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# Development of Customized Fire Behavior Fuel Models for Boreal Forests of Northeastern China

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**Abstract** Knowledge of forest fuels and their potential fire behavior across a landscape is essential in fire management. Four customized fire behavior fuel models that differed significantly in fuels characteristics and environmental conditions were identified using hierarchical cluster analysis based on fuels data collected across a boreal forest landscape in northeastern China. Fuel model I represented the dense and heavily branched *Pinus pumila* shrubland which has significant fine live woody fuels. These forests occur mainly at higher mountain elevations. Fuel model II is applicable to forests dominated by *Betula platyphylla* and *Populus davidiana* occurring in native forests on hill slopes or at low mountain elevations. This fuel model was differentiated from other fuel models by higher herbaceous cover and lower fine live woody loading. The primary coniferous forests dominated by *Larix gmelini* and *Pinus sylvestris* L. var. *mongolica* were classified as fuel model III and fuel model IV. Those fuel models differed from one another in average cover and height of understory shrub and herbaceous layers as well as in aspect. The potential fire behavior for each fuel model was simulated with the BehavePlus5.0 fire behavior prediction system. The simulation results indicated that the *Pinus pumila* shrubland fuels had the most severe fire behavior for the 97th percentile weather condition, and had the least severe fire behavior under 90th percentile weather condition. Fuel model II presented the least severe fire potential across weather conditions. Fuel model IV resulted in greater fire severity than Fuel model III across the two weather scenarios that were examined.

**Keywords** Fire behavior fuel models · Potential fire behavior · Fire management · Northeastern China

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## Introduction

Wildland fuels, weather, and terrain are main factors influencing wildland fire occurrence and behavior (Rothermel 1972; Carlson and Burgan 2003; Pierce and others 2009), among which fuel is the only factor that can be controlled by humans. Forest fuel inventory, classification, and description are critical to estimate fire hazard, risk, behavior and effects (Rothermel 1972; Keane and others 2001; Fernandes 2001). The shape, size, density, loading, moisture content, chemical properties, and spatial configuration of forest fuels affect the ignition, intensity, spread, fuel consumption, and effects of wildland fire (Brown 1970; Burgan 1987; Reich and others 2004). Accurate information about the characteristics of fuels across a landscape is essential in fire management decision-making (Chuvieco and Congalton 1989; Keane and others 2001; Miller and others 2003; Piñol and others 2005).

However, fuels are difficult to inventory, classify and describe due to their high complexity and variability in structure and distribution (Burgan 1987). They are commonly grouped into three classes: ground fuels, surface fuels and aerial fuels (Pyne and others 1996; Sandberg and others 2001; Reich and others 2004; Arroyo and others 2008). Ground fuels are the dead organic matter that can be classified into litter and duff depending on the degree of decomposition (Keane and others 2001). Surface fuels include live and dead trees, shrubs, grass and forbs and downed dead woody debris that are separated into diameter size classes according to their rate of drying, namely 1-h (h = hour), 10-, 100- and 1000-h timelag fuels (Reich and others 2004). Aerial fuels are live and dead crown biomass suspended within vegetation canopies (van Wagner 1977; Keane and others 2001). Forest fuel characteristics are temporally and spatially complex and can vary widely across regions. Temporally, fuel characteristics are affected by vegetation succession, climate change, fuels accumulation and decomposition stage and fire cycle period (Sah and others 2006; McKenzie and others 2007). Spatially, fuel composition and characteristics vary with vegetation type, environmental condition, and natural (e.g. wind, fire) or anthropogenic disturbance history (e.g. harvest, forestation) (Riccardi and others 2007; Stottlemyer and others 2009).

Because it is difficult to describe all physical characteristics for all fuels classes across a landscape, classifying forest fuels into groups that synthesize the various aspects of forest fuels is essential to improving wildland fire management strategies at many spatial and temporal scales (Pyne and others 1996; Dymond and others 2004). Historically, some forest fuels classification efforts directly assigned forest fuels attributes to vegetation types (Wilson and others 1994; Burgan and others 1998). The vegetation-based classification was the most widely used method and it was easy to implement since vegetation maps were available or could be derived (e.g., from satellite data). However, forest fuel characteristics and the corresponding fire behavior are often poorly correlated with vegetation types, because the same vegetation types may present completely different forest fuel characteristics and fire behavior if the forest fuel loading, density, size and arrangement characteristics change across space and time (Deeming and others 1978; Andrews 1986; Miller and others 2003; Lutes and others 2009). Moreover, with vegetation-based classification it is hard to account for change agents such as logging, insects and disease, etc.

Some other techniques also have been used to predict fuel characteristics including: gradient modeling (Kessell 1976; Keane and others 2001), kriging (Garnica 2001), classification and regression tree (Krasnow and others 2009), and expert judgment (Burgan and others 1998). However, it is difficult and costly to describe all characteristics of forest fuel, and currently there is no standard methodology for such a work (Krasnow and others 2009).

At present, classifying forest fuels into a standardized forest fuels system (also called fuel model) with similar fire behavior has been shown to be very useful for wildland fire management (Burgan and Rothermel 1984). A fuel model is defined as "an identifiable association of forest fuel components of distinctive species, form, size, arrangement, and continuity that will exhibit characteristic fire behavior under defined burning conditions" (Anderson 1982). Fuel models can be used as: (1) map units to spatially simulate fire dynamics; (2) a simple fuels inventory system for quantifying biomass and carbon stocks; and (3) an indirect measure of fire hazard and risk (Keane and others 2001; Sandberg and others 2001; Mckenzie and others 2007; Lutes and others 2009). Many standardized forest fuel models that are currently in use were developed for fire behavior prediction worldwide. The well-known fire behavior fuel model systems are the American Northern Forest Fire Laboratory (NFFL) system (Anderson 1982), the NFDRS fuel models (Burgan 1988), the Canadian Fire Behavior Prediction (FBP) System (Forestry Canada Fire Danger Group 1992), the Australia Fire Danger Rating system (Cheney 1992), and the PROMETHEUS system adapted to fuels in Mediterranean ecosystems (Dimitrakopoulos 2002). In addition to fuel model systems mentioned above, the Scott and Burgan fuel model system (Scott and Burgan 2005) and the Fuel Characteristic Classification System (FCCS) (Ottmar and others 2007) are other options that can be used to model fuels. However, at present, China does not have any forest fuel models, so the development and application of fire behavior prediction systems are limited.

Due to the high risk and cost of landscape scale fire experiments, forest fuel models are commonly used as inputs to fire behavior prediction systems, such as FARSITE and BEHAVE (Burgan and Rothermel 1984; Scott and Burgan 2005), to aid in predicting fire behavior and to forecast fire spread rates over time for alterative climate scenarios (Dimitrakopoulos 2002; Carlson and Burgan 2003; Stottlemyer and others 2009). The vast forests of Great Xing' an Mountains in Northeastern China are an important forest resource that delivers a range of societal, economic and environmental benefits to the country (Xu and others 1997). Historically, fire regimes in this region were characterized by frequent, low intensity surface fires mixed with sparse stand-replacing fires on relatively small areas. However, the wildfires that occur in this region are often more severe and intensity than fires that occurred before the 1950s due to aggressive fire suppression carried out for over a half century. For instance, on 6 May 1987, a catastrophic fire occurred in this region, burning a total area of $1.3 \times 10^6$ ha, which had disastrous effects on forest and environment (Liu and others 2010).

The objectives of this study are to (a) use fuels data collected from the Great Xiang' an Mountains with hierarchical cluster analysis as a process to develop custom fire behavior fuel models for the Huzhong Forest Bureau in Northeastern China and (b) simulate their potential fire behavior using the BehavePlus fire behavior prediction system (Andrews and others 2008). The high forest fuels accumulation in the region coupled with a warmer and drier climate in recent decades makes this a study of great practical significance.

## Materials and Methods

### Study Area

The study area, the Huzhong Forest Bureau, is located on the north side of the Great Xing' an Mountains, in Northeastern China (52°25′00″N, 122°39′30″E to 51°14′40″N, 124°21′00″E). It covers 937,244 ha, ranging in elevation from 440 to 1500 m (Fig. 1). The study area falls within the cool temperature zone affected by the Siberian cold air mass and has a typical terrestrial monsoon climate (Liu and others 2010). Mean annual temperature for the study area is 4.7°C with a January mean minimum of −28.9°C and a July mean maximum of 17.1°C. Mean annual precipitation is 500 mm, more than 60% of which occurs between June and August.

Most of the study area is forested, primarily with larch (*Larix gmelini*), pine (*Pinus sylvestris* L. var. *mongolica*), spruce (*Picea koraiensis*), birch (*Betula platyphylla*), and two species of aspen (*Populus davidiana* and *Populus suaveolens*). With the exception of some wetland areas near rivers, larch is widely distributed over 65% of the study site. Birch and pine are mixed with larch in most areas owing to fire disturbance and forest harvesting, with pine having a small area of distribution (1.8%). Aspen is confined to terraces along the rivers where water is plentiful. Spruce, being highly shade tolerant, occurs mostly in valleys and high elevation areas, and dwarf Siberian Pine (*Pinus pumila*) occurs mostly in elevations >800 m (Xu 1998; Chen and others 2008; Liu and others 2010).

### Sample Design

A total of 106 plots that were 20 m × 20 m in size were randomly located and sampled throughout the Huzhong Forest Bureau in September 2006. In each plot, three 2 m × 2 m subplots were established at 7, 14 and 21 m along one diagonal line of the 20 m × 20 m plot to measure shrubs. Three 1 m × 1 m subplots were established at 7, 14 and 21 m along the other diagonal line to measure herbaceous plants and downed dead woody material (Fig. 2). An existing vegetation map and constructive advice from local forest managers provided the necessary information about vegetation/fuel distribution and structure to support field sample plots selection and design. Field plots were selected so the surrounding vegetation type and environmental setting were homogeneous (Miller and others 2003). Sample plots were oriented in a random direction, and georeferenced using a global positioning system (GPS). The terrain variables of elevation, slope and aspect were extracted from the digital elevation model (DEM) of the Huzhong Forest Bureau. The aspect was classified by degree from the north: 0 represented flat (−1); 1 represented north (337.5–22.5°); 2 represented northeast (22.5–67.5°); 3 represent northwest (292.5–337.5°); 4 represented east (67.5–112.5°); 5 represented west (247.5–292.5°); 6 represent southeast (112.5–157.5°); 7 represented southwest (202.5–247.5°); 8 represented south (157.5–202.5°).

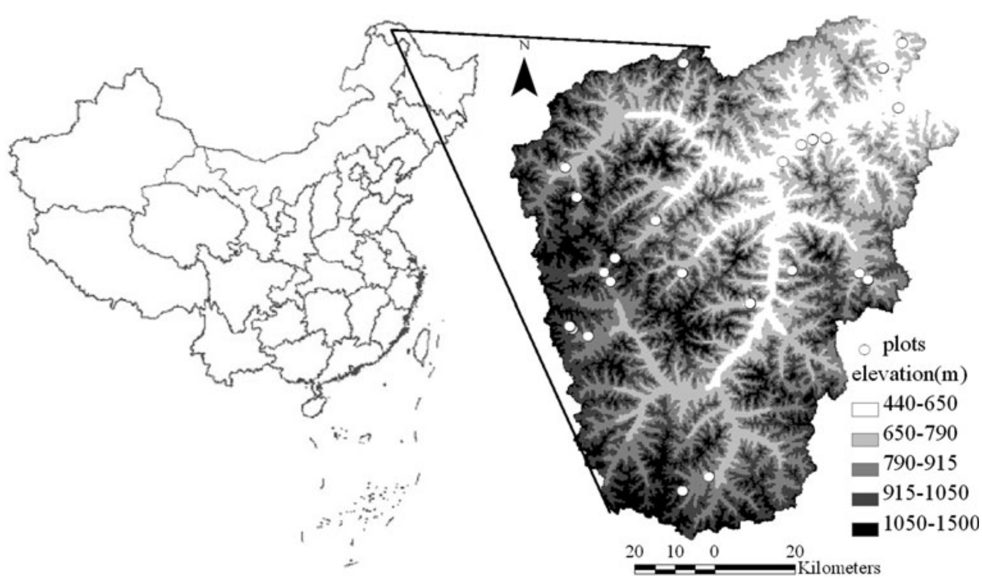


**Fig. 1** The geographic location of the study site and location of 106 sample plots overlaid on a digital elevation model of the Huzhong Forest Bureau

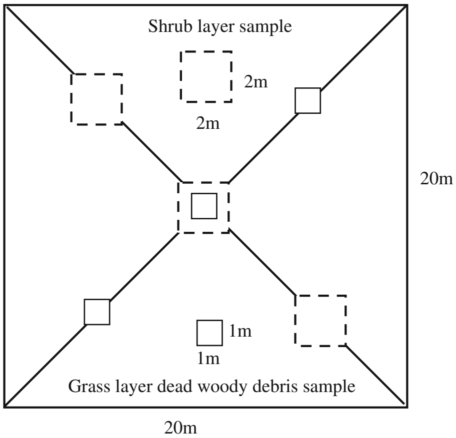


**Fig. 2** Plot layout diagram

## Data Collection

The fuels characteristics and loadings were collected according to the BehavePlus fire prediction system input requirements. Live canopy fuels data collected on the 20 m × 20 m sample plots included vegetation species for all trees>5 cm in diameter at breast height (cm), average tree height (m), average height to the base of the crown (m), canopy closure, and number of trees per ha (trees $ha^{-1}$). The average tree height (m) and average height to the base of the crown (m) in each plot were computed as the average height of five sample trees measured with a tree altimeter. Canopy closure was estimated visually and recorded in 10% categories. Diameter at breast height (DBH) and number of trees (tree density) were obtained by measuring every tree in each plot.

Shrub height and percent cover was measured on three 2 m × 2 m subplots (Fig. 2). The fuel loadings for shrubs in each subplot were calculated using multiple regression equations developed by Shan (2003) and Hu (2005) in the study area. The herbaceous plant fuels and downed dead woody material fuels were measured on three 1 m × 1 m subplots. Herbaceous materials measurement on the 1 m × 1 m subplots included average height and percentage cover. The downed dead woody material inventory tallied combustible fuels that in following size classes: 0–0.64 cm (1-h timelag fuels), 0.64–2.54 cm (10-h timelag fuels), and 2.54–7.6 cm (100-h timelag fuels), respectively (Byram 1963). The 1-h timelag fuels included needles, leaves, small twigs, cured herbaceous plants and fine dead stems of plants. The 10- and 100-h timelag fuels were branches and large branches. Fuel loadings for downed dead woody material fuels were measured by the clip-and-weight method (Dimitrakopoulos 2002; Reich and others 2004). Specifically, in each subplot, all the collected fuels for each fuel category were bagged and weighed in the field, and then oven-dried at 105°C for 30 min in the laboratory, then at 70°C until constant weight was obtained. Fuel loadings were converted to Mg per hectare on a dry weight basis.

Besides the downed woody material data, information for the litter/slash (cm) in each subplot was measured. Fuel bed depth was calculated as the average of the heights of the different surface fuel strata (above the top duff layer) weighted by their fuel loadings (Burgan and Rothermel 1984).

## Fuels Model Development

Hierarchical cluster analysis with relative Euclidean distances and Ward's method was used to identify forest fuel models by clustering all the plots' fuel parameters collected in the field (Poulos and others 2007). Forest fuels parameters were standardize to $z$ scores before clustering analysis to account for differences in means and variances (Miller and others 2003; Poulos and others 2007). Some plots with similar fuel structure and terrain conditions (that should be clustered into the same cluster according to our field knowledge) were classified into different clusters; when automated classification ran counter to established field knowledge we reclassified plots to the suitable clusters manually. The cluster analysis processing was performed with the SPSS13.0 statistical software package.

After the clustering analysis, the parameters for a fuel model were assigned by the average values of all the plots that were classified into the same cluster. Significant differences of forest fuels parameters among fuel models were tested by non-parametric Kruskal–Wallis tests (Poulos 2009).

## Simulation of Fire Behavior

The potential fire behavior for each fuel model was simulated with the BehavePlus5.0 fire behavior prediction system (Burgan and Rothermel 1984; Scott and Burgan 2005). The main inputs for fire behavior simulation with BehavePlus 5.0 were fuel parameters, fuel moisture scenarios, weather (Midflame Wind speed) and terrain conditions (Slope degrees). The simulated potential fire behavior for each fuel model in the study included Surface rate of spread (m/min), Fireline intensity (Mw/m), Flame length (m), and Heat per unit area ($MJ/m^2$).

To facilitate comparisons of the potential fire behavior of the developed fuel models, we employed two weather and fuel moisture content conditions to represent the burning conditions in northeastern China (Table 1) (Burgan and Rothermel 1984; Andrews and others 2003). The burning wind condition was simulated by setting 15 km/h for midflame wind speed (Shan 2003). All fire behavior simulation referred to zero slopes (horizontal terrain). Heat

**Table 1** 90th and 97th percentile conditions for Weather and fuel moisture used for fire behavior simulations

| Weather | 97th percentile | 90th percentile |
|---|---|---|
| 1-h moisture content (%) | 3 | 12 |
| 10-h moisture content (%) | 4 | 13 |
| 100-h moisture content (%) | 5 | 14 |
| Live herbaceous fuel moisture content (%) | 70 | 170 |
| Live shrub fuel moisture content (%) | 70 | 170 |
| Maximum temperature (°C) | 25 | 15 |
| Minimum temperature (°C) | 18 | 10 |
| Maximum humidity (%) | 15 | 45 |
| Minimum humidity (%) | 10 | 25 |
| Wind speed (km $h^{-1}$) | 15 | 15 |
| Precipitation (mm) | 0 | 0 |

content, dead fuel moisture of extinction and surface area-to-volume ratio (SAV) values were obtained from Shan (2003).

## Results and Discussion

### Fuel Models Characteristics and Distribution Patterns

Four fuel models that differed significantly in forest fuel characteristics and local environmental conditions were identified across Huzhong Forest Bureau (Tables 2, 3; Fig. 3). Fuel model I was the dense and heavily branched *Pinus pumila* shrublands that occur as island-like inclusions distributed at higher-mountains in the Huzhong Forest Bureau. The key characteristics that distinguished fuel model I from the other three fuel models were a closed canopy shrub layer and a deep fuel bed depth (up to 1.25 m). This fuel model had the greatest fuel loading in the live woody fuel class with relatively low levels of 1-h fuels due to lower herbaceous fuels and canopy litters loadings.

Fuel model II, mainly dominated by *Betula platyphylla* and *Populus davidiana*, was the representative of the secondary forest. It differed from other fuel models by having lower fine live woody fuels (0.25 Mg/ha). Due to the fact that the field data collection took place during autumn (late in September), most of the grassland fuel load and fine shrub foliage were allocated to the dry fine fuels (1-h fuels 7.39 Mg/ha). Forest conditions associated with this fuel model were widely distributed in hills and lower-mountains in the Huzhong Forest Bureau.

According to the different geographic distribution in aspect and understory compositions, the primary coniferous forests could be classified into two separate fuel models: Fuel model III and Fuel model IV. Fuel model III was mainly associated with shady slopes, and the main understory shrub layers were *Ledum palustre* and *Vaccinium uliginosum* (up to 0.4 m). In contrast, Fuel model IV was mainly associated with sunny slopes, and the main

**Table 2** Mean values (±SE) for fuel models obtained from the hierarchical cluster analysis

| Forest fuel characteristic variables | Fuel model | | | |
|---|---|---|---|---|
| | Model I | Model II | Model III | Model IV |
| Shrub loading (Mg/ha)** | 12.14 ± 1.48 | 0.25 ± 0.02 | 2.05 ± 0.15 | 3.15 ± 0.16 |
| Shrub coverage (%)* | 71 ± 4.93 | 38 ± 9.63 | 78 ± 3.99 | 53 ± 4.41 |
| Height of shrub (m)* | 2.5 ± 0.30 | 1.0 ± 0.36 | 0.4 ± 0.04 | 1.5 ± 0.10 |
| Herbaceous coverage (%)** | 5.5 ± 1.35 | 61 ± 13.52 | 8.6 ± 3.20 | 34.9 ± 4.66 |
| Litter depth (cm)** | 1.5 ± 4.11 | 6.3 ± 0.63 | 3.2 ± 0.60 | 5.6 ± 0.44 |
| 1-h fuel loading (Mg/ha)** | 4.86 ± 0.44 | 7.39 ± 0.58 | 6.70 ± 0.65 | 9.95 ± 0.53 |
| 10-h fuel loading (Mg/ha) | 3.95 ± 0.53 | 2.45 ± 0.52 | 2.41 ± 0.30 | 4.02 ± 0.26 |
| 100-h fuel loading (Mg/ha) | 2.31 ± 0.88 | 2.79 ± 0.63 | 1.66 ± 0.79 | 2.70 ± 0.40 |
| Canopy closure (%) | 50 ± 4.84 | 60 ± 2.98 | 50 ± 3.52 | 50 ± 2.65 |
| Tree diameter (cm)** | 7.4 ± 1.38 | 9.3 ± 1.41 | 6.9 ± 0.52 | 11.3 ± 0.87 |
| Tree height (m) | 9.0 ± 1.55 | 12.5 ± 0.81 | 11 ± 0.85 | 14 ± 0.85 |
| Height to base of crown (m)* | 4.0 ± 0.63 | 4.85 ± 0.64 | 3.95 ± 0.31 | 4.5 ± 0.33 |
| Live trees $ha^{-1}$** | 3000 ± 332.01 | 2500 ± 442.58 | 3100 ± 333.14 | 1800 ± 100.92 |
| Elevation (m)** | 907.40 ± 9.82 | 714.50 ± 30.89 | 790.75 ± 15.66 | 748.84 ± 19.86 |
| Aspect** | 3 | 6 | 4 | 7 |
| Slope degree | 18 ± 2.83 | 12 ± 3.21 | 15 ± 2.24 | 14 ± 1.77 |

Asterisks (*) next to the fuel variables indicate significant differences between fuel models according to Kruskal–Wallis tests, with* indicating significance at the $P < 0.05$ level, ** indicating significance at the $P < 0.01$ level

**Table 3** Fuel model parameters of Huzhong Forest Bureau

| Fuel model | Fuel loading (Mg/ha)/SAV ($m^2/m^3$) | | | | Fuel bed depth (m) | Moisture of extinction dead fuels (%) | Dead/live heat content (kJ/kg) |
|---|---|---|---|---|---|---|---|
| | 1-h | 10-h | 10-h | live | | | |
| I | 4.86/7030 | 3.95/358 | 2.31/98 | 12.14/2680 | 1.25 | 30 | 21052/21541 |
| II | 7.39/7349 | 2.45/358 | 2.79/98 | 0.25/3790 | 0.15 | 45 | 20131/20561 |
| III | 6.7/11259 | 2.41/358 | 1.66/98 | 2.05/3448 | 0.20 | 60 | 21281/21866 |
| IV | 9.95/8673 | 4.02/358 | 2.70/98 | 3.15/2196 | 0.40 | 35 | 20971/21384 |

*SAV* surface-area-to-volume-ratio

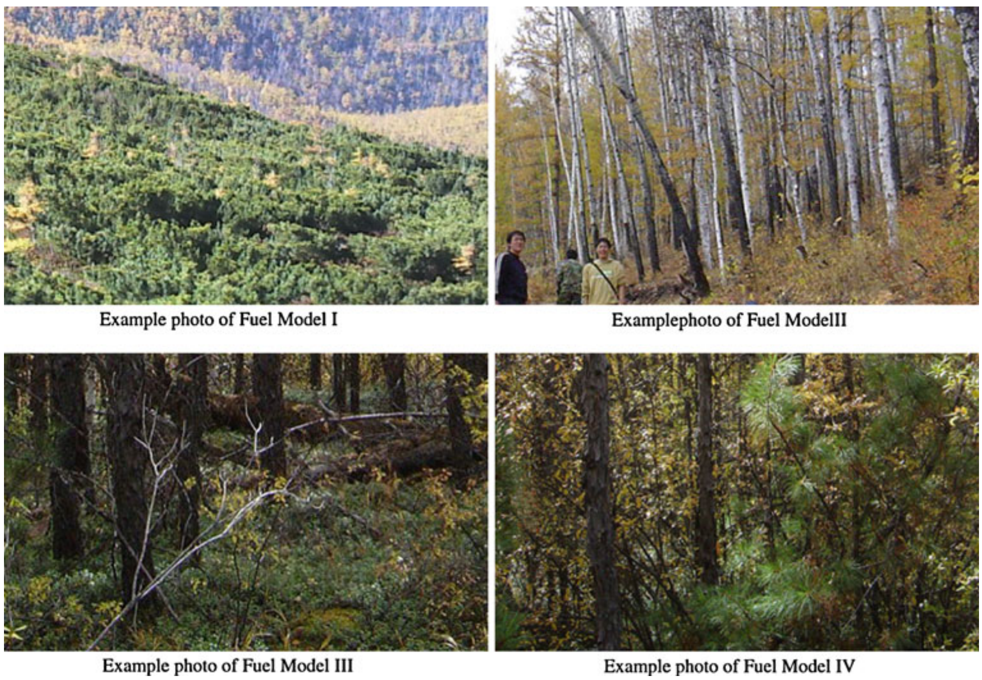


**Fig. 3** Example photos of fuel models

understory composition was *Rhododendron dauricum* (up to 2.0 m). Fuel model IV (9.95 Mg/ha) had much more 1-h fuel loading than Fuel model III (6.7 Mg/ha) partly because it had a large proportion of cured herbaceous vegetation that had died and been cured prior to the autumn inventory period.

## Potential Fire Behavior of Fuel Models

Surface rate of spread (m/min), Fireline intensity (Mw/m), Flame length (m), and Heat per unit area ($MJ/m^2$) were estimated for each of the four fuel models by Behave-Plus5.0 (Fig. 4). The simulated result indicated that the *Pinus pumila* shrubland fuels (Fuel model I) had the most severe fire potential for the 97th percentile weather condition, and had the least severe potential fire behavior for the 90th percentile weather conditions. Fuel model II presented the least severe fire danger across the both weather conditions, and presented the second lowest fire danger for the 90th percentile weather condition. Fuel model IV resulted greater fire severity than Fuel model III across both weather scenarios because it had heavier fuel loadings. However, it should be noted that the relative behavior may be different in other weather scenarios and environment conditions.

The primary carrier of fire in Fuel model I is live and dead shrub twigs and foliage in combination with dead and down shrub litter. The results indicated that the impact of moisture content on the fire behavior of shrubland is strongest because it has a lot of fine live woody fuels (up to 4 m). In the 97th percentile weather condition, the shrubland fuel model has the most severe fire behavior since the large component of fine live fuels is dry enough to ignite; for the 90th percentile weather condition, fire severity for

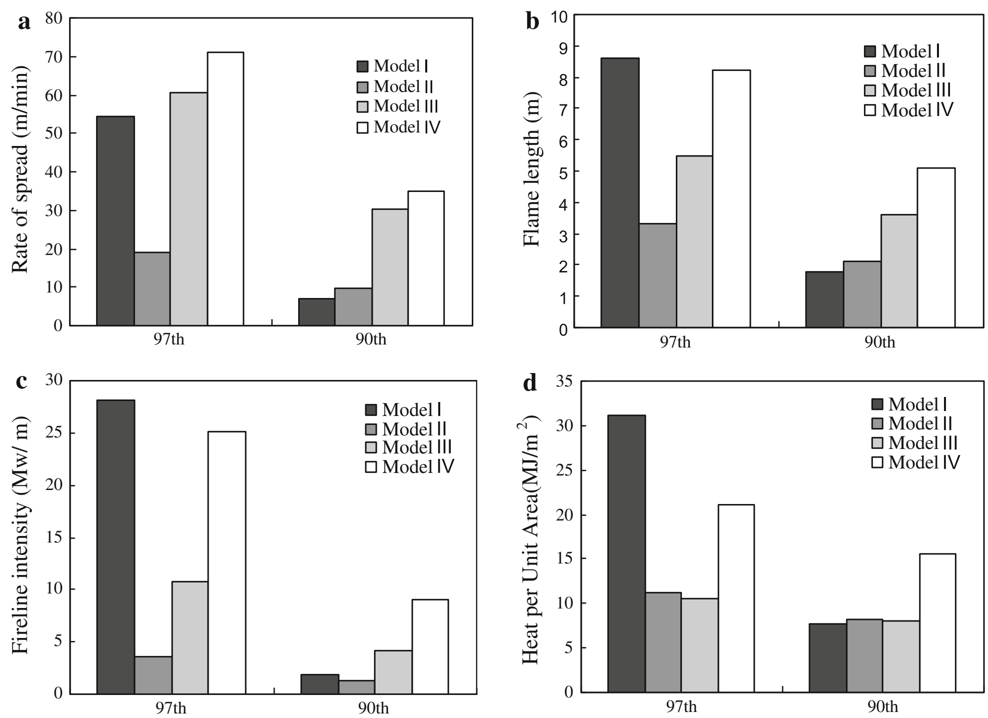


**Fig. 4** Potential fire behavior for four fuel models under 90th and 97th percentile weather conditions: **a** rate of spread, **b** flame length, **c** fireline intensity, **d** heat per unit area

Fuel model I is greatly reduced. Given that *Pinus pumila* shrublands (Fuel model I) primarily occur at high elevations and far from human settlements or roads, those ecosystems are less likely to be ignited than ecosystems associated with the other three fuel models. However, if ignited the *Pinus pumila* shrublands may have high fireline intensity and even spotting fires under high wind speeds (Dymond and others 2004; Shu and others 2004).

The primary carrier of fire in Fuel model II is broadleaf litter and herbaceous plants. This fuel model has the least severe potential for severe fire behavior compared with other fuel models (Fig. 4). However, in forest conditions associated with Fuel model II high winds may actually cause higher rates of spread than predicted because of spotting caused by rolling and blowing leaves (Anderson 1982).

The primary carrier of fire in Fuel model III and Fuel model IV is coniferous forest litter with grass and shrub components. The results showed that fuel model III is generally considered to have lower fire risk than fuel model IV due to higher humidity, higher rates of litter and duff decomposition and lower loadings of herbaceous and shrubs beneath the closed canopy. Most forest fires are surface fires in the study area (Shu and others 2003), but under severe drought weather conditions, crowning, spotting, and torching of individual trees can occur in Fuel model III and Fuel model IV (Wang and others 2004).

## Management Implications

The information provided by this study is particularly useful in identifying fuels, assessing fire risk and guiding fire and fuel management activities. In this study, we described the characteristics of four fuel models and presented their physiognomic photos that could help investigators to identify fuel types. In the field, an investigator would walk into a stand or plot and compare observed fuel characteristics with the parameters (Tables 2, 3) and photos (Fig. 3) to identify a potential fuel model with low cost and less time. The investigator need only determine if the observed fuels are above or below threshold values or characteristics (Lutes and others 2009).

Moreover, understanding of fuel characteristics and their potential fire behavior will help managers strategically select the most critical stands or locations for fuel reduction treatment, and predict fuel treatment effects according to the resources available. Once fuels characteristics and their potential fire behavior across a forest landscape are identified and simulated, managers can input this information into a fire simulation program to answer several questions related to fuel treatments and fire management under different weather conditions, such as: (1) where fuel treatment activities should be placed; (2) what amount of fuel treatment is optimal; 3) which fuel treatments are most effective (Kim and others 2009). For example, fuel model II had the least and the second least severe fire spread behavior under the 97th and 90th percentile weather condition, respectively; it could serve as natural fire break. Managers may consider converting other fuel types into Fuel model II in the Wildland Urban Interface areas to reduce potential fire spread behavior and fire risk adjacent to settlement. In addition, Fuel model I is a natural fire break under normal weather conditions, but may pose a great fire danger during extreme weather conditions.

## Conclusions

The high complexity and variability in composition and structure of forest fuels across space and time limit the accuracy of the vegetation-based classification approaches, such as remote sensing and gradient modeling (Keane and others 2001; Arroyo and others 2008). The main defect of vegetation-based approaches is that it is hard to account for structural stages of forest fuels, especially surface fuels, resulting from disturbance and succession (Miller and others 2003). Moreover, sometimes the simulated fire behavior is similar when using the vegetation-based fuel model parameters.

Our study corroborated other prior research which further demonstrated the utility of hierarchical cluster analysis for classifying fuels (Miller and others 2003; Poulos and others 2007; Poulos 2009). We identified four forest fuel models by classifying vegetation and fuels structure and environmental conditions in the Huzhong Forest Bureau using hierarchical cluster analysis and simulated their potential fire behavior with BehavePlus 5.0 fire behavior prediction system. The results can be used for a range of forest and fire management activities. However, the development of four fuels models was intended as a starting point for much needed fuel model identification in China. There are some limitations in this work:

(1) The live fuels biomass measurements, such as herbaceous biomass, may have been affected by the timing of the plot sampling. In this study, because the field data collection was conducted late in September 2006, the fuel model types were static and only can be used to asses the fall fire hazard and risk. In order to better address wildland fire management, fuels information during the growing season should be obtained.

(2) In this study, the number of sample plots was limited in quantity due to difficulty of access. The lack of field data for vast forest areas that occur far away from settlements and roads may be a problem because the vegetation/fuels conditions and structure can differ greatly due to differences in the environmental setting. Therefore, the sample plots should be more evenly distributed across the study area to reflect the variability of fuels spatial distribution.

(3) The primary fire behavior according to BehavePlus5.0 was surface fire behavior in the study. The crown fire behavior should also be considered while conducing fire behavior simulation if the crown parameters (e.g., canopy bulk density) used as inputs to fire behavior and effects simulations system can be obtained.

(4) As Keane and others (2001) pointed out, forest fuels maps are essential for estimating spatial fire hazard and risk and simulating fire spread and intensity across a landscape under different weather conditions. Future research should focus on the integrated use of remote sensing, GIS and environmental biophysical-gradient models to map forest fuels in the Huzhong Forest Bureau.

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