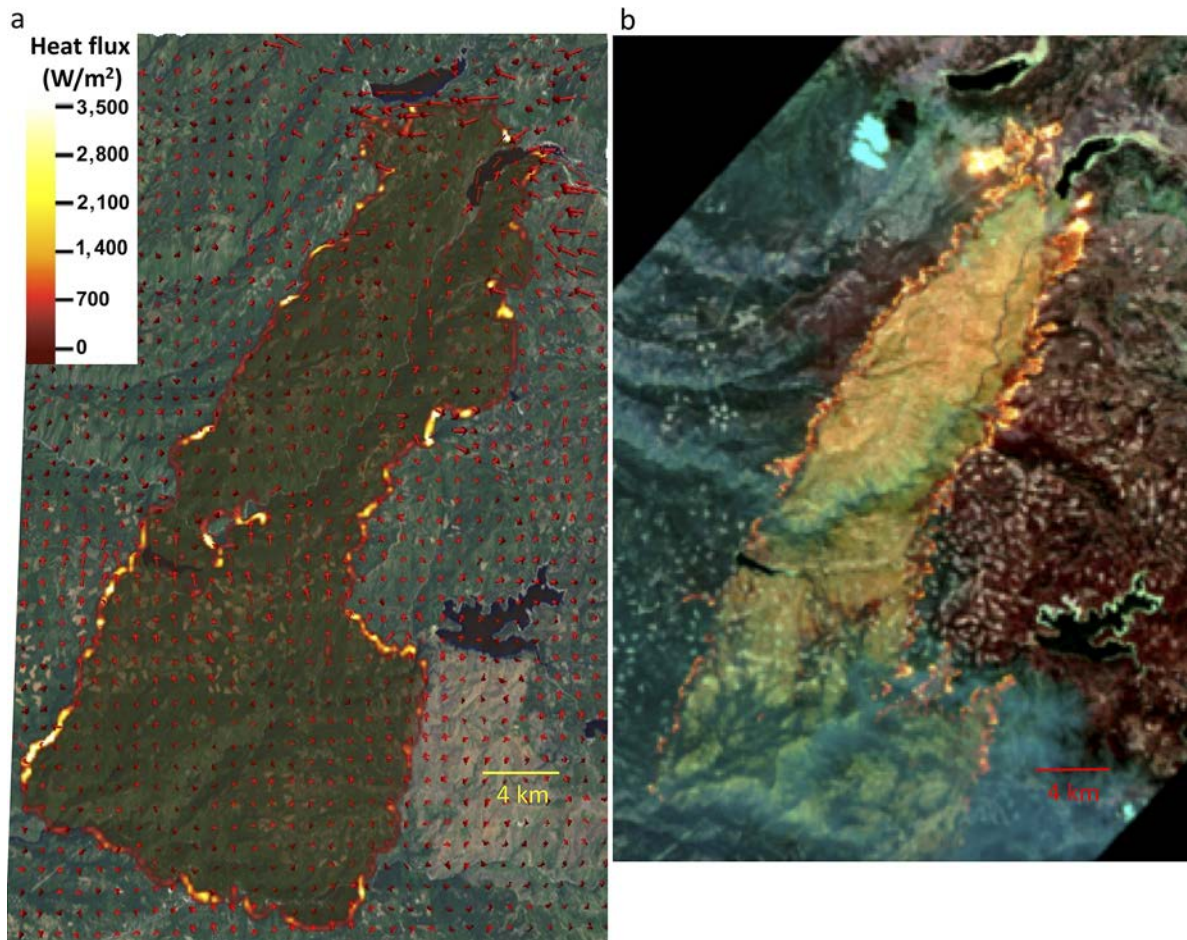


FIG. 6. Simulation and MASTER imagery of King Fire at 12:00 on 19 September. (a) Model simulation of King Fire at 12:00 on 19 September using LANDFIRE fuels at the time of (b) MODIS-ASTER (MASTER) airborne infrared imagery of the King Fire. Reproduced from Lee et al. (2015).

Sensitivity to fuel accumulation

We tested the effect of surface fuel accumulation due to fire suppression by comparing a simulation with standard conditions (the control) to a simulation with one-half the surface fuel load in one-half the depth (thereby keeping the packing ratio constant) to approximate fuels before accumulation. Increased fuel during the early growth period on rolling terrain extended the fire perimeter by up to 3 km. Fuel accumulation had much greater impact on inclined terrain, increasing fire extent by 16 km during the up-canyon run (Fig. 9), but although it accelerated fire spread, ultimately did not increase the final extent due to the topographic and weather constraints.

Unlike surface fuel load, which is input into the spread rate formula, the canopy fuel load does not directly affect the spread rate. However, the sensible and latent heat released by its consumption contribute to vertical motion as, when climbing sloped terrain, a component of the fire plume updraft lies along the surface in the direction of fire propagation; that is, the canopy fuel load can impact fire spread rate through fire-induced winds. Consistent with this rationale, increasing the canopy fuel load by a factor of three had little effect on early growth over rolling hills before reaching the Rubicon Canyon,

but had more effect later on growth up the canyon, increasing fire extent by 12 km over the control by 24 h (Fig. 10). Again, this ultimately did not lead to a greater fire extent.

Sensitivity to spatial distribution of fuel models

To evaluate the effect of limitations with spatial maps of fuel models, we compared periods 1 and 2 of the control simulation, which used fuel models classified into the Anderson (1982) 13 fuel models from the fire management standard LANDFIRE database, against simulations using a fuel model map also classified into the Anderson 13 fuel models that was developed from a technique called MapFUELS (Stavros et al. 2018), which employs only remote sensing observations. Applied to the King Fire data set, MapFUELS fuel maps varied from LANDFIRE most clearly in areas with harvesting and replanting, recovering burn scars, or dense plantation (Fig. 3). CAWFE simulations using MapFUELS data experienced different fire behavior producing a narrower fire by correctly not spreading through harvested patches or into the Cleveland Fire scar, the successional recovery of which appears faster than indicated in LANDFIRE, and better predicting the fire's passage north to the Rubicon Canyon through harvested areas (Fig. 11). However, the MapFUELS simulation

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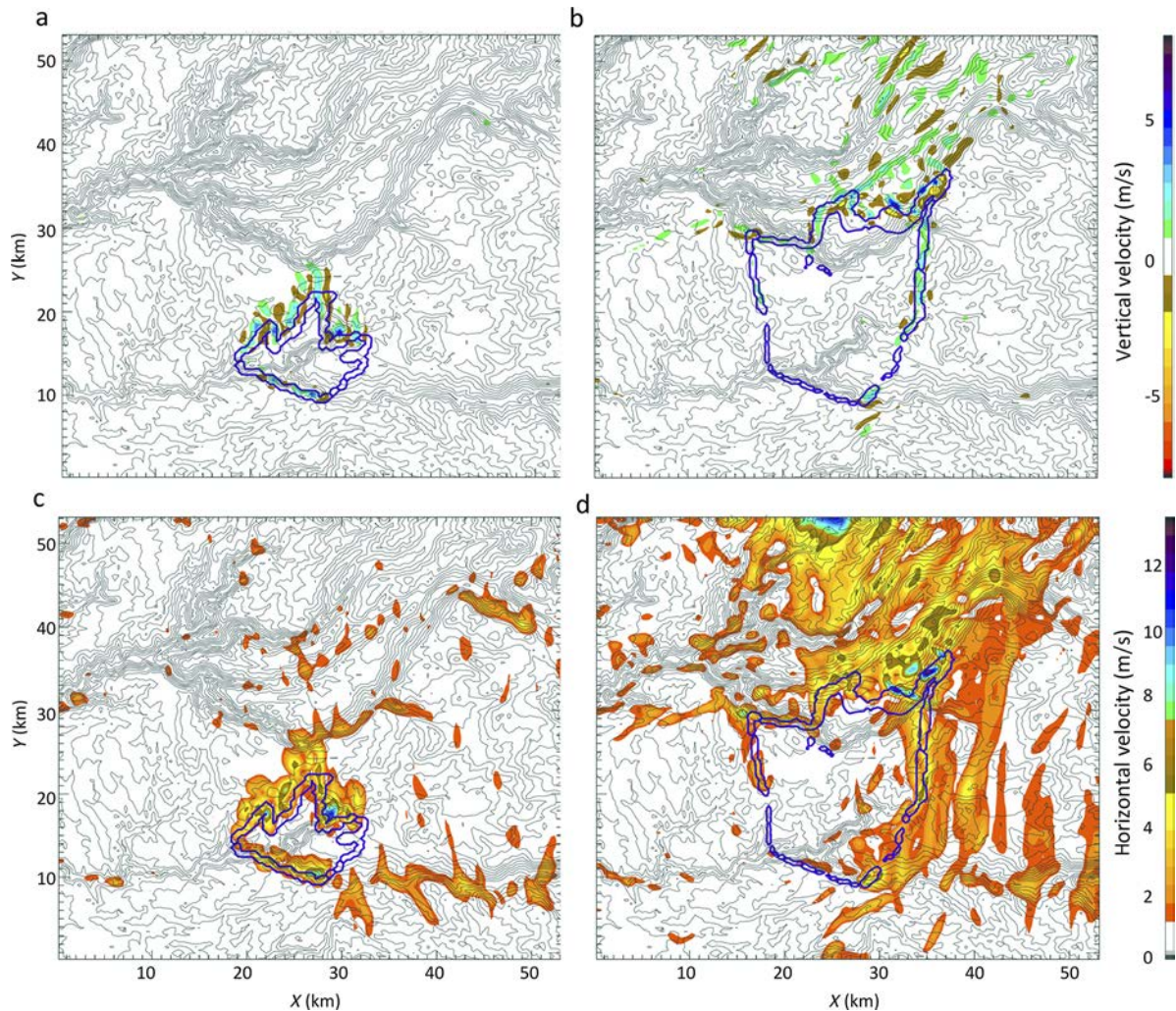


FIG. 7. Fire-induced winds. Fire-induced vertical (a, b) and horizontal (c, d) winds in m/s at 22:00 on 16 September (a, c) and 16:40 on 17 September (b, d).

produced too slow a run up the Rubicon Canyon and slightly exaggerated fire spread into the 2001 Star Fire scar, erroneously extending the fire by an additional 1–2 km. (Fig. 12).

Burn severity

Burn severity is distinct from instantaneous fire intensity (Keeley 2009) and is broadly defined as the degree to which fire has affected a site, a combined effect of fire intensity and residence time. Different severity metrics exist and depend on the medium being affected, for example, tree and shrub mortality, organic matter loss, or soil hydrologic impacts. The postfire Rapid Assessment of Vegetation Condition (RAVG) Composite Burn Index (CBI) severity assessment (distributed by the USDA Forest Service) represents the magnitude of fire-caused changes to the understory (grass and shrub layers), mid-story, and overstory (data available online).⁸ The RAVG CBI showed that much of the Rubicon Canyon experienced high burn severity (Fig. 13a).

⁸ https://apps.fs.usda.gov/arcx/rest/services/RDW_Wildfire/RAVG_CompositeBurnIndex/MapServer

Because CAWFE simulates a fire's intensity and heat flux to the atmosphere, we used total heat flux released over time at each point (related to the intensity of burning and integrated consumption over the residence time) as a proxy for severity for comparison with CBI. A visual comparison with results using LANDFIRE fuels (Fig. 13b) showed the simulated burn severity using MapFUELS fuels (Fig. 13c) better represented the extent and location of high severity areas.

DISCUSSION

Recent large, high-impact fires around the world have stimulated discussions that fire behavior has entered a new regime. Changing climate conditions that may create long-term drought and land management policies that emphasize fire exclusion leading to fuel accumulation are frequently cited as causes of large, severe fires. This is an intuitively obvious conclusion that is apparently supported by statistical studies that interpret correlations between atmospheric state variables or live fuel moistures and regional or national area burned as evidence of a causal relationship that can be repurposed to explain individual megafires. However, our work

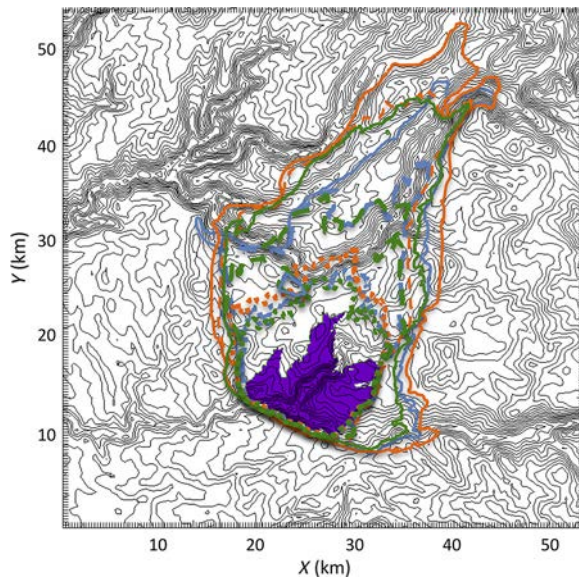


FIG. 8. Effect of dead fuel moisture content on fire evolution. The simulated evolution of fires with historical high (8%; green), low (3%; orange), and measured (5%; blue) dead fuel moisture content at 12 h (dotted line), 24 h (dashed line), and 36 h (solid line). The fire perimeter detected by NIROPs (purple) was introduced at 21:49 on 16 September.

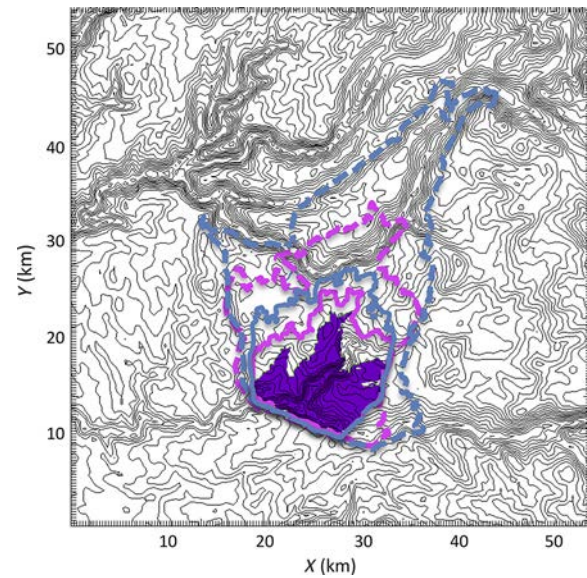


FIG. 9. Effect of surface fuel amount on fire evolution. The simulated evolution of fires with current surface fuel load and depth (blue) and with one-half the load and one-half the depth (pink), representative of conditions before fuel accumulation due to fire suppression, at 12 h (solid line) and 36 h (dashed line) into the simulation. The fire perimeter detected by NIROPs (purple) was introduced at 21:49 on 16 September.

suggests that the issue of what causes megafires and how future conditions will shape their frequency is not settled and should be critically re-examined from other perspectives.

Taking a different approach—that of a process study—this work used a physically based coupled NWP–wildland fire behavior model to reveal and examine the key processes underpinning the rapid growth and ultimate size of a specific megafire, the 2014 King Fire. More broadly, this study drew from fire behavior science to show the mechanisms through which both external and internally generated factors, with varying relative degrees of importance, drive any wildfire. Sensitivity experiments quantified how and to what degree drought and fuel accumulation contributed to this fire’s behavior and how sensitive the results were to the type of fuel by using fuel maps derived solely from a unique set of remote sensing data, which, if applied in other settings, offer the potential to better monitor vegetation structure and composition.

We found that the CAWFE coupled weather–wildland–fire model reproduced the expanding fire extent and features documented by airborne and satellite observations, including an afternoon run during which the fire grew over 16,200 ha (40,000 acres) and other distinctive features. Results showed that the King Fire’s growth primarily resulted from submesoscale winds within the Rubicon Canyon, beneath the resolution of sparse meteorological surface observation networks characteristic of remote areas or standard weather forecast models, and fire-induced winds that were on the order of or greater than ambient winds and enhanced by the convex canyon’s upward tilt. While the fine-scale winds and fire-induced circulations were not detectable in widely spaced weather station data, the data used by macroscale statistical studies, nor were they captured in current operational fire growth tools that underestimated the growth, both were captured by CAWFE. Thus,

while this megafire’s behavior was not outside current understanding of fire behavior, it required a newer, coupled model to capture fire–atmosphere feedbacks and how the impacts of contributing factors can multiply through dynamic interactions—effects missing from all kinematic operational tools, including the different fire spread models used in the United States, Canada, and Australia. The perceived unpredictability of fires, which may merely reflect the limitations of current models, and notion that fire behavior is entering a new regime may reflect an increasingly dominant role of internal dynamics in driving fire behavior, supporting Alvarado et al.’s (1998) observation that megafires may behave differently than less extreme events.

There are broader implications. Fire behavior modeling is performed not only for fire management but also to support decision-making for preserving ecological resources, managing carbon emissions, establishing policy promoting forest resilience, and protecting endangered species habitat. So, rather than dismissing this underestimate by current operational tools of an extreme event as an anomaly, it is important to recall that the largest 1% of fires account for 80–96% of area burned (Strauss et al. 1989) and a disproportionately large portion of impacts. Understanding the mechanisms and actual contributing factors leading to megafires, and being able to model the full extent of outliers, is vital for shaping policy recommendations aimed at mitigating a disturbance dominated by extreme events.

Additional simulations isolated the contribution from fuel moisture—the primary path through which drought impacts fire behavior—and fuel amount, which is the most direct way to indicate how preventing fuel accumulation might have created a different outcome. We found that varying the surface dead fuel moisture content across its historical range had little impact on the rate of fire progression in the growth

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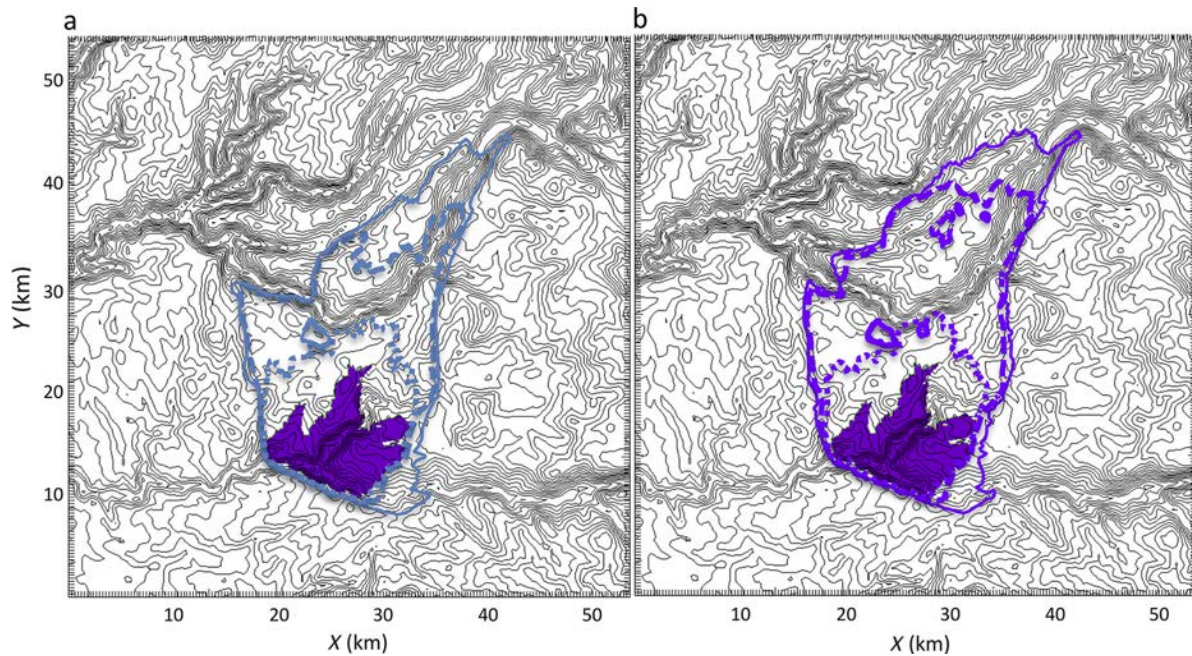


FIG. 10. Effect of canopy fuel load on fire evolution. The simulated evolution of fires with (a) current canopy fuel load and depth (blue) and with (b) three times the canopy fuel load (purple) at 12 h (dotted line), 24 h (dashed line), and 36 h (solid line). The fire perimeter detected by NIROPs (solid purple fill) was introduced at 21:49 on 16 September.

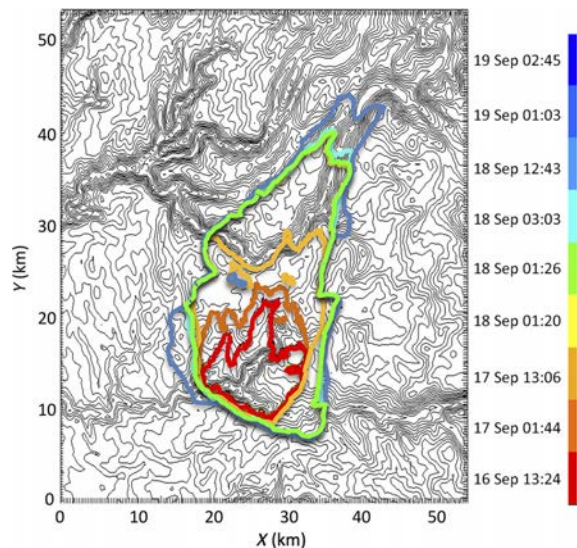


FIG. 11. Simulated fire evolution using remotely sensed fuel data. NIROPs extent used to initialize fire in progress at 21:49 on 16 September and simulated perimeters at later VIIRS fire detection times using MapFUELS-derived fuel type.

toward the Rubicon Canyon, where terrain was essentially flat. And, despite a prolonged drought reflected in live canopy fuel moisture and larger surface fuels, the dead fuel moisture content that impacts spread rate was measured as average from a historical perspective. In addition, it caused little difference, and in the case of live fuel moisture content, effectively no difference, in how fast the fire would have traveled up the Rubicon Canyon compared to historically high

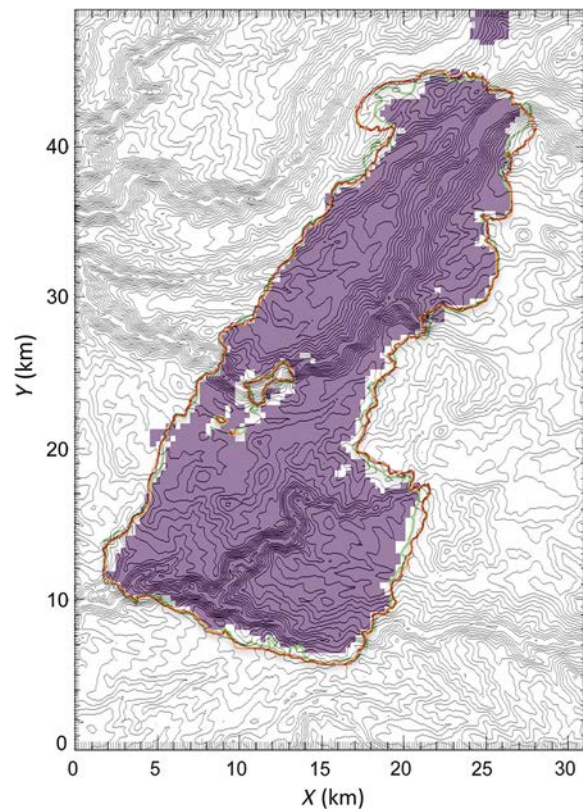


FIG. 12. Simulated fire evolution using two fuel sources and comparison to satellite active fire detection data. The VIIRS active fire map near the end of period 2 (purple), at 14:08 on 19 September. CAWFE simulated extent at the same time using LANDFIRE fuel model data (green) and MapFUELS-derived data (orange).

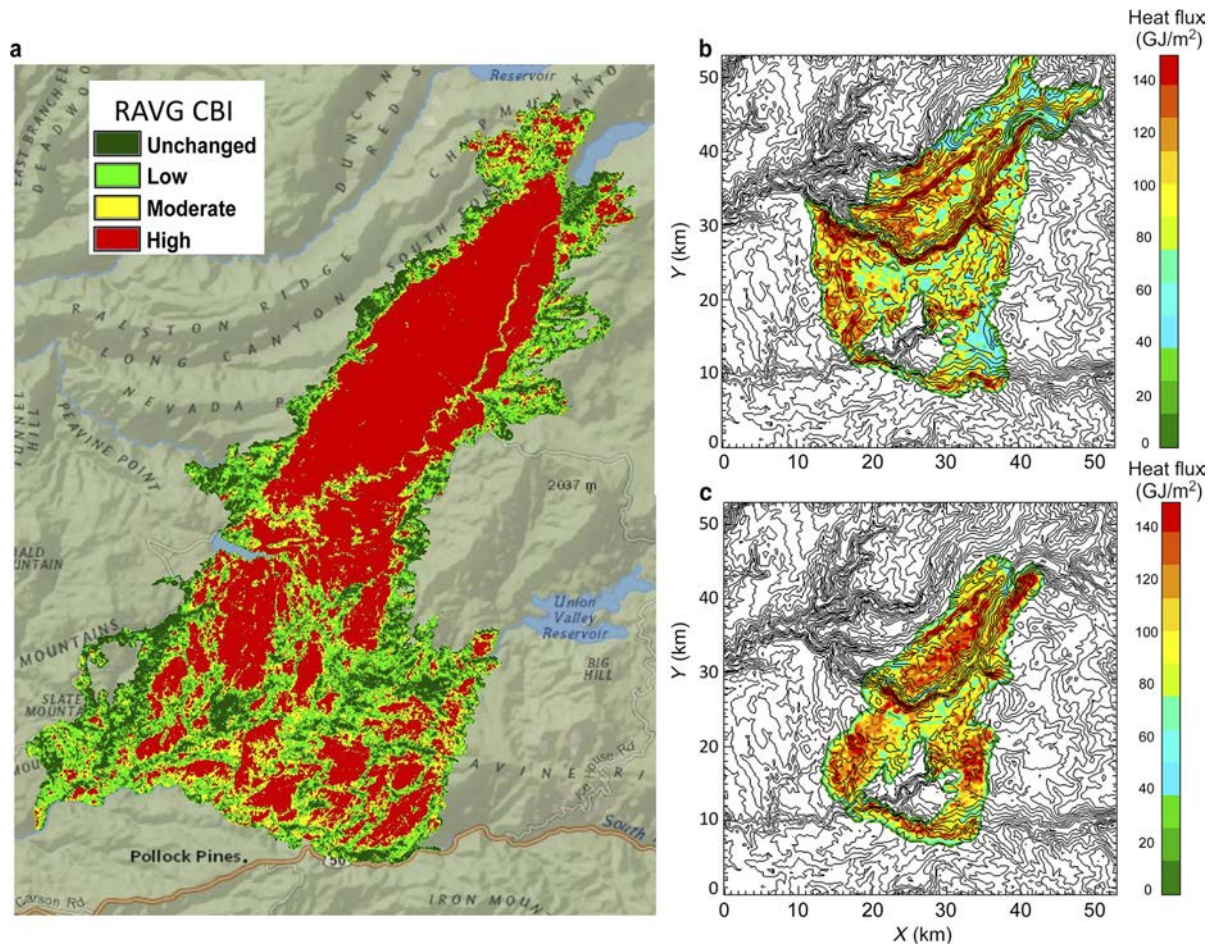


FIG. 13. Observed soil burn severity and simulated severity using fuel data from two sources. (a) Rapid Assessment of Vegetation Condition (RAVG) Composite Burn Index (CBI) severity product from the USDA Forest Service Geospatial Technology and Applications Center. Simulated sensible and latent heat flux summed over time at each point using (b) LANDFIRE and (c) MapFUELS fuel models.

fuel moisture conditions, suggesting drought contributed little to this fire's behavior throughout the event on its own. However, had dead fuel moisture content been at its historical low, the fire would have arrived at the canyon's top 3 h earlier—a change in behavior that could have had implications for suppression activity and personnel safety. Interestingly, although a faster moving simulated fire would have reached waypoints sooner, results suggested it would not have ultimately become a larger fire because growth was slowed by terrain at the canyon's top and constrained by weakening and shifting winds and increasing humidity and rain, a reflection of the complex terrain and episodic nature of weather periods that shape wildfire growth.

Intuitively, it seems that drought should increase fire rate of spread, a belief bolstered by regional or national correlations between drought indices and areas burned and indications of fuel moisture thresholds that trigger fire behavior (Dennison and Moritz 2009), but our outcomes and the limited mechanisms through which drought may influence a fire's spread rate (Appendix S1) show that drought's effect on surface and canopy fuels as represented in landscape-scale fire behavior models is secondary. The effect of drought on fuel moisture, which can have high spatial variability, may instead be more nuanced than directly

influencing the rate of spread. For example, drought may sustain more ignitions or may assure the spatial continuity of sufficiently dry fuels to maintain fire spread across the landscape (M. Gill, *public communication*) and dehydrate fuel on sheltered, moister facets of terrain (Bradstock 2010).

The impact of fuel accumulation was also modulated by topography. Specifically, less fuel accumulation would have had little impact on the rate at which the King Fire spread across rolling terrain toward the Rubicon Canyon but would have slowed fire spread up the canyon. The fire would have consumed less fuel, produced lower heat fluxes and weaker updrafts, and thus caused weaker fire-induced winds. Likewise, experiments with greater canopy fuel load, which solely impact fire spread indirectly through additional heat fluxes that generate stronger fire-induced winds, increased fire spread rate only on inclined terrain. Because increased fuel amounts only accelerated the fire when climbing sloped terrain, fuel reduction efforts aimed at reducing some metrics of fire behavior could be focused on inclined terrain for maximum impact on fire behavior. This work complements studies (LaCroix et al. 2006, Finney 2007, Syphard et al. 2011, Dicus and Osborne 2015) that indicate how treatment patterns may be optimized at the landscape scale to obstruct wildfire growth. However, those conclusions should be re-examined

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with very-high-resolution coupled weather–fire models such as CAWFE that capture the fine-scale weather and fire-induced winds that can dominate extreme behavior and create outlier events that cause disproportionate impact.

This work found that both drought and fuel accumulation's impacts on the King Fire occurred primarily when the fire was burning in inclined terrain, where fuel amount and moisture dynamically compounded each other through the medium of fire-induced winds. That fire growth frequently occurs in complex terrain suggests this reinforcement effect on fire behavior by terrain could be widespread, and because of the implications, warrants further study and highlights the need to investigate climate and fuel impacts on fire behavior and effects jointly. In investigating a specific case, this work supports findings from statistical regression models relating climate factors to wildfire, for example, (Riley et al. 2013), that emphasize short-term indicators of drought (the rapidly responding dead fuel moisture content) more than long-term factors (such as live fuel moisture content). Simulations support studies that show short-term fire weather to be a significant predictor (Barbero et al. 2014), as weather windows enable and curtail fire growth. This suggests the cautionary point that in some conditions, for example, when a fire's expansion is limited by topography or the duration of a weather window favorable for growth, as in the King Fire, conditions can create instantaneously rapid spread rates and affect when a fire reaches its ultimate extent yet not have an opportunity to create a bigger fire.

We found that dead fuel moisture was a less significant factor in this case than winds and fire-induced winds, reinforcing previous conclusions (Coen and Schroeder 2015), that the degree to which changing fuel properties (either amount or dead fuel moisture) affect fire behavior is secondary to the spread rate's sensitivity to winds, when winds are significant. We suggest caution in interpreting studies that use statistical regression on variables such as wind measured at surface weather stations as this may misinterpret fire weather influence. This is because significant contributions come from wind patterns that occur at spatial scales finer than resolved by station data and from fire-induced winds, neither of which are reflected in meteorological data. However, these results do not contradict the macroscale statistical correlations between burned area and climate factors such as drought, because the macroscale correlations represent how these locally heterogeneous climate impacts would appear when summed over all fires over large areas.

In totality, this work—event simulations, sensitivity experiments, and synthesis of fire behavior studies—indicates that the events distinguishing the King fire in particular, and perhaps other megafires more generally, can be interpreted as arising through self-reinforcing, internal system dynamics (e.g., fire-generated winds) rather than from the direct effect imposed by individual external factors (e.g., drought, fuel accumulation, ambient wind). In both interpretations, the factors, various measures of fuel moisture and amount, wind, etc., affect the fire to varying degrees through their individual direct impacts on fire behavior. However, the escalation to another level of intensity, becoming a megafire, is possible in fires where factors fortuitously align and their effects amplify one another, manifesting as and feeding back on each other through dynamic effects such as fire-induced winds and

airflow acceleration from topographic channeling or thermodynamics. But importantly, this interpretation allows that extreme behavior/high-impact fires need not arise from an extreme fire environment condition (either winds or fuels), as in the King fire, no individual environmental factor foretold megafire behavior. Further, varying individual fire behavior input parameters across their observed natural range did not make or break the megafire. This finding contradicts a widespread belief within the forestry community, partially generated by longtime use of kinematic fire spread models that omit dynamic feedbacks, that the energy needed to drive extreme fires requires exceptional amounts of burnable biomass, amounts exceeding those given by the Albini (1976) and Anderson (1982) surface fuel models and canopy fuel loads used here. In addition, this work casts doubt on the effectiveness of using predicted broad climate variables to explain and predict future megafire occurrence.

Fuel type and structure derived solely from an unprecedented set of airborne remote sensing data provided a more physically based representation of fuel models, and in conjunction with a physically based model, allowed attribution of various aspects of this fire's behavior to specific controls. Since this analysis depended on serendipitous collection of prefire data, this opportunity is not easily repeated, and so provides unique insights. Remote-sensing-derived fuel models generally improved simulations, notably in disturbed areas, which is important because megafires frequently encounter previous burn scars and managed lands that may impede or accelerate fire progression. The remote sensing-based fuels visually improved the simulated spatial distribution of burn severity, supporting studies that assert the importance of forest successional state on fire impacts (Lyons-Tinsley and Peterson 2012). Current analyses are limited to areas mapped by airborne missions and depend on availability of preburn data and resources to collect post-fire observations. Data from similar instrumentation, LiDAR and spectroscopy, on upcoming satellite remote sensing missions may expand the opportunity for such analyses (Dubayah et al. 2014, Jetz et al. 2016).

This approach and the different perspective it provides on the origin of the King megafire, and possibly megafires more generally, suggests several steps as part of a broad-based community path forward. These include broader use of coupled models to investigate fire behavior and revisiting conclusions made based on uncoupled models. A second step is developing widespread and regularly updated remote-sensing-based fuel mapping products, culminating in inclusion in community databases, as in Peterson et al. (2015b). Improved global forest structural, compositional, and moisture data could enable megafire growth and effects to be better predicted in the future. While progress has been made, as noted in Appendix S1, a third need is better understanding of crown fires, notably, collecting large enough samples to make stronger conclusions about how fuel properties and condition affect crown fire initiation, growth, and fire effects and continuing progress toward mapping canopy fuel moisture accurately with remote sensing data. Further pre-, during, and post-megafire observations, including unsaturated thermal infrared airborne observations, and coupled modeling studies are needed to better understand the internal dynamics of these events and their effects. Fourth, studies

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on the potential for future megafires in particular should perhaps be focused on the degree to which weather will be more episodic and have more frequent or longer multiday fire weather periods and how this coincides with changing ignition patterns rather than on broad climate variables and fire season length. Regional climate simulations are now being run at approximately 10 km grid spacing (Prein et al. 2013), and although these still do not explicitly resolve convective precipitation, they may indicate changing patterns. The scales influencing fires range over several orders of magnitude and it is not feasible to test all factors or all fires with one approach. Diverse methods, arising from different areas of expertise, each of which providing a unique, partial insight, are needed to unravel this important problem.

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SUPPORTING INFORMATION

Additional supporting information may be found online at: <http://onlinelibrary.wiley.com/doi/10.1002/eap.1752/full>

DATA AVAILABILITY

Data available from NASA ORNL DAAC: <https://doi.org/10.3334/ornl daac/1288>

EXHIBIT I

Does increased forest protection correspond to higher fire severity in frequent-fire forests of the western United States?

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Abstract. There is a widespread view among land managers and others that the protected status of many forestlands in the western United States corresponds with higher fire severity levels due to historical restrictions on logging that contribute to greater amounts of biomass and fuel loading in less intensively managed areas, particularly after decades of fire suppression. This view has led to recent proposals—both administrative and legislative—to reduce or eliminate forest protections and increase some forms of logging based on the belief that restrictions on active management have increased fire severity. We investigated the relationship between protected status and fire severity using the Random Forests algorithm applied to 1500 fires affecting 9.5 million hectares between 1984 and 2014 in pine (*Pinus ponderosa*, *Pinus jeffreyi*) and mixed-conifer forests of western United States, accounting for key topographic and climate variables. We found forests with higher levels of protection had lower severity values even though they are generally identified as having the highest overall levels of biomass and fuel loading. Our results suggest a need to reconsider current overly simplistic assumptions about the relationship between forest protection and fire severity in fire management and policy.

Key words: biodiversity; climate; fire frequency; fire severity; fire suppression; Gap Analysis Program levels; logging; protected areas.

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INTRODUCTION

It is a widely held assumption among federal land management agencies and others that a lack of active forest management of some federal forestlands—especially within relatively frequent-fire forest types such as ponderosa pine (*Pinus ponderosa*) and mixed conifers—is associated with higher levels of fire severity when wildland fires occur (USDA Forest Service 2004, 2014, 2015, 2016). This prevailing forest/fire management hypothesis assumes that forests with higher levels of protection, and therefore less logging, will burn more intensely due to higher fuel loads and forest density. Recommendations have been made to increase logging as fuel

reduction and decrease forest protections before wildland fire can be more extensively reintroduced on the landscape after decades of fire suppression (USDA Forest Service 2004, 2014, 2015, 2016). The concern follows that, in the absence of such a shift in forest management, fires are burning too severely and may adversely affect forest resilience (North et al. 2009, 2015, Stephens et al. 2013, 2015, Hessburg 2016). Nearly every fire season, the United States Congress introduces forest management legislation based on this view and aimed at increasing mechanical fuel treatments via intensive logging and weakened forest protections.

However, the fundamental premise for this fire management strategy has not been rigorously

tested across broad regions. We broadly assessed the influence of forest protection levels on fire severity in pine and mixed-conifer forests of the western United States with relatively frequent-fire regimes to test this assumption. We used vegetation burn severity data from all fires >405 ha over a three-decade period, 1984–2014, in forests with varying levels of protection.

Study area

Pine and mixed-conifer forests at low/mid-elevations, where historical fires were relatively frequent, are broadly distributed across several ecoregions in the western United States (Fig. 1; Appendix S1: Table S1). Although ponderosa pine often dominates these forests, they can also include Jeffrey pine (*Pinus jeffreyi*), which in places intermix with, and are similar to, ponderosa pine forests, and Madrean pine-oak (*Quercus* spp.) forests with a diversity of pines. Mixed-conifer forests at low/mid-elevations are also broadly distributed across multiple ecoregions (Fig. 1). They can include additional pines (e.g., lodgepole pine, *Pinus contorta*; sugar pine, *Pinus lambertiana*), true firs (*Abies* spp.), Douglas-fir (*Pseudotsuga menzeisii*), and incense-cedar (*Calocedrus decurrens*).

METHODS

We used Gap Analysis Program (GAP) protection classes (USGS 2012), as described below, to determine whether areas with the most protection (i.e., GAP1 and GAP2) had a tendency to burn more severely than areas where intensive management is allowed (i.e., GAP3 and GAP4). We compared satellite-derived burn severity data for 1500 fires affecting 9.5 million hectares from years for which there were available data (1984–2014) among four different forest protection levels (Fig. 1), accounting for variation in topography and climate. We analyzed fires within relatively frequent-fire forest types comprised of pine and mixed-conifer forests mainly because these are the predominant forest types at low to mid-elevations in the western United States, there is a large data set on fire occurrence, and they have been a major concern of land managers for some time due to decades of fire suppression. We defined geographic extent of forest types from the Biophysical Settings data set (BpS) (Rollins 2009; public communication, <http://www.landfire.gov>)

that derived forest maps from satellite imagery and represents plant communities based on NatureServe's Ecological Systems classification. Baker (2015) noted that some previous work found ~65% classification accuracy of this system with regard to specific forest types and, accordingly, he analyzed groups of related forest types in order to improve accuracy. We followed his approach (see Appendix S1: Table S1). The categories selected from the Biophysical Settings map were ponderosa/Jeffrey pine and mixed-conifer forest types with relatively frequent-fire regimes (e.g., Swetnam and Baisan 1996, Taylor and Skinner 1998, Schoennagel et al. 2004, Stephens and Collins 2004, Sherriff et al. 2014), compared to other forest types with different fire regimes such as high-elevation forests and many coastal forests not studied herein. Forest types in our study totaled 29.2 million hectares (Fig. 1; Appendix S1: Table S1). We used the BpS data to capture areas that were classified as forests before fire, because postfire vegetation maps can potentially show these same areas as temporarily changed to other vegetation types. We sampled our response and predictor variables on an evenly spaced 90 × 90 m grid within these forest types using ArcMap 10.3 (ESRI 2014). This created a data set of 5,580,435 independent observations from which we drew our random samples to create our models. The 90-m spacing was chosen because it was the smallest spacing of points that was computationally practical with which to operate.

Fires

The Monitoring Trends in Burn Severity project (MTBS, public communication, <http://www.mtbs.gov>) is a U.S. Department of Interior and Department of Agriculture-sponsored program that has compiled burn severity data from satellite imagery, which became available in 1984, for fires >405 ha, and was current up to 2014 (Eidenshink et al. 2007). The MTBS Web site allows bulk download of spatial products that include two closely related indices of burn severity: differenced normalized burn ratio (dNBR) (Key and Benson 2006) and relative differenced normalized burn ratio (RdNBR) (Miller and Thode 2007). Both indices are calculated from Landsat TM and ETM satellite imagery of reflected light from the earth's surface at infrared wavelengths from before and after fire to



Fig. 1. Pine and mixed-conifer forests, fires, and ecoregions analyzed in this study.

measure associated changes in vegetation cover and soil characteristics. We defined burn severity with the RdNBR index because it adjusts for pre-fire conditions at each pixel and provides a more consistent measure of burn severity than dNBR when studying broad geographic regions with many different vegetation types (Miller et al.

2009a, Norton et al. 2009). RdNBR values typically range from negative 500 to 1500 with values further away from zero representing greater change from prefire conditions. Negative values represent vegetation growth and positive values increasing levels of overstory vegetation mortality. The RdNBR values could be used to classify

fires into discrete burn severity classes of low, medium, and high but this was not performed in our study, as we desired to have a continuous response variable in our models.

We intersected forest sampling points with fire perimeters downloaded from MTBS to determine fires that occurred in our analysis area, and censored fires with <100 sampling points (81 ha). The remaining points represented sampling locations from 2069 fires (Fig. 1). We extracted RdNBR values at each sampling point as our response variable as well as predictor variables that included topography, geography, climate, and GAP status. These sampling points were used to investigate the relationship between forest protection levels and burn severity (Appendix S1: Tables S2 and S3). We chose topographic and climatic variables based on previous studies that quantified the relationship between burn severity, topography, and climate (Dillon et al. 2011, Kane et al. 2015).

Topographic and climatic data

To account for the effects of topographic and climatic variability, we derived several topographic indices (Appendix S1: Table S2) from seamless elevation data (*public communication*, <http://www.landfire.gov/topographic.php>) downscaled to 90-m² spatial resolution due to computational limits when intersecting sampling points. These indices capture categories of topography, including percentage slope, surface complexity, slope position, and several temperature and moisture metrics derived from aspect and slope position. We used the Geomorphometry and Gradient Metrics Toolbox version 2.0 (*public communication*, <http://evansmurphy.wix.com/evansspatial>) to compute these metrics. We also computed several temperature and precipitation variables (Appendix S1: Table S3) by downloading climatic conditions for each month from 1984 to 2014 from the PRISM climate group (*public communication*, <http://prism.oregonstate.edu>). Climate grids record precipitation and minimum, mean, and maximum temperature at a 4-km grid scale created by interpolating data from over 10,000 weather stations. To determine the departure from average conditions, we subtracted each climate grid by its 30-yr mean monthly value. These “30-yr Normals” data sets were also downloaded from the PRISM Web site and reflected the mean values from the most recent full decades (1981–2010). We

determined mean seasonal values with summer defined as the mean of July, August, and September of the year before a given fire; fall being the mean of October, November, and December of the previous year; winter the mean of January, February, and March of the current year of a given fire; and spring the mean of April, May, and June of the current year.

Protected area status and ecoregion classification

We used the Protected Areas Database of the United States (PAD-US; USGS 2012) to determine forest protection status, which is the U.S. official inventory of protected open space. The PAD-US includes all federal and most State conservation lands and classifies these areas with a GAP ranking code (see map at: <http://gis1.usgs.gov/csas/gap/viewer/padus/Map.aspx>). The GAP status code (herein referred to interchangeably as GAP class or protection status) is a metric of management to conserve biodiversity with four relative categories. GAP1 is protected lands managed for biodiversity where disturbance events (e.g., fires) are generally allowed to proceed naturally. These lands include national parks, wilderness areas, and national wildlife refuges. GAP2 is protected lands managed for biodiversity where disturbance events are often suppressed. They include state parks and national monuments, as well as a small number of wilderness areas and national parks with different management from GAP1. GAP3 is lands managed for multiple uses and are subjected to logging. Most of these areas consist of non-wilderness USDA Forest Service and U.S. Department of Interior Bureau of Land Management lands as well as state trust lands. GAP4 is lands with no mandate for protection such as tribal, military, and private lands. GAP status is relevant to the intensity of both current and past managements.

We made one modification to GAP levels by converting Inventoried Roadless Areas (IRAs) from the 2001 Roadless Area Conservation Rule (S_USA.RoadlessArea_2001, *public communication*, <http://data.fs.usda.gov/geodata/edw/dataset.php>) to GAP2 unless these areas already were defined as GAP1. We considered most IRAs as GAP2 given they are prone to policy changes and because they allow for certain limited types of logging (e.g., removal of predominately small trees for fuel reduction in some circumstances).

However, we note that very little logging has occurred within IRAs since the Roadless Rule, although there occasionally have been proposals to log portions of some IRAs pre- and postfire, and fire suppression often occurs.

We modified level III ecoregions (U.S. Environmental Protection Agency (EPA) 2013) to create areas of similar climate and geography (Fig. 1). We did this by extracting ecoregions and combining adjacent provinces in our study region.

Random Forests analysis

We investigated the relationship between protection status and burn severity using the data-mining algorithm Random Forests (RF) (Breiman 2001) with the “randomForestSRC” add-in package (Ishwaran and Kogalur 2016) in R (R Core Team 2013). This algorithm is an extension of classification and regression trees (CART) (Breiman et al. 1984) that recursively partitions observations into groups based on binary rule splits of the predictor variables. The main advantage of using RF in our study is that it can work with spatially autocorrelated data (Cutler et al. 2007). It can also model complex, nonlinear relationships among variables, makes no assumption of variable distributions (Kane et al. 2015), and produces accurate predictions without overfitting the available data (Breiman 2001).

Our independent observations were a random subset of our 5.5 million points, from which we drew three random samples of 25,000 points each. Each sample consisted of 500 fires randomly selected without replacement from the pool of 2069 fires. Fifty points were then randomly selected within each of the 500 fires. Our dependent variables were all continuous (Appendix S1: Tables S2 and S3) except for the main variable of interest, protected area status, which included the four GAP levels. The three observation samples were used to create three RF model runs, each consisting of 1000 regression trees. We conducted three RF model runs to assess whether our random samples of 25,000 points produced fairly consistent results.

The RF algorithm samples approximately 66% of the data to build the regression trees, and the remaining data are used for validation and to assess variable importance. We used this validation sample to determine the amount of variance explained and variable importance.

The algorithm also produces individual variable importance measures by calculating differences in prediction mean-square-error before and after randomly permuting each dependent variable's values. Variable importance is a measure of how much each variable contributes to the model's overall predictive accuracy.

Unlike linear models, RF does not produce regression coefficients to examine how a change in a predictor variable affects the response variable. The analogy to this in RF is the partial dependence plot which is a graphical depiction of how the response will change with a single predictor while averaging out the effects of the other predictors, such as the climatic and topographic variables (Cutler et al. 2007). We used this approach, in addition to using RF to determine overall variable importance as described above, in order to determine the effect of GAP status, in particular, on fire severity, while averaging out effects of climate and topography.

Mixed-effects analysis

We performed a linear mixed-effects analysis using the “nlme” add-on package in R (Pinheiro et al. 2015). We used a random intercept model and identified year of fire ($n = 31$) and ecoregion ($n = 10$) as random effects. Similar to our RF models, our independent observations were a random subset of our 5.5 million points but for these models we drew three random samples of 50,000 points each. Each sample consisted of 500 fires randomly selected without replacement, and within each of those fires, 100 points were randomly selected. Our dependent variables were the same used in our RF models, and we log-transformed the non-normal variables of slope, surface roughness, and topographic radiation aspect index. We removed dependent variables that were correlated with each other (Pearson's $r > 0.5$), retaining 21 of 45 candidate dependent variables, and centered these on their means. Model reduction was performed in a stepwise process using bidirectional elimination with Bayesian information criterion selection criterion.

Spatial autocorrelation analysis

Spatial autocorrelation (SA) is the measure of similarity between pairs of observations in relationship to the distance between them. Ecological variables are inherently autocorrelated because

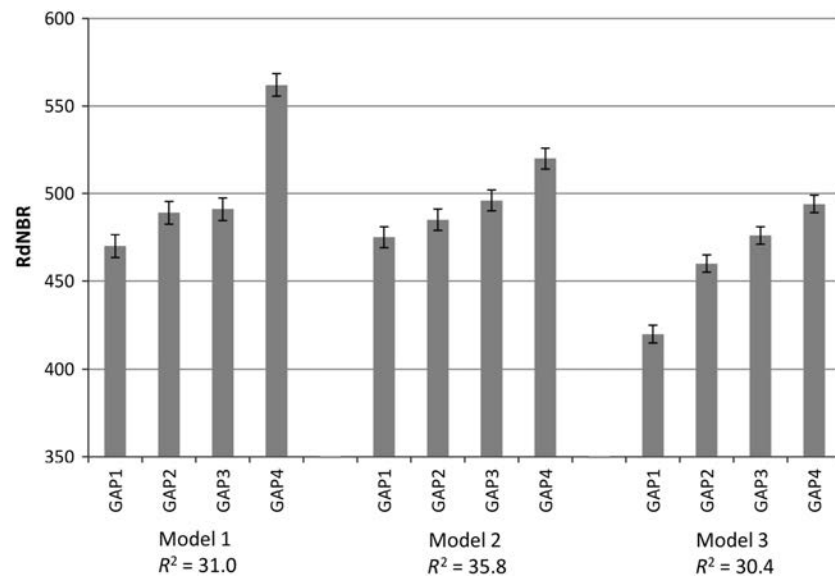


Fig. 2. Random Forests partial dependence of protection status vs. RdNBR burn severity for each model ($n = 25,000$). The variance explained is shown as pseudo R^2 .

landscape attributes that are closer together are often more similar than those that are far apart.

We assessed the SA in the Pearson residuals with inspection of Moran's I autocorrelation index using the "APE" package add-in in R (Paradis et al. 2004) after removing points that shared the same x and y coordinates. Moran's I is an index that ranges from -1 to 1 with the sign of the values indicating strength and direction of SA. Values close to zero are considered to have a random spatial pattern. Our mixed-effects models all had a Moran's I values statistically different from 0 at the 95% confidence level ($P < 0.001$) so we included a spatial correlation structure in our model using the "nlme" package in R. Of Gaussian, exponential, linear, and spherical spatial correlation structures, we determined that the exponential structure produced the lowest Akaike's information criterion (AIC). Despite these additions, our second measurements still found relatively small, but significant, autocorrelation (Moran's I for model runs 1, 2, 3 = 0.10, 0.08, 0.10, all $P < 0.001$).

RESULTS

With regard to ranking of variables in the model runs, variable importance plots from the three RF model runs show that protection status

was consistently ranked as one of the 10 most important of the 45 variables in explaining burn severity (Appendix S1: Table S4). The most important variable explaining burn severity was ecoregion for models 1 and 2 and maximum temperature from the previous fall for model 3.

With regard to the GAP status variable in particular, after averaging out the effects of climatic and topographic variables, the RF partial dependence plots show an increasing trend of fire severity with decreasing protection status (Fig. 2). Fires in GAP4 had mean RdNBR values greater than two standard errors higher than all other GAP levels. Fires in GAP3 had mean RdNBR values two standard errors higher than GAP1 in all model runs. GAP3 differences with GAP2 were less pronounced with only one model showing differences greater than two standard errors. Fires in GAP1 were consistently the least severe, being two standard errors less than GAP3 in all model runs and two standard errors less than GAP2 in two of three model runs.

Our mixed-effects models validated these findings with similar results (Fig. 3, Appendix S1: Table S5). Like our RF models, our linear mixed-effects models showed GAP4 fires to have significantly higher RdNBR values and GAP1 fires to have significantly lower RdNBR values when compared to all other GAP classes. Fires in GAP

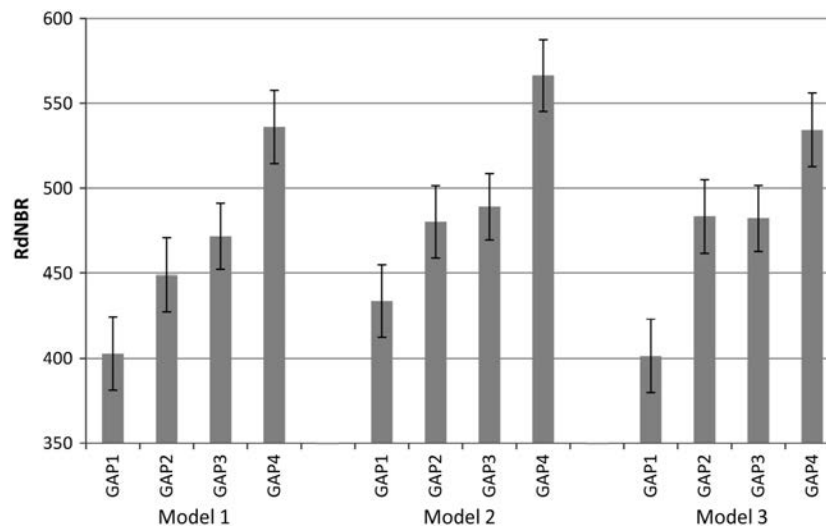


Fig. 3. Linear mixed effects models of protection status vs. RdNBR burn severity ($n = 50,000$).

status levels 2 and 3 were not significantly different in the mixed-effects models. Although the level of autocorrelation was significant, it was small in our model (Moran's $I \sim 0.1$) and not enough to account for such a substantial difference in burn severity among protection classes.

DISCUSSION

Protected forests burn at lower severities

We found no evidence to support the prevailing forest/fire management hypothesis that higher levels of forest protections are associated with more severe fires based on the RF and linear mixed-effects modeling approaches. On the contrary, using over three decades of fire severity data from relatively frequent-fire pine and mixed-conifer forests throughout the western United States, we found support for the opposite conclusion—burn severity tended to be higher in areas with lower levels of protection status (more intense management), after accounting for topographic and climatic conditions in all three model runs. Thus, we rejected the prevailing forest management view that areas with higher protection levels burn most severely during wildfires.

Protection classes are relevant not only to recent or current forest management practices but also to past management. Millions of hectares of land have been protected from logging since the 1964 Wilderness Act and the 2001 Roadless Rule, but these areas are typically categorized

as such due to a lack of historical road building and associated logging across patches >2000 ha, while GAP3 lands, for instance, such as National Forests lands under “multiple use management,” have generally experienced some form of logging activity over the last 80 yr.

We expect that the effects of historic logging from nearly a century ago to gradually lessen over time, as succession and natural disturbance processes reestablish structural and compositional complexity, but it was beyond the scope of this study to attempt to assess the relative role of recent vs. historical logging. Similarly, industrial fire suppression programs that intensified in the 1940s influenced fire extent across forest protection classes. While more recent let-burn policies have been applied in GAP1 and GAP2 forests in some circumstances, evidence indicates that protected forests nevertheless remain in a substantial fire deficit, relative to the prefire suppression era (Odion et al. 2014, 2016, Parks et al. 2015). Thus, we believe it is unlikely that recent decisions to allow some backcountry fires to burn, largely unimpeded, account for much of the differences in fire severity among protection classes that we found, simply because such let-burn policies have not been extensive enough to remedy the ongoing fire deficit.

While forests in different protection classes can vary in elevation, with protected forests often occupying higher elevations, our results indicate that protection class itself produced notable

differences in fire severity after averaging out the effects of elevation and climate (see Fig. 2 and *Results* above). In our study, GAP1 forests were 284 m on average higher in elevation than GAP4 forests, while GAP1 forests experienced lower fire severity. This is the opposite of expectations if elevation was a key influence because higher elevation forests are associated with higher fire severity (see, e.g., Schoennagel et al. 2004, Sherriff et al. 2014). We note that we are not the first to determine that increased fire severity often occurs in forests with an active logging history (Countryman 1956, Odion et al. 2004).

Prevailing forest–fire management perspectives vs. alternative views

An extension of the prevailing forest/fire management hypothesis is that biomass and fuels increase with increasing time after fire (due to suppression), leading to such intense fires that the most long-unburned forests will experience predominantly severe fire behavior (e.g., see USDA Forest Service 2004, Agee and Skinner 2005, Spies et al. 2006, Miller et al. 2009b, Miller and Safford 2012, Stephens et al. 2013, Lydersen et al. 2014, Dennison et al. 2014, Hessburg 2016). However, this was not the case for the most long-unburned forests in two ecoregions in which this question has been previously investigated—the Sierra Nevada of California and the Klamath-Siskiyou of northern California and southwest Oregon. In these ecoregions, the most long-unburned forests experienced mostly low/moderate-severity fire (Odion et al. 2004, Odion and Hanson 2006, Miller et al. 2012, van Wagendonk et al. 2012). Some of these researchers have hypothesized that as forests mature, the overstory canopy results in cooling shade that allows surface fuels to stay moister longer into fire season (Odion and Hanson 2006, 2008). This effect may also lead to a reduction in pyrogenic native shrubs and other understory vegetation that can carry fire, due to insufficient sunlight reaching the understory (Odion et al. 2004, 2010).

Another fundamental assumption is that current fires are becoming too large and severe compared to recent historical time lines (Agee and Skinner 2005, Spies et al. 2006, Miller et al. 2009b, Miller and Safford 2012, Stephens et al. 2013, Lydersen et al. 2014, Dennison et al. 2014, Hessburg 2016). However, others have shown

that this is not the case for most western forest types. For instance, using the MTBS (www.mtbs.gov) data set, Picotte et al. (2016) found that most vegetation groups in the conterminous United States exhibited no detectable change in area burned or fire severity from 1984 to 2010. Similarly, Hanson et al. (2009) found no increase in rates of high-severity fire from 1984 to 2005 in dry forests within the range of the northern spotted owl (*Strix occidentalis caurina*) based on the MTBS data set. Using reference data and records of high-severity fire, Baker (2015) found no significant upward trends in fire severity from 1984 to 2012 across all dry western forest regions (25.5 million ha), nearly all of which instead were too low or were within the range of historical rates. Parks et al. (2015) modeled area burned as a function of climatic variables in western forests and non-forest types, documenting most forested areas had experienced a fire deficit (observed vs. expected) during 1984 to 2012 that was likely due to fire suppression.

Whether fires are increasing or not depends to a large extent on the baseline chosen for comparisons (i.e., shifting baseline perspective, Whitlock et al. 2015). For instance, using time lines predating the fire suppression era, researchers have documented no significant increases in high-severity fire for dry forests across the West (Williams and Baker 2012a, Odion et al. 2014) or for specific regions (Williams and Baker 2012b, Sherriff et al. 2014, Tepley and Veblen 2015). Future trends, with climate change and increasing temperatures, may be less simple than previously believed, due to shifts in pyrogenic understory vegetation (Parks et al. 2016).

This is more than just a matter of academic debate, as most forest management policies assume that fire, particularly high-severity fire, is increasing, is in excess of recent historical baselines, and needs to be reduced in size, intensity, and occurrence over large landscapes to prevent widespread ecosystem damages (policy examples include USDA Forest Service 2002, Healthy Forests Restoration Act 2003, USDA Forest Service 2009, HR 167: Wildfire Disaster Funding Act 2015). However, large fires (landscape scale or the so-called megafires) produce myriad ecosystem benefits underappreciated by most land managers and decision-makers (DellaSala and Hanson 2015a, DellaSala et al. 2015). High-severity fire

patches, in particular, provide a pulse of “biological legacies” (e.g., snags, down logs, and native shrub patches) essential for complex early seral associates (e.g., many bird species) that link seral stages from new forest to old growth (Swanson et al. 2011, Donato et al. 2012, DellaSala et al. 2014, Hanson 2014, 2015, DellaSala and Hanson 2015a). Complex early seral forests are most often logged after fire, which, along with aggressive fire suppression, exacerbates their rarity and heightens their conservation importance (Swanson et al. 2011, DellaSala et al. 2014, 2015, Hanson 2014).

Limitations

One limitation of our study is that, due to the coarseness of the management intensity variables that we used (i.e., GAP status), we cannot rule out whether low intensities of management decreased the occurrence of high-severity fire in some circumstances. However, the relationship between forest density/fuel, mechanical fuel treatment, and fire severity is complex. For instance, thinning without subsequent prescribed fire has little effect on fire severity (see Kalies and Yocum Kent 2016) and, in some cases, can increase fire severity (Raymond and Peterson 2005, Ager et al. 2007, Wimberly et al. 2009) and tree mortality (see, e.g., Stephens and Moghaddas 2005, Stephens 2009: Figure 6)—the effects depend on the improbable co-occurrence of reduced fuels (generally a short time line, within a decade or so) and wildfire activity (Rhodes and Baker 2008) and can be over-ridden by extreme fire weather (Bessie and Johnson 1995, Hély et al. 2001, Schoennagel et al. 2004, Lydersen et al. 2014). Empirical data from actual fires also indicate that postfire logging can increase fire severity in reburns (Thompson et al. 2007), despite removal of woody biomass (tree trunks) described by land managers as forest fuels (Peterson et al. 2015). While our study did not specifically test for these effects, such active forest management practices are common on GAP3 and GAP4 lands. Recognizing these limitations, researchers have stressed the need for managers to strive for coexistence with fire by prioritizing fuel reduction nearest homes and allowing more fires to occur unimpeded in the backcountry (Moritz 2014, DellaSala et al. 2015, Dunn and Bailey 2016, Moritz and Knowles 2016).

Follow-up research at finer scales is needed to determine management emphasis and history in relation to fire severity. However, we believe our findings are robust at the subcontinental and ecoregional scales.

CONCLUSIONS

In general, our findings—that forests with the highest levels of protection from logging tend to burn least severely—suggest a need for managers and policymakers to rethink current forest and fire management direction, particularly proposals that seek to weaken forest protections or suspend environmental laws ostensibly to facilitate a more extensive and industrial forest–fire management regime. Such approaches would likely achieve the opposite of their intended consequences and would degrade complex early seral forests (DellaSala et al. 2015). We suggest that the results of our study counsel in favor of increased protection for federal forestlands without the concern that this may lead to more severe fires.

Allowing wildfires to burn under safe conditions is an effective restoration tool for achieving landscape heterogeneity and biodiversity conservation objectives in regions where high levels of biodiversity are associated with mixed-intensity fires (i.e., “pyrodiversity begets biodiversity,” see DellaSala and Hanson 2015b). Managers concerned about fires can close and decommission roads that contribute to human-caused fire ignitions and treat fire-prone tree plantations where fires have been shown to burn uncharacteristically severe (Odion et al. 2004). Prioritizing fuel treatments to flammable vegetation adjacent to homes along with specific measures that reduce fire risks to home structures are precautionary steps for allowing more fires to proceed safely in the backcountry (Moritz 2014, DellaSala et al. 2015, Moritz and Knowles 2016).

Managing for wildfire benefits as we suggest is also consistent with recent national forest policies such as 2012 National Forest Management Act planning rule that emphasizes maintaining and restoring ecological integrity across the national forest system and because complex early forests can only be produced by natural disturbance events not mimicked by mechanical fuel reduction or clear-cut logging (Swanson et al. 2011, DellaSala et al. 2014). Thus, managers

wishing to maintain biodiversity in fire-adapted forests should appropriately weigh the benefits of wildfires against the ecological costs of mechanical fuel reduction and fire suppression (Ingalsbee and Raja 2015) and should consider expansion of protected forest areas as a means of maintaining natural ecosystem processes like wildland fire.

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