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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 km^2 burned globally (Doerr and Santín 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 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

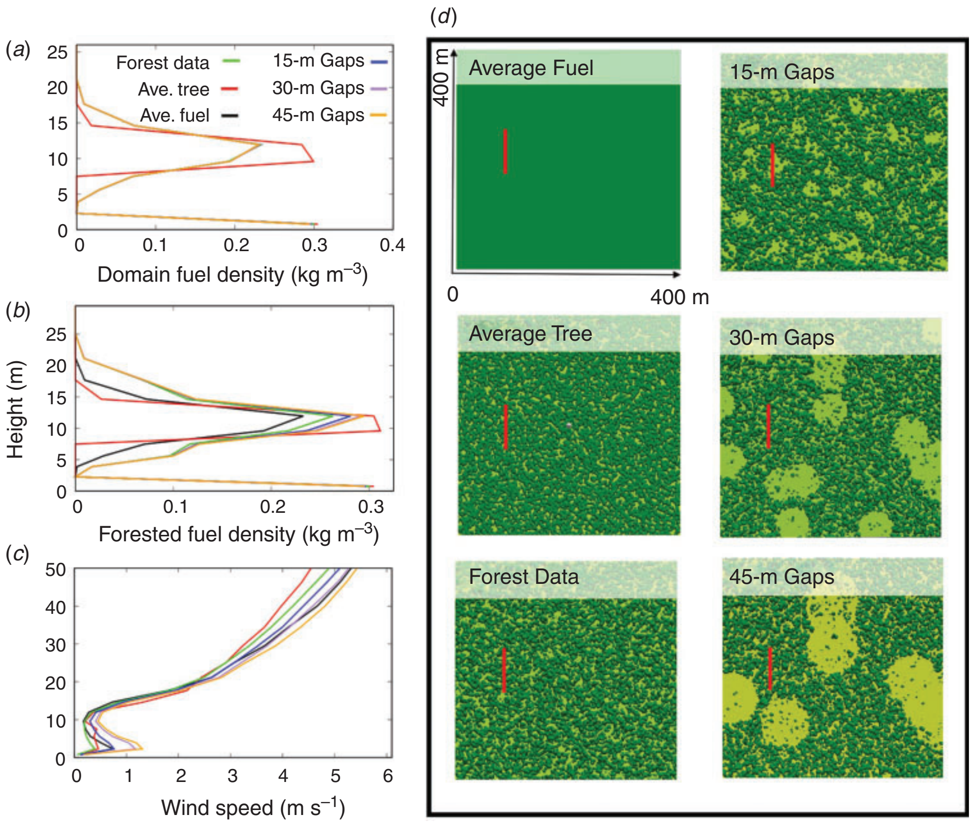

Fig. 1. (*a*) Domain-average vertical fuel density profiles for each ensemble; note that all ensembles except Ave. Tree overlap. (*b*) Vertical fuel density profiles averaged over areas with canopy fuel densities above zero. Note that excluding areas where vertical fuel density equalled zero resulted 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-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 (kg $m^{-3})^2$ for the Average Fuel ensemble and increasing to 0.377 (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. 1*a*). 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

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. 1*b*), 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. 1*a*; 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:

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

where:

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

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,

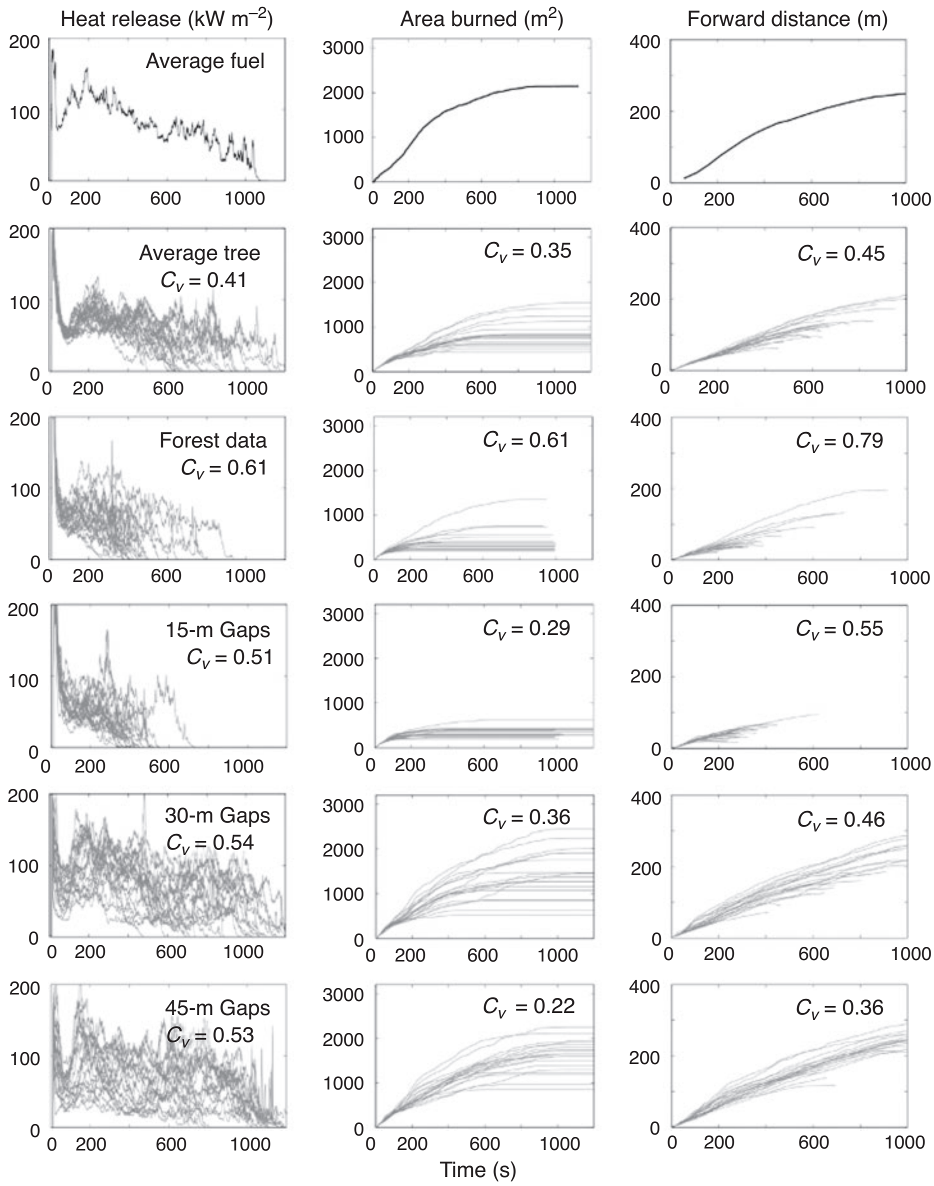

Fig. 2. Time series of fire intensity (left), area burned (centre), and forward progress of fire (right) highlight variability in fire metrics for all ensembles except for Average Fuel, which only has one ensemble member. The coefficient of variation, $C_v = \frac{\sigma}{\overline{X}}$ (σ is the standard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

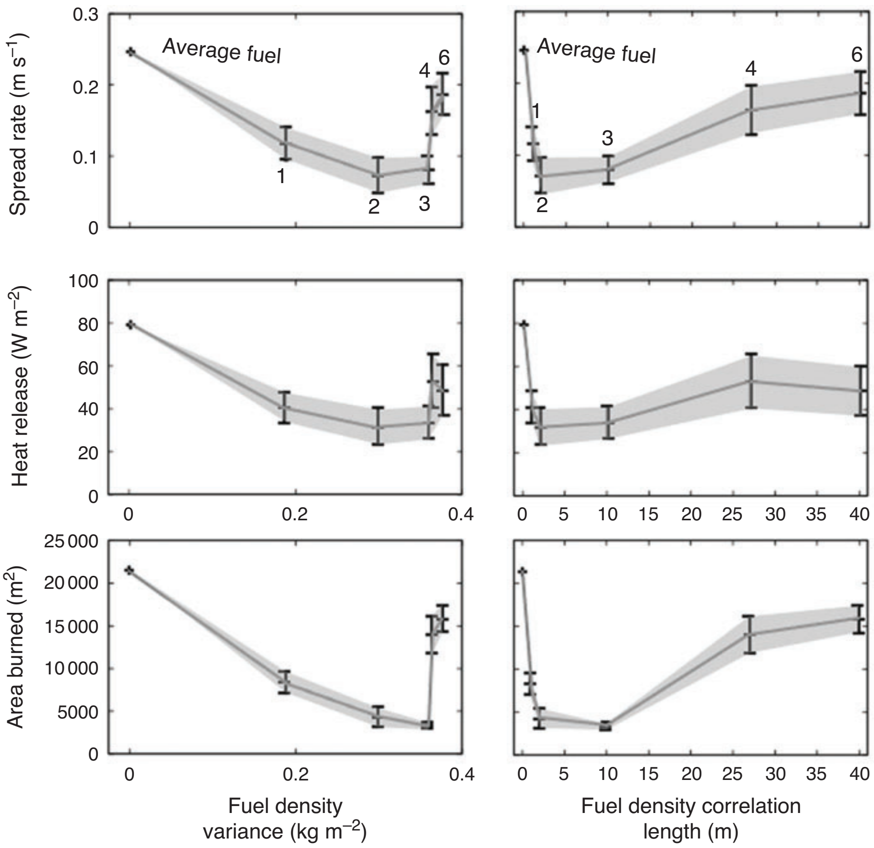

Fig. 3. Mean and the 95th confidence interval of spread rate, heat release rate, and area burned for each ensemble plotted against variation in fuel density and correlation length of fuel density. Numbered ensembles are cross-referenced in Table 1.

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

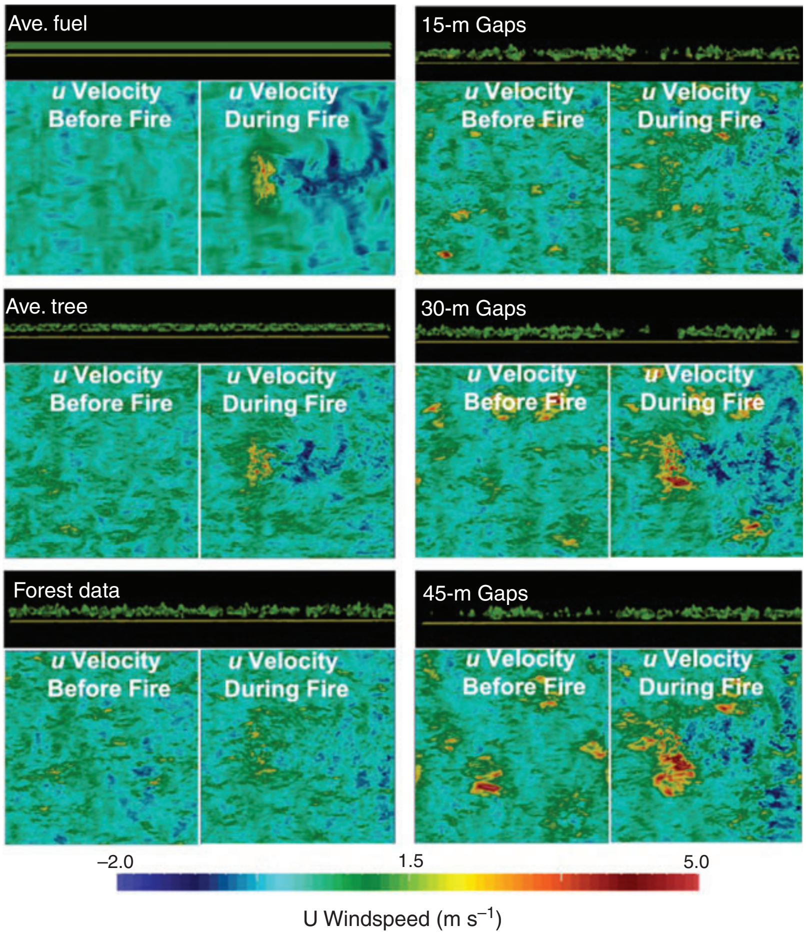

Fig. 4. Horizontal fuel profiles from a sample realisation of each ensemble, a *u* velocity snapshot at mid-canopy height (11 m) before ignition and after ignition showing the interaction of wind flow with the fire. Note the disaggregated *u* velocities in the Forest Data and 15-m Gaps ensembles.

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

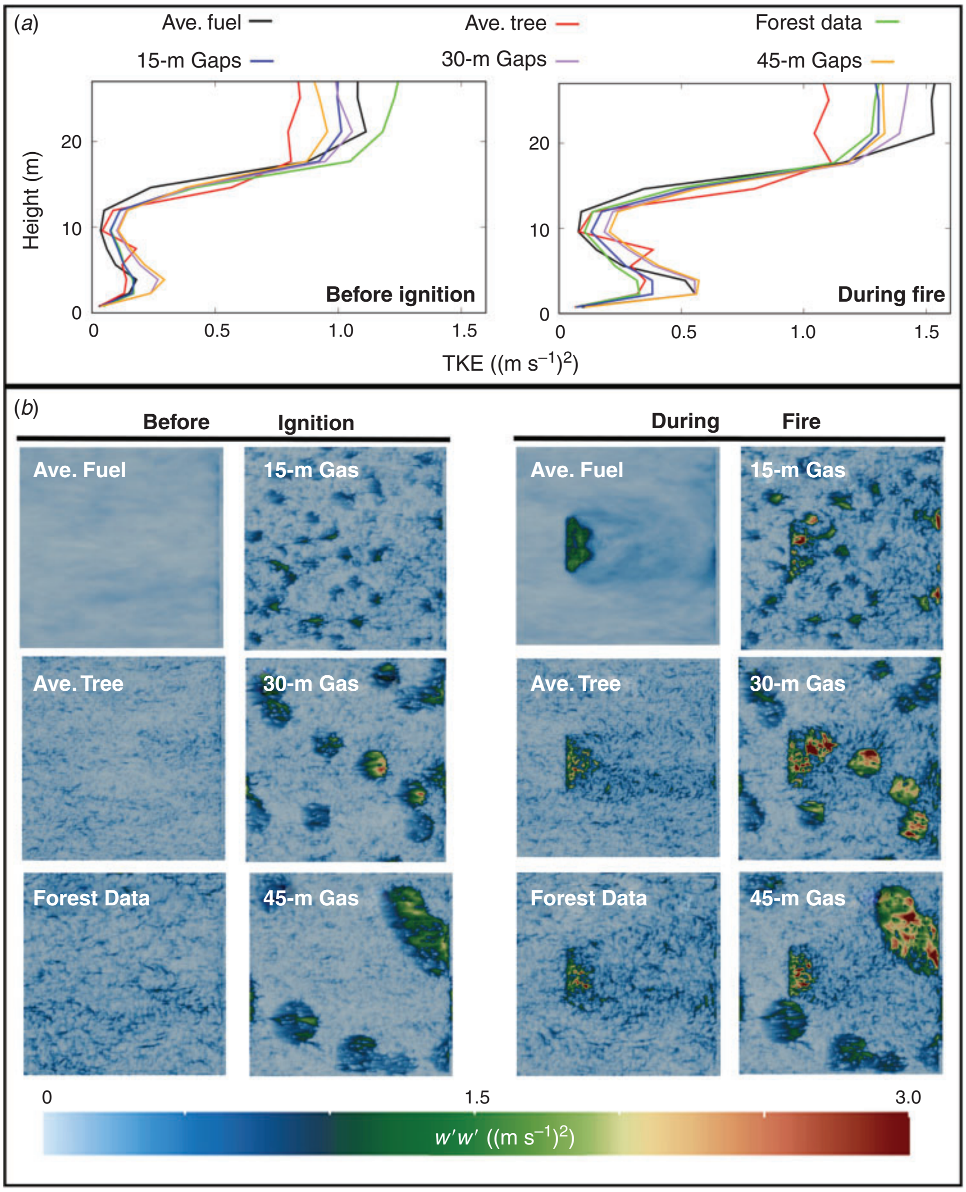

Fig. 5. Average turbulent kinetic energy (TKE) for the 2.5 min before the time of ignition is plotted on the left in panel (*a*) and the average TKE for the 2.5 min after ignition on the right of panel (*a*). Panel (*b*) shows the average $w'w'$ magnitude for the 2.5 min before ignition (left) compared 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. 1*b*). 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 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. 1*c*, 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 heterogenous 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.

Conflicts of interest

The authors declare no conflicts of interest.

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