

Analysis of the uncertainty of fuel model parameters in wildland fire modelling of a boreal forest in north-east China

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Abstract. Fire propagation is inevitably affected by fuel-model parameters during wildfire simulations and the uncertainty of the fuel-model parameters makes forecasting accurate fire behaviour very difficult. In this study, three different methods (Morris screening, first-order analysis and the Monte Carlo method) were used to analyse the uncertainty of fuel-model parameters with FARSITE model. The results of the uncertainty analysis showed that only a few fuel-model parameters markedly influenced the uncertainty of the model outputs, and many of the fuel-model parameters had little or no effect. The fire-spread rate is the driving force behind the uncertainty of other fire behaviours. Thus, the highly uncertain fuel-model parameters associated with spread rate should be used cautiously in wildfire simulations. Monte Carlo results indicated that the relationship between model input and output was non-linear and neglecting fuel-model parameter uncertainty of the model would magnify fire behaviours. Additionally, fuel-model parameters have high input uncertainty. Therefore, fuel-model parameters must be calibrated against actual fires. The highly uncertain fuel-model parameters with high spatial-temporal variability consisted of fuel-bed depth, live-shrub loading and 1-h time-lag loading are preferentially chosen as parameters to calibrate several wildfires.

Additional keywords: FARSITE, fire behaviour, fuel model, uncertainty analysis, wildfire modelling.

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Introduction

Great uncertainty surrounds fire propagation because many factors (e.g. terrain, weather, and fuel cover) affect this process (Carlson and Burgan 2003; Pierce *et al.* 2009; Cruz *et al.* 2013; Wu *et al.* 2013; Zhang *et al.* 2017; Gharun *et al.* 2018). The uncertainty makes obtaining reasonable predictions of wildfire events very complex. Simulating wildfires using fire-behaviour simulation models is an effective method to predict fire behaviours. Thus, the uncertainty of fire-behaviour simulation models, particularly that of spatially explicit models (e.g. FARSITE model), has become a hot area of research in wildfire simulation (Finney 1998; Cruz *et al.* 2004; Mutlu *et al.* 2008; de Rigo *et al.* 2013; Benali *et al.* 2016; Benali *et al.* 2017).

The sources of uncertainty must be identified before analysing their effects on model predictions. Parameter uncertainty, input data uncertainty and structural uncertainty are three parts of uncertainty in model outputs. Some studies have been conducted on structural uncertainty and input data (e.g. weather conditions, fuel spatial resolution, topography and wind spread) during fire simulations (Finney 1998; Bossert *et al.* 2000; Cruz *et al.* 2004; Weise *et al.* 2007; Cruz and Fernandes 2008;

Mutlu *et al.* 2008). For example, Mutlu *et al.* (2008) analysed the sensitivity of a fire-behaviour simulation using higher spatial resolution surface-fuel maps obtained from LiDAR, compared with that calculated with QuickBird-derived fuel maps. The results showed that the LiDAR-derived variables provided more detailed information about fire characteristics. However, uncertainty analyses of fuel-model parameters are rarely reported. A fuel model is defined as a stylised set of fuel-bed characteristics used as input for a variety of wildfire modelling applications (Anderson 1982). Studies have shown that a fuel model with different parameters usually has a different effect on fire behaviour (Arca *et al.* 2007a; Iliopoulos *et al.* 2013; Cai *et al.* 2014). Thus, understanding the uncertainty of fuel-model parameters is gaining increasing attention.

Numerous methods can be used to assess the uncertainty of parameters, such as sensitivity analysis, Bayesian analysis, maximum likelihood, the Monte Carlo method, first-order analysis and the neural network method (Kitanidis 1986; Morris 1991; Kuczera and Parent 1998; Freissinet *et al.* 1999; Richardson and Hollinger 2005; Wang *et al.* 2006). These methods identify parameters that significantly affect model

outputs. Among them, a sensitivity analysis (Morris 1991; Wagner et al. 1996; Arabi et al. 2007; Sun et al. 2012; Qin et al. 2013), first-order analysis (Freissinet et al. 1999; Zhang 2001; Yegnan et al. 2002) and the Monte Carlo method (Kuczera and Parent 1998; Greenland 2001; Jampani et al. 2008) are widely used to analyse the uncertainty of parameters worldwide. The sensitivity analysis method (e.g. Morris screening analysis) is convenient to determine the most sensitive model-efficiency parameters (Morris 1991; van Griensven et al. 2006). However, parameters with low uncertainty and high sensitivity are likely to have smaller effects on model output than parameters that have high uncertainty and low sensitivity (Melching and Bauwens 2001). Thus, further uncertainty analyses must be carried out after a parameter sensitivity analysis. First-order analysis is an appropriate method to determine uncertainty of parameters and is widely used to identify the critical origins of uncertainty (Orban et al. 1992; Melching and Yoon 1996; Freissinet et al. 1999; Shen et al. 2008). The Monte Carlo method is also an effective method to determine the complete range of parameter uncertainties in complex spatial models, and it uses random variables as the input data (Kuczera and Parent 1998; Greenland 2001; Jampani et al. 2008). The use of random variables can eliminate the uncertainty of model input.

The forests of the Great Xing'an Mountains provide a large number of wood and timber products in China (Zhou 1991). High intensity fires occur in this area mainly because of fuel accumulation (Liu et al. 2012). Thus, it is important to study fuel status in this area to predict fire behaviour and reduce losses resulting from wildfires. Many studies have been conducted on fuels and their behaviour in fires that occur in boreal forests (Shan 2003; Du 2004; Chen et al. 2008; Hu et al. 2012), and some studies have developed forest-fuel models; however, the fuel models have not been tested against actual fire behaviours (Shan 2003; Du 2004). Cai et al. (2014) attempted to establish standard fuel models in this area by adjusting highly sensitive fuel-model parameters against some actual fires, but the results indicated that low accuracy of fire prediction during verification. This was very likely because the calibrated fuel models did not fully reflect the fuel conditions. Therefore, it has become necessary to further calibrate the highly uncertain fuel model parameters against several actual fires.

This present study focused on the Great Xing'an Mountains in north-eastern China and used the FARSITE model in conjunction with a Morris screening analysis, the Monte Carlo method and a first-order analysis to research the uncertain fuel-model parameters that significantly affect fire prediction. The overall objective of this study was to identify the relative importance of uncertainty of each fuel-model parameter and to determine the regulatory parameters for calibration to provide suggestions for wildfire modelling and fuel management in the Great Xing'an Mountains.

Materials and methods

Study area

The study area was located in north-east China (121°12'–127°00'E, 50°10'–53°33'N) and covered 8.46×10^6 ha (Fig. 1). This area has a long and severe continental monsoon climate. Mean annual precipitation ranges from 240 to 442 mm in a

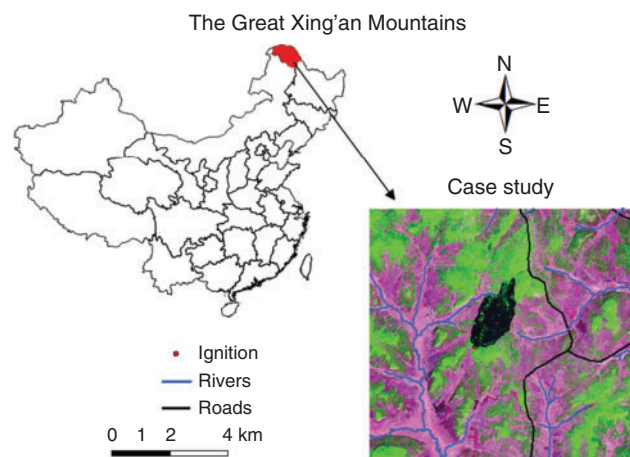


Fig. 1. The geographic location of the study area and the case study that was used to analyse fuel model parameter uncertainty in this study; fire patch map was obtained through a combination of band_{MIR}, band_{NIR} and band_{RED} of a LANDSAT ETM⁺ image in May 2000.

northwestern to southeastern direction, and mean annual temperature varies from -6 to 1 °C in a northwestern to southeastern direction. The vegetation in this area is cool, temperate, coniferous forests (Zhou 1991). Overstorey species mainly include willow (*Chosenia arbutifolia*), birch (*Betula platyphylla*), larch (*Larix gmelini*), spruce (*Picea koraiensis*), pine (*Pinus sylvestris* var. *mongolica*) and a shrub species (*Pinus pumila*).

Fire simulations using the FARSITE model

FARSITE is commonly used to simulate fire propagation and fuel treatments (Finney et al. 1997; Fujioka 2002; Stratton 2004; Ryu et al. 2007) and was developed by the United States Department of Agriculture (Finney 1998). FARSITE is a Rothermel fire-spread model (Rothermel 1972). Several geographical information system (GIS)-based layers are required to run the model, including the fuel model, fuel distribution, elevation, aspect, slope and three crown-fuel layers (i.e. crown bulk density, stand height and crown base height). Fuel-model parameters have a major influence on fire simulations, as reported in many previous studies (Arca et al. 2007a; Iliopoulos et al. 2013; Cai et al. 2014). The fuel-model parameters consist of 1-h time-lag loading (diameter < 0.64 cm), 10-h time-lag loading ($0.64 \text{ cm} \leq \text{diameter} < 2.54$ cm), 100-h time-lag loading ($2.54 \text{ cm} \leq \text{diameter} < 7.62$ cm), live-shrub loading, 1-h time-lag surface area-to-volume (SAV), dead-fuel moisture of extinction, dead heat content, live-shrub SAV, fuel-bed depth and live heat content. In addition, meteorological-input data include wind speed and direction, air temperature, rain intensity, relative humidity, and cloud cover.

The surface fire spread rate (R) is expressed as:

$$R = \frac{I_R \xi (1 + \Phi_w + \Phi_s)}{\rho_b e Q_{ig}} \quad (1)$$

where R is the steady-state spread rate of the heading fire (m min^{-1}), I_R is reaction intensity ($\text{kJ min}^{-1} \text{m}^{-2}$), ξ denotes the propagating flux ratio, ρ_b is oven-dried bulk density

Table 1. Parameters of fuel models for the historical human-caused fire, May 2000

Fuel model (FM) is a static fuel model in this study and live grass is included in the dead grass content. SAV, surface area-to-volume

Fuel model parameters	FM-1	FM-2	FM-3
1-h fuel loading (Mg ha^{-1}) v. SAV (cm^{-1})	2.87, 83.7	4.16, 97.3	5.46, 98.6
10-h fuel loading (Mg ha^{-1}) v. SAV (cm^{-1})	3.57, 3.58	6.87, 3.58	6.35, 3.58
100-h fuel loading (Mg ha^{-1}) v. SAV (cm^{-1})	–	1.24, 0.98	2.04, 0.98
Live shrub (Mg ha^{-1}) v. SAV (cm^{-1})	2.30, 21.90	0.66, 23.8	1.70, 32.02
Fuel bed depth (cm)	36.45	18.39	29.46
Moisture of extinction (%)	52.20	40.19	36.62
Dead v. live heat content (kJ kg^{-1})	18 942, 20 477	19 847, 20 242	20 820, 21 199

(kg m^{-3}), Φ_w is the wind coefficient (dimensionless), Φ_s is a slope factor (dimensionless), ε represents effective heating number (dimensionless), and Q_{ig} is the heat of preignition of the fuel (kJ kg^{-1}).

Fireline intensity (I_b) describes the rate of energy release per unit length of the fire front (kW m^{-1}):

$$I_b = \frac{I_R}{60} \frac{12.6R}{\sigma} \quad (2)$$

where σ is the characteristic surface area-to-volume ratio of the fuel bed (m^{-1}).

Heat per unit area (H_A) denotes the heat released from a square foot of fuel when the flaming zone is in that area (Andrews 1986). It is calculated as:

$$H_A = \frac{60I_b}{R} \quad (3)$$

Flame length (F_L) is directly associated with fireline intensity. Flame length is a function of fireline intensity (m) (Byram 1959), which is calculated as (Andrews 1986):

$$F_L = 0.45(I_b)^{0.46} \quad (4)$$

In the present study, the fire simulation was conducted on a historical fire caused by humans, which occurred in the Great Xing'an Mountains during May 2000 (Fig. 1). Parameterisation of the FARSITE model was based on topography data, meteorological data and a fuel-model map. The fire patch contained three types of fuel models: FM-1 (shrub fuel model, 8.8%), FM-2 (broadleaf fuel model, 40.5%) and FM-3 (coniferous fuel model, 50.7%). Further details about this fire simulation are available in our previous study (Cai *et al.* 2014).

The temporal and spatial resolution of the simulation was set as follows: time step was 30 min, perimeter resolution was 30 m, and distance resolution was 20 m. A conditioning period of 24 h was used to adjust the fuel moisture before the fire simulation to reduce the effect of the initial fuel moisture on the fire simulation. Fire-suppression activities were not considered during fire-simulation processes. Roads and rivers were used as barriers to fire spread (Fig. 1). The established FARSITE model was then used for the sensitivity and uncertainty analysis of fuel model parameters.

Methods for the uncertainty analysis of fuel model parameter

Morris screening method

This study used the Morris screening method (Morris 1991) to analyse sensitivity of the fuel-model parameter. The Morris screening method proposes a random one factor at a time design, in which only a parameter x_i is changed between two successive runs of the model (Francos *et al.* 2003). The change in the model output $y(x) = y(x_1, x_2, x_3, \dots, x_n)$ can be directly ascribed to the modification using the elementary effect e_i , which is defined by the following equation:

$$e_i = \frac{y_{i+1} - y_i}{\Delta x_i} \quad (5)$$

where y_{i+1} is the new outcome, y_i is the previous outcome, and Δx_i is the step interval in parameter x .

In this study, the revised Morris screening method was employed to assess the effect of the change of the factor:

$$S = \sum_{i=0}^{n-1} \frac{(Y_{i+1} - Y_i)/Y_0}{(P_{i+1} - P_i)/100} / (n - 1) \quad (6)$$

where S represents the index of sensitivity; Y_i is the model output for time i ; Y_{i+1} is the model output for time $(i + 1)$; Y_0 is the initial value of the model output; P_i is the percentage change of the parameter for time i ; P_{i+1} is the percentage change of the parameter for time $(i + 1)$; and n is the number of predictions.

The fuel-model parameters for calculating fire behaviours using the FARSITE model are listed in Table 1 (Shan 2003). All parameters were kept constant, except one that was changed with a fixed step length (−20, −15, −10, −5, 5, 10, 15 and 20%). The fuel-model parameters were varied as inputs to the FARSITE model. The model output variables consisted of spread rate (m min^{-1}), heat per unit area (kJ m^{-2}), fireline intensity (kW m^{-1}) and flame length (m). We used the mean values of the model outputs to analyse the sensitivity and uncertainty of fuel model parameters. The duration of each model was 24 h (0800 to 0800 hours the next day).

In the present study, the fuel-model parameters that had a greater effect on fire behaviours were identified by the Morris screening method. This process screens the more sensitive fuel-model parameters and selected the parameters that were used for

further first-order and Monte Carlo analyses. These fuel-model parameters were assumed to be independent of each other.

First-order analysis method

First-order analysis is a widely used method for uncertainty estimates and is based on the Taylor series expansion (Cornell 1972). Unlike traditional sensitivity analysis (e.g. the Morris screening method), the first-order method not only considers parameter sensitivity but also considers the uncertainty of the parameter during this procedure. The components of total uncertainty in the model outcome that are induced by each random input variable are provided. Each input variable is assumed to be independent and the model is linear without considering the higher-order terms of the Taylor equation. Therefore, the function $y = f(x)$ is expressed as:

$$y = f(X) \cong f(\bar{X}) + \sum_i \frac{\partial f}{\partial p_i} (X_i - \bar{X}_i) \quad (7)$$

where y is output during the fire simulations. The means 'equal in the first order sense' and X_i denotes the fuel model parameter mean.

Assuming small parameter modifications around the average value, the first-order estimated value and variance are as follows:

$$E[f(X)] = f(\bar{X}) \quad (8)$$

$$\text{var}[f(X)] \cong \sum_i \sum_j \frac{\partial f}{\partial X_i} \frac{\partial f}{\partial X_j} \text{cov}(X_i, X_j) \quad (9)$$

where $\text{cov}(X_i, X_j) = r_{ij} \text{var}(X_i)^{1/2} \text{var}(X_j)^{1/2}$. The correlations are disregarded if the parameters act independently. Thus, $r_{ij} = 1$ for $i = j$ and $r_{ij} = 0$. Otherwise, Eqn 9 leads to:

$$\text{var}[f(X)] = \sum_i \left[\frac{\partial f}{\partial p_i} \right]^2 \text{var}(X_i) \quad (10)$$

In this study, the effects of the fuel-model parameters on the FARSITE model output variables were calculated with the following equation:

$$SC = \left(\frac{\partial f}{\partial X_i} \right) \text{var}(X_i) \quad (11)$$

Therefore, the contribution (%) to the total output variance from each uncertain fuel-model parameter was determined using Eqn 12.

$$\begin{aligned} \text{Contribution} &= \frac{\text{Contribution of a fuel model parameter}}{\text{Total Variance}} \\ &= \frac{SC_i}{SC_{\text{Total}}} \times 100\% \end{aligned} \quad (12)$$

If the rate of contribution of a fuel-model parameter to the total variance was $<5\%$, the fuel-model parameter was not a source of uncertainty. The coefficient of variation (CV) was also

calculated and used as a measure of dispersion degree of the outputs.

Monte Carlo method

The Monte Carlo method is defined as any technique making use of random numbers to solve a problem as a conventional approach to address uncertainty assessment (James 1980; Rodriguez and Dabdub 2003). This method provides approximate solutions to different mathematical problems by conducting statistical sampling tests. There are three steps in the Monte Carlo simulation procedure: (i) randomise samples from the possible range of input variables according to the probability distribution of the input variable; (ii) input the sampling variable values into the model; and (iii) run the model and assess the model results. A fire-propagation time span of 5 h was simulated.

In the present study, the fuel-model parameters were assumed to be independent of each other because of the difficulty of defining the correlation structure among them. Fuel-model parameters are supposed to be uniformly distributed, because their distributions are lacking. A Monte Carlo analysis using a large number of random samples yields reasonable estimates, but is computationally expensive (Doucet *et al.* 2001). In the present study, a constrained Monte Carlo sampling scheme, called Latin hypercube sampling (LHS), was used to sample the parameters and improve the calculation efficiency of the Monte Carlo simulations (Rodriguez and Dabdub 2003). LHS selects k different values from each parameter. We divided each input variable into k non-overlapping intervals based on equal probability, and a value from each interval was chosen randomly. The appropriate size of the Latin hypercube sampling sample (m) was determined by the number of input variables, n ($k > 4n \div 3$). Thus, for the five screened sensitive fuel-model parameters for each fire behaviour, we divided the range of each fuel-model parameter into 10 sub-intervals of equal probability and the median of each sub-interval was chosen as the sampling value. The combinations of randomly sampled values were then input into the FARSITE model and a simulation was run. In this study, simulation times were determined by two steps: (i) we carried out the simulation and then analysed the model outputs (i.e. mean and standard variance) (Haan *et al.* 1998); and (ii) if the number of predictions was insufficient to attain accurate convergence, we iteratively expanded the simulation to a larger scale until satisfactory results were obtained.

Table 2 provides the fuel model parameters used in the Monte Carlo simulation. The definition and ranges of the fuel model parameters are also shown in Table 2.

Results

Morris screening

The five most sensitive fuel-model parameters for each fire behaviour variable are shown in Table 3. Based on the results, the sensitivity levels of the fuel-model parameters differed among the four fire behaviours, and the five sensitive fuel-model parameters for each fire-behaviour variable were not the same. However, both dead heat content and 1-h time-lag loading had fairly higher sensitivities for all four variables. The five most sensitive fuel-model parameters for the model outputs were then used for further uncertainty analyses.

Table 2. Fuel model parameters and their ranges used in the Monte Carlo simulation
SAV, surface area-to-volume

Parameters	Definition	Minimum	Maximum
1-h time-lag loading (Mg ha^{-1})	Oven-dry weight per unit square of dead fuel (diameter <0.64 cm)	0	20
Live-shrub loading (Mg ha^{-1})	Oven-dry weight per unit square of live shrub	0	20
1-h time-lag SAV (cm^{-1})	Surface area-to-volume of 1-h time-lag	1.5	120
Live-shrub SAV (cm^{-1})	Surface area-to-volume of live shrub	1.5	120
Dead heat content (kJ kg^{-1})	Energy release per unit square of dead fuel load	18 000	22 000
Live heat content (kJ kg^{-1})	Energy release per unit square of live fuel load	18 000	22 000
Fuel-bed depth (m)	Average depth of fuel bed	0	3

Table 3. Fuel model parameters sensitivity analysis with Morris qualitative screening method
SAV, surface area-to-volume

Rate of spread		Heat per unit area		Fireline intensity		Flame length		Rank
Fuel model parameter	Sensitivity	Fuel model parameter	Sensitivity	Fuel model parameter	Sensitivity	Fuel model parameter	Sensitivity	
Fuel-bed depth	0.901	1-h SAV	-0.988	1-h time-lag loading	1.191	1-h time-lag loading	0.545	1
1-h SAV	0.723	Dead heat content	0.616	Dead heat content	1.187	Dead heat content	0.541	2
1-h time-lag loading	0.627	1-h time-lag loading	0.56	Fuel-bed depth	0.975	Fuel-bed depth	0.448	3
Dead heat content	0.560	Live heat content	0.392	Live heat content	0.72	Live heat content	0.331	4
Live-shrub SAV	-0.406	Live-shrub loading	0.352	Live-shrub SAV	-0.462	Live-shrub SAV	-0.207	5

Table 4. Statistics of key parameters by first-order analysis method

s.d., standard deviation; K, sensitivity coefficient = $dy \div dx$; variance = $SD^2 \times K^2$; CTU, contribution to overall uncertainty; SAV, surface area-to-volume

Fire behaviour	Parameter	s.d.	K	Variance	CTU (%)
Rate of spread	1-h time-lag loading	5.57	0.51	8.0723531	64.90%
	Fuel-bed depth	89.11	0.016	2.0329168	16.35%
	Live-shrub loading	5.57	-0.24	1.7889597	14.38%
	Total				95.63%
Heat per unit area	1-h time-lag loading	5.57	1914.7	113778779	67.10%
	Live-shrub loading	5.57	811.7	20462993	12.07%
	Live-shrub SAV	35.28	-112.47	15745133	9.29%
	1-h SAV	34.38	-92.5	10113495	5.96%
	Fuel-bed depth	89.11	-33.03	8663567.9	5.11%
	Total				99.53%
Fireline intensity	1-h time-lag loading	5.57	237.39	1748979.2	92.40%
	Fuel-bed depth	89.11	3.79	114066.48	6.03%
	Total				98.43%
Flame length	1-h time-lag loading	5.57	0.349	3.7801641	95.13%
	Total				95.13%

First-order analysis

The uncertainty of the five most sensitive fuel-model parameters for each output variable was subsequently analysed using first-order analysis. Table 4 shows that only a few number of fuel-model parameters clearly affected the uncertainty of the model outputs. The 1-h time-lag loading, live-shrub loading and fuel-bed depth were the primary contributors to uncertainty for rate of spread. The most uncertain factors for heat per unit area were 1-h time-lag loading, live-shrub loading, live-shrub SAV, fuel-bed depth and 1-h time-lag SAV. The fuel-model parameters,

fuel-bed depth and 1-h time-lag loading were the most uncertain factors influencing fire intensity. Finally, the uncertainty factor for flame length was 1-h time-lag loading. 1-h time-lag loading had a substantial effect on all model output variables. The total contributions from these fuel-model parameters to the uncertainty of spread rate, heat per unit area, fireline intensity and flame length were 95.63, 99.53, 98.43 and 95.13% respectively.

The average value, CV values and variance of the model output variables are listed in Table 5. The dispersion degree of the predicted fire behaviour decreased with a decrease in the CV

value; namely, the uncertainty of the predicted fire behaviours decreased with a decrease in the CV. Among the output variables, fireline intensity had largest CV (87.29%) and heat per unit area had the smallest CV (35.03%), indicating that the uncertainty of fireline intensity was the greatest and the uncertainty of heat per unit area was the least.

Monte Carlo simulation

A total of 90 Monte Carlo simulations were run in this study. The mean, standard variance and CV among the three groups with different simulation times were similar (Table 6), indicating that 90 simulations were sufficient to acquire dependable results for the Monte Carlo uncertainty estimate.

Among the output variables, fireline intensity had the highest CV (95.2%), whereas heat per unit area had the lowest CV (47.5%) (Table 6), indicating that the uncertainty of heat per unit area was the smallest, and the uncertainty of fireline intensity was the largest. The model outputs calculated using the average input fuel-model parameters were all larger than those from the

Monte Carlo simulations that considered the uncertainty of fuel model parameters (Table 6).

Table 7 shows the CV values and contributions of the fuel-model parameters. Fuel-bed depth, 1-h time-lag loading, live-shrub loading, 1-h time-lag SAV and live-shrub SAV were the main sources of uncertainty for spread rate and heat per unit area, whereas fuel-bed depth, 1-h time-lag loading, 1-h time-lag SAV and live-shrub SAV were the primary sources of uncertainty for fireline intensity. Finally, 1-h time-lag loading, fuel-bed depth and live-shrub SAV were the primary sources of flame-length uncertainty. The respective contributions of these main fuel-model parameters to the uncertainty of spread rate, heat per unit area, flame length and fireline intensity were 97.45, 96.41, 89.52 and 93.98% respectively.

Discussion

Some studies have analysed the effect of different fire-fuel models on behaviour simulations (Arca *et al.* 2007a; Iliopoulos *et al.* 2013). For example, Salazar (1985) analysed the sensitivity of fire-behaviour simulations in 13 fuel models under different weather conditions so that the fire manager could select proper combinations of fuel models to describe different fuel situations. As far as we know, the effects of different fuel models on behaviour simulations were tested by Michele Salis from University of Sassari of Italy (Cai *et al.* 2014). The results showed that suitable customised fuel models were of utmost importance to obtain accurate predictions of fire behaviour. However, these studies regarded the fuel model as a whole without analysing sensitivity and uncertainty of the fuel-model parameters, so the uncertain fuel-model parameters were not identified. As illustrated in Fig. 2, fuel models can predict

Table 5. Statistics of model outputs of first-order analysis

s.d., standard deviation; CV, coefficient of variation

Parameters	Mean	Variance	s.d.	CV (%)
Rate of spread	2.74	4.23	2.06	74.97
Heat per unit area	18731.7	43047277	6561.04	35.03
Fireline intensity	937.92	670327.9	818.74	87.29
Flame length	1.77	1.19	1.09	61.57

Table 6. Statistics of model outputs of Monte Carlo simulation

s.d., standard deviation; CV, coefficient of variation

Output variable	Results by mean input parameters	1-80			1-85			1-90		
		Mean	s.d.	CV	Mean	s.d.	CV	Mean	s.d.	CV
Rate of spread	2.66125	2.6	2.0	76.9%	2.6	2.0	76.9%	2.5	1.9	76.0%
Heat per unit area	22809.4	18984	8947	47.1%	18494	8755	47.3%	18265	8685	47.5%
Fireline intensity	1011.79	931.66	868.86	93.3%	894.61	837.06	93.6%	853.19	812.14	95.2%
Flame length	1.84456	1.771	1.184	66.9%	1.718	1.137	66.2%	1.665	1.095	65.8%

Table 7. Coefficient of variation (CV) and contribution ratio of fuel model parameters in Monte Carlo simulation

SAV, surface area-to-volume

Parameter	Rate of spread		Heat per unit area		Fireline intensity		Flame length	
	CV (%)	Contribution	CV (%)	Contribution	CV (%)	Contribution	CV (%)	Contribution
1-hour time-lag loading	87.38	37.689	87.48	50.481	129.77	46.204	101.92	59.538
1-hour time-lag SAV	22.97	9.907	14.72	8.494	24.69	8.790	5.33	3.116
Live-shrub loading	25.55	11.019	21.05	12.146	4.77	1.697	6.77	3.954
Live-shrub SAV	30.46	13.139	28.35	16.358	61.12	21.759	25.05	14.632
Dead heat content	3.12	1.345	3.19	1.838	6.32	2.252	2.91	1.702
Live heat content	2.80	1.206	3.04	1.754	5.83	2.075	2.92	1.708
Fuel-bed depth	59.57	25.695	15.47	8.929	48.37	17.223	26.28	15.351

significantly different fire behaviours because of different fuel-model parameters (Arca *et al.* 2007a; Iliopoulos *et al.* 2013). Thus, understanding the uncertainty of the input fuel-model parameters is critical to fire simulation and management.

Tables 3, 4 and 7 illustrate that only a few fuel-model parameters clearly affected the uncertainty of fire behaviours and the rankings of sensitivity and uncertainty of fuel-model parameters were different, except for 1-h time-lag loading for fireline intensity and flame length. Furthermore, the rankings of sensitivity and uncertainty were opposite for several of the fuel-model parameters. For example, the sensitivity of 1-h time-lag loading (0.560) was smaller than that of fuel-bed depth (0.901) for the rate of spread, whereas 1-h time-lag loading had a higher contribution ratio than fuel-bed depth for spread rate based on the results of the two uncertainty analysis methods in the present study (Tables 4, 7); dead heat content was a highly sensitive fuel-model parameter for four variables; however, it was a poor uncertainty parameter for all model outputs according to the Monte Carlo uncertainty analysis results; the fuel-model parameter live-shrub SAV had a higher sensitivity for spread rate, fireline intensity and flame length, but it was not identified as a key parameter in the first-order uncertainty analysis. The above-mentioned phenomenon occurred because a sensitivity analysis does not consider the relationships among the fuel-model parameters. Thus, a parameter with less sensitivity but high uncertainty is likely to have much more of an effect on uncertainty of the model outcome than a highly sensitive fuel-model

parameter. A sensitivity analysis is not suitable for identifying the main uncertainty sources influencing model outputs. However, an uncertainty analysis not only considers the effects of fuel-model parameter sensitivity but also that of uncertainty of the fuel-model parameters when determining the parameters that significantly affect the uncertainty of the model output.

According to the Monte Carlo results, fireline intensity had the largest CV value (95.2%), followed by rate of spread (76.0%) and flame length (65.8%), whereas heat per unit area had the smallest CV value (47.5%) (Table 6). This ranking of uncertainty of the four variables was the same as the results of the first-order analysis (Table 5). Similarly, the same sources of uncertainty for the output variables were generated by the first-order analysis and the Monte Carlo results. For example, 1-h time-lag SAV, live-shrub SAV 1-h time-lag loading, fuel-bed depth and live-shrub loading were the main uncertainty parameters for heat per unit area based on results of the first-order and Monte Carlo analyses. Therefore, the two methods can both be effectively used to determine the primary sources of uncertainty.

However, there were also some differences between these two methods. The relative ranking of 1-h time-lag loading was consistent for heat per unit area, but the relative rankings of 1-h time-lag SAV, fuel-bed depth, live-shrub loading, and live-shrub SAV were different. This may be due to the fact that the first-order analysis method is assumed to be linear because it does not consider the higher-order terms of Taylor expansion, which are not appropriate for a complex non-linear model, such as the FARSITE model. By contrast, non-linearity was considered for the Monte Carlo method. Thus, Monte Carlo is a better method than the first-order for a fuel model parameter uncertainty analysis using the FARSITE model.

The model outputs from the Monte Carlo simulations that fully consider uncertainty of fuel-model parameters were all smaller than the results obtained by mean fuel-model parameters (Table 6). The discrepancy occurred because of the non-linear relationships between the inputs and outputs of FARSITE model. Non-linearity suggests that model input uncertainty does not translate into model output uncertainty directly but rather appears to reduce or magnify the effects on model outputs significantly. Model predictions based on mean input fuel-model parameters usually may magnify fire behaviours because of the neglect of fuel-model parameter uncertainty. This emphasises the importance of considering fuel-model parameter uncertainty when simulating wildfire behaviours.

The results of the first-order and Monte Carlo analyses indicated that the uncertainty of the fire behaviours was significantly affected by the fuel-model parameters uncertainty associated with spread rate, such as 1-h time-lag loading, live-shrub loading, fuel-bed depth and live-shrub SAV, particularly 1-h time-lag loading (Tables 5, 7). For example, the respective contribution of 1-h time-lag loading to flame-length uncertainty according to the first-order and Monte Carlo analyses reached 95.13% (Table 4) and 59.53% (Table 7) respectively. This is because of the influence of heat per unit area, fireline intensity and flame length were generated, accompanied by the rate of fire spread (Finney 1998), as described by Eqn 1–4 in this study. Similarly, the results of a previous study showed that 1-h time-lag loading significantly affects fire behaviour (Sparks *et al.* 2002).

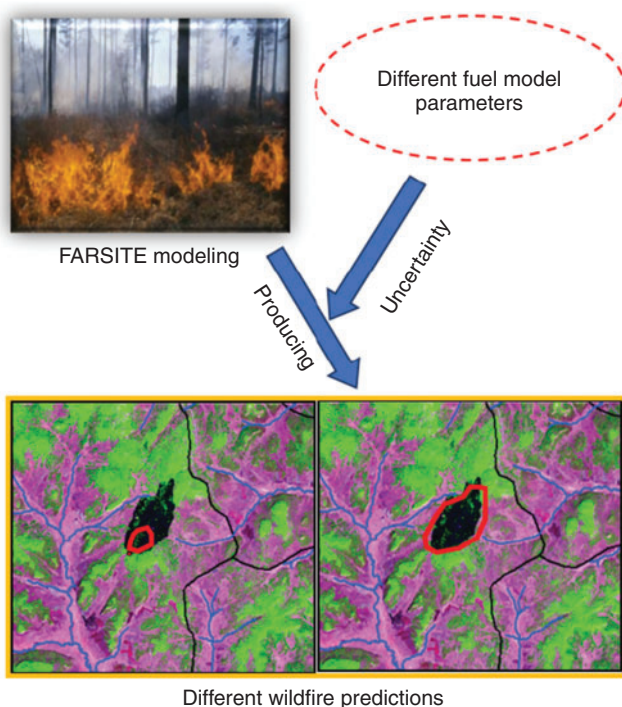


Fig. 2. An illustration of different wildland fire predictions resulting from the effects of the uncertainty of fuel model parameters; fire patch map was obtained by a combination of band_{MIR}, band_{NIR} and band_{RED} of a LANDSAT ETM⁺ image that was acquired for May 2000 and the red solid line represents simulated fires.

That study revealed that the fire-spread rate is the driving force behind the uncertainty of the other relevant fire behaviours. Therefore, the highly uncertain fuel-model parameters associated with rate of spread, including fuel-bed depth, 1-h time-lag loading, live-shrub loading and live-shrub SAV, should be used with caution when forecasting fire behaviour. Because live-shrub SAV also had high contributions to heat per unit area, fireline intensity and flame length, it should be determined carefully when predicting wildland fires.

However, a lack of data, measurement limitations and environmental variations often lead to high input uncertainty of the model parameters (Beck 1987). First, a default parameter value of the model or reference value from other regions can be used when modelling wildfire behaviours when fuel model parameters are lacking. A subjective decision may produce a considerable amount of uncertainty in the fuel-model parameters of the model. Second, uncertainty in the fuel-model parameter input can arise from the limitations of measurement, such as sampling site, range of sampling and the professionalism of the surveyors (Beck 1987; Ramsey and Argyraki 1997; Phillips *et al.* 1998; De Zorzi *et al.* 2002; Palmer and Brohan 2011). Mean values of measured fuel-model parameters are generally used as model input data (Burgan and Rothermel 1984), which could cause prediction errors based on our results (Table 6). Finally, variations in environmental conditions are an important source of uncertainty in model input parameters (Beck 1987). Fuel-model parameters change with time (Dodge 1972; McCaw *et al.* 2002) and are subject to climate change (Clark 1988) and human activities (e.g. fire suppression) (Wang *et al.* 2007).

As a result, when developed without calibrating the parameters against fire-behaviour observations, fuel models are more likely to be unsuccessful (Cruz and Fernandes 2008). Thus, fuel models need to be calibrated before they are used to predict fire behaviours. For example, Cruz and Fernandes (2008) developed fuel models for maritime pine stands using a calibration procedure based on backtracking, the rate of spread, and fire intensity as evaluation indicator. They varied the fuel-model parameters within their range of variability to establish fuel models that best simulated fire sprawl. They also conducted extensive field-work to determine all fuel-model parameters using the traditional method. According to the Monte Carlo results (Table 7), the total contribution ratio of the fuel-model parameters, fuel-bed depth, 1-h time-lag loading, live-shrub loading and live-shrub SAV to the uncertainty of the model outputs exceeded 86%, indicating that the four fuel-model parameters can take the place of all fuel-model parameters to explain the influence of fuel-model parameter uncertainty on model outputs. Therefore, the four fuel-model parameters are expected to be chosen as adjustment parameters during calibration.

In addition, the fuel-model parameters selected as adjustment parameters for calibration should also meet two conditions: (i) high sensitivity and uncertainty for model outputs, and (ii) high temporal and spatial variability. Parameters that have low variability were not considered because they can be accurately measured in the field and can be used to predict fire behaviours as a constant. Of the four fuel model parameters, live-shrub SAV exhibits very low temporal and spatial variability over the landscape for any given fuel type (Shan 2003; Scott

and Burgan 2005; Arca *et al.* 2007b). For example, it is widely known that shrub-fuel models (SH6, SH7 and SH8) in the US have the same SAV value. Studies have shown that fuel-bed depth, live-shrub loading and 1-h time-lag loading are the primary fuel-model parameters influencing fire behaviour (van Wageningen 1996; Sparks *et al.* 2002). Sparks *et al.* (2002) showed that fireline intensity increased significantly, if 1-h time-lag fuels increased at the expense of live herbaceous fuels during a drought. Therefore, fuel-bed depth, live-shrub loading and 1-h time-lag loading were finally selected as adjustment parameters. Using FARSITE fire-simulation model to calibrate the fuel model by reasonably tuning these high uncertain fuel-model parameters (fuel-bed depth, live-shrub loading and 1-h time-lag loading) until the simulated fires (e.g. rate of spread, fire perimeter and fire size) matched the actual fires is an effective method for developing fuel models. This process can be used to quickly and effectively improve the prediction capabilities of fuel models for predicting fires. More importantly, this approach reduces the vast field workload to determine accurate fuel-model parameters through field experiments. Note that only one fire was simulated in this study, which may not represent a full range of fire and fuel conditions.

The results of fuel-model parameter uncertainty analysis in this study advance the fuel-model classification in boreal forests. In general, different fuel models have widely different fire behaviours because of different fuel-model parameter combinations. As discussed above, the main uncertainty parameters that have high spatial-temporal variability were fuel-bed depth, 1-h time-lag loading and live-shrub loading, particularly fuel-bed depth and 1-h time-lag loading (Table 7). Therefore, according to the differences of the measured values of the above fuel-model parameters, we could classify fuel models more effectively. For example, assuming that the above-mentioned parameter values of a same fuel type have great differences, it is necessary to establish multiple fuel models to represent this type of fuel and the fire behaviours, such as different shrub-fuel models (SH6, SH7 and SH8) in the US; if there is little or no difference of the above-mentioned parameter values of a same fuel type, one fuel model could be sufficient to represent the characteristic of this fuel to predict fire behaviours reliably.

Conclusion

This study successfully analysed the uncertainty of fuel-model parameter for wildfire modelling in north-eastern China. The results indicated that only a few fuel-model parameters substantially affected uncertainty of the FARSITE model. Most of the fuel-model parameters had little or no effect on uncertainty of the model output. Of all of the fuel-model parameters, 1-h time-lag loading had the greatest effect on model outputs for the four fire behaviours. The results also indicated that fire-spread rate was largely responsible for the uncertainty of other fire behaviours in this study. Therefore, the highly uncertain fuel-model parameters associated with rate of spread, 1-h time-lag loading, live-shrub loading, live-shrub SAV and fuel-bed depth should be used with caution and determined carefully when predicting fire behaviours.

In addition, the model outcomes attained by the mean input fuel-model parameters were all larger than those from the Monte

Carlo method, which considered uncertainty of the fuel-model parameter. This finding suggests that there were non-linear relationships between inputs and outputs of the FARSITE model and the neglect of fuel-model parameter uncertainty of the model generally may magnify fire behaviours (mean fuel-model parameter input method). Thus, it is crucial to consider the uncertainty of input fuel-model parameters when modelling wildfire behaviours. With the average input fuel-model parameter method, a small change in a key fuel-model parameter is very likely to have a large effect on model output and the magnification error would increase with an increase in uncertainty of the fuel model parameters. Unfortunately, there is great input uncertainty in the fuel-model parameters of the model, such as the measurement uncertainty from field surveys. As a result, parameters of fuel models should usually be calibrated against actual fires to predict wildfires in practice. The highly uncertain fuel-model parameters with highly temporal and spatial variability, including 1-h time-lag loading, live-shrub loading and fuel-bed depth are expected to be chosen as parameters to adjust the calibration against several actual fires and to effectively improve the fire prediction capabilities of fuel models. Our study provides useful references for the uncertainty of fuel-model parameter in other regions around the world.

Conflicts of interest

The authors declare that they have no conflicts of interest.

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