J. For. Res. (2021) 32:1177–1187
https://doi.org/10.1007/s11676-020-01109-7

ORIGINAL PAPER

Diurnal variation models for fine fuel moisture content in boreal forests in China

Ran Zhang[1] · Haiqing Hu[1] · Zhilin Qu[2] · Tongxin Hu[1]

Received: 29 August 2018 / Accepted: 17 August 2019 / Published online: 4 April 2020

Abstract Studying diurnal variation in the moisture content of fine forest fuel (FFMC) is key to understanding forest fire prevention. This study established models for predicting the diurnal mean, maximum, and minimum FFMC in a boreal forest in China using the relationship between FFMC and meteorological variables. A spline interpolation function is proposed for describing diurnal variations in FFMC. After 1 day with a 1 h field measurement data testing, the results indicate that the accuracy of the sunny slope model was 100% and 84% when the absolute error was < 3% and < 10%, respectively, whereas the accuracy of the shady slope model was 72% and 76% when the absolute error was < 3% and < 10%, respectively. The results show that sunny slope and shady slope models can predict and describe diurnal variations in fine fuel moisture content, and provide a basis for forest fire danger prediction in boreal forest ecosystems in China.

Keywords Forest fuel · Forest fire · Moisture content · Prediction model · Diurnal variation

Introduction

Forest fires have significant impact on forest ecosystems, often resulting in the release of large amounts of energy in short periods of time, causing massive deaths of wildlife (Gisborne 1925; Wotton et al. 2010; Nolan et al. 2016). Simultaneously, forest fires affect air temperatures, humidity, light availability and other factors within forests and change the composition, structure, and function of understory communities (Meyn et al. 2007; Jonathan et al. 2016; Santín et al. 2016; Hu et al. 2019), thereby causing ecosystem imbalances (Viegas et al. 1992; Shan et al. 2005; Fulé and Laughlin 2007). The majority of forest fires are surface fires and the moisture content of dead surface fuel is a major factor in forest fire occurrences (Bradstock 2010; Jin and Chen 2012). The moisture content of fine forest fuel (FFMC), defined as litter and woody debris with diameters < 2.54 cm (Schiks and Wotton 2015; Slijepcevic et al. 2018), is particularly important in fire danger rating systems (McArthur 1966; Bradshaw et al. 1984; Rothermel et al. 1986; Van Wagner 1987), which are subsequently used to make short-term decisions about staffing and the movement of resources from low to high risk areas (Beck and Armitage 2001; De Dios et al. 2015). Therefore, establishing methods to accurately predict the moisture content of fine forest fuel (FFMC) is key to understanding forest fire danger prediction (Simard 1968; Van Wagner 1969), and understanding variation in

Project funding: This research was financially supported by the Special Fund for Forest Scientific Research in the Public Welfare (No. 201404402) and Fundamental Research Funds for the Central Universities (Nos. C2572014BA23 and 2572019BA03).

The online version is available at http://www.springerlink.com.

Corresponding editor: Yu Lei.

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s11676-020-01109-7) contains supplementary material, which is available to authorized users.

✉ Zhilin Qu
q_zhilin@nefu.edu.cn

✉ Tongxin Hu
htxhtxapple@sina.com

1 Key Laboratory of Sustainable Forest Ecosystem Management-Ministry of Education, Northeast Forestry University, Harbin 150040, China

2 College of Science, Northeast Forestry University, Harbin 150040, China

FFMC can help predict the occurrence and the control of forest fires (Matthews 2014; Slijepcevic et al. 2013).

Several studies have reported that variation in FFMC is influenced by a variety of factors, with meteorological ones having a dominant role. Therefore, studying the relationship between meteorological factors and variations in FFMC is key to establishing reliable forest fire prediction models (McCammon 1976; Van Wagner and Pickett 1985; Saglam et al. 2006; Aguado et al. 2007; Pellizzaro et al. 2007). The methods currently used to predict FFMC are based on equilibrium moisture content, meteorological factors, remote sensing, and process models (Toomey and Vierling 2005; Yebra et al. 2006; Liu and Jin 2007; Yu et al. 2013). The equilibrium moisture content method has been widely used in the United States, Canada, and other countries that use a forest fire danger rating system (Ralph and Nelson 1984; Anderson 1990; Viney and Catchpole 1991; Catchpole et al. 2001), where the equilibrium moisture content response to environmental factors is used to calculate the equilibrium moisture content at different temperature and humidity levels. In addition, differential equations have been established to describe the continuous variation in FFMC (Matthews 2006), using an initial FFMC and associated meteorological factors (Van Wagner 1972; Viegas et al. 2001). As such, models based on the equilibrium moisture content can accurately estimate FFMC over a short time. However, prediction error increases with increasing time interval (Matthews 2010). Variability in the diurnal variation of moisture content of fine fuels is complex, which reduces the accuracy of the method based on the equilibrium moisture content (Page et al. 2013). Therefore, establishing a suitable model for the diurnal variation of FFMC is key to improving the precision of FFMC prediction. Few studies have investigated the prediction of short-term diurnal variation in FFMC (Slijepcevic and Anderson 2006; Sun et al. 2015). A previous study selected a particular time (e.g., 14:00) for FFMC as today's FFMC to study diurnal variation, whereas other studies have used various indicators (e.g. maximum, minimum, or average FFMC) to describe diurnal variations (Slijepcevic et al. 2015). However, it is difficult to accurately describe the diurnal variation of FFMC using such methods (Viney 1991; Castro et al. 2003; Li et al. 2012). Forest fires are a major disturbance factor to forest ecosystems of the Daxing'an Mountain region. However, an in-depth study of diurnal variations in fuel moisture is lacking. The aims of this study are to investigate diurnal variations in moisture content of fine forest fuels using field data to establish a predictive model that would use current forest fuel moisture content estimations and related meteorological factors to predict future FFMC. This study will provide a theoretical basis for predicting FFMC in the Daxing'an Mountains of China, thereby improving the accuracy of diurnal fire risk.

Materials and methods

Study area

The research area was located in the Daxing'an Mountains, Nanwenghe Forest Ecological Station, northeast China (51° 05′ 07″ N–51° 39′ 24″ N, 125° 07′ 55″ E–125° 50′ 05″ E). Elevations range in 500–800 m a.s.l.; the climate is a cold temperate continental monsoon zone affected by the Siberian cold air mass. The frost-free period is approximately 98 days and mean annual precipitation and temperature are 500 mm and −3 °C, respectively. The area receives about 2500-h sunshine annually, the growing season generally starts in May and ends in September, whereas the dormant is from October and to April. All soils in the area are podzols, infertile acidic soils formed over granite bedrock, and typical of boreal forests from which minerals have been leached into a lower stratum. The dominant tree species include *Larix gmelinii* Rupr., *Betula platyphylla* Suk., and *Populus davidiana* Dode; the dominant herb species are *Lespedeza bicolour* Turcz., *Rosa davurica* Pall., *Vaccinium vitis-idaea* L., *Rhododendron simsii* Planch., *Calamagrostis angustifolia* Kom., and *Maianthemum bifolium*.

The Daxing'an Mountains have the largest boreal forest area in China. The predominant forest type is *L. gmelinii*, which covers 80% of the area and accounts for about 30% of timber production (Xu 1998; Hu et al. 2019). Over 1600 fires occurred in the area from 1965 to 2010, burning nearly 3.5×10^6 ha with an average annual burn of 7.7×10^4 ha (Hu et al. 2012, 2017).

Measurement of the moisture content of fine forest fuel

Data were collected from experimental plots at the Nanweng River Forest Ecological Stationin the Da Xing'an Mountains, from May 26 to June 24, 2015, and from May 18 to June 8, 2016. The plots were located downhill of areas with sunny slopes or shady slopes, both were *B. platyphylla* and *L. gmelinii* mixed forest. A total of six 40 m × 80 m plots were established, with three each in both the sunny slope and shady slope areas (Table 1).

Three instruments were installed in each plot to automatically measure and record FFMC on an hourly basis (Fig. 1). The moisture contents of small dead sticks (20 cm × 0.6 cm) were used as a proxy for FFMC in each of the corresponding plots. Metal probes were inserted into both ends of each stick, and the density calibrated according to the fuel air-dry density and the temperature recorded as the ambient temperature. The instrument was capable of measuring moisture content values of 0.0–99.9%, densities of 0.10–1.25 g cm^{-3}, and temperatures from −20 to 70 °C; it had an output signal of 4–20 mA, measurement accuracy of ± 3%, and calibration range of from −5.0 to +5.0. The metal probes were 2-mm

Table 1 Characteristics of study plots

Forest type	Aspect	Tree species composition (*B. platyphylla*: *L. gmelinii*)	Understory composition	Elevation (m)	Mean DBH (m)	Mean height (cm)	Canopy density
Mixed forest of *B. platyphylla* and *L. gmelinii*	Sunny slope	3:7	*Rhododendron Simsii* Planch., *Vaccinium vitis-idaea* L., Paris quadrifolia, *Pyrola calliantha* H. Andr., *Vaccinium uliginosum* Linn.	411.2	14.5	14.97	0.81
Mixed forest of *B. platyphylla* and *L. gmelinii*	Shady slope	3:7	*Lespedeza bicolor* Turcz., *Rosa davurica* Pall., *Vaccinium vitis-idaea* L., *Rhododendron simsii* Planch., *Calamagrostis angustifolia* Kom., *Maianthemum bifolium*	401	11.5	11.3	0.72

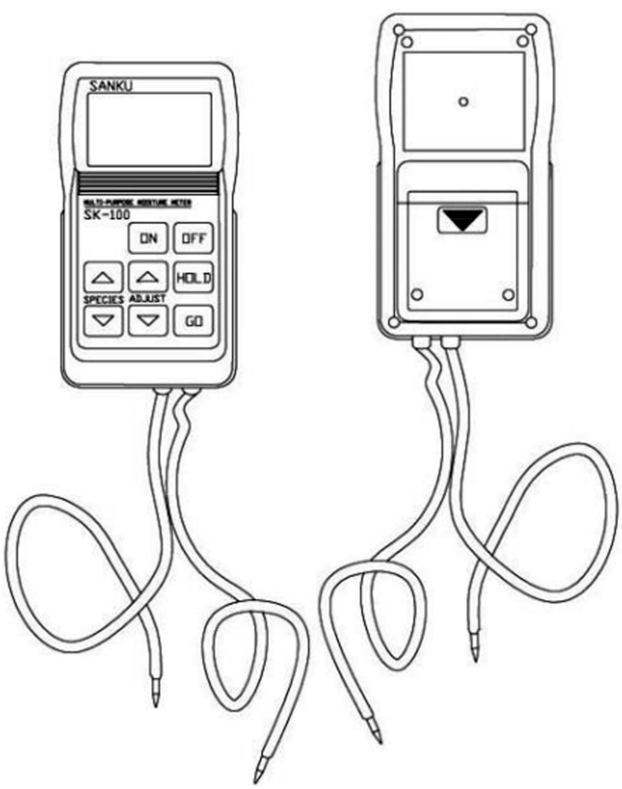

Fig. 1 Instrument used to measure the moisture content of fine forest fuel

diameter 10-mm long stainless steel attached to the instrument by 2-m wires. A battery powered the instrument in order to achieve 24-h measurements. The ecological station provided hourly meteorological data (i.e. air temperature, relative humidity, wind speed, and rainfall) for the periods May 26–June 24, 2015, and May 18–June 8, 2016 (Table 2). The ecological station was located at about 200 m from the study plots.

Table 2 Variation in meteorological data

Factor	Range
Air temperature (°C)	− 3.4 to 31.9
Relative humidity (%)	22.2–100
Wind speed (m s^{-1})	0–3.9
Moisture content (%)	11.1–50.2
Rainfall (mm)	0–5.5

Model construction

Thirty variables were identified, including today's mean, maximum and minimum temperatures (TT_{mean}, TT_{max}, TT_{min}, respectively), today's mean, maximum and minimum relative humidity (TRH_{mean}, TRH_{max}, TRH_{min}, respectively), today's rainfall (*TR*), today's mean and maximum wind speed (TW_{mean}, TW_{max}, respectively), today's mean, maximum and minimum sunny slope FFMC (TMC_{mean}, TMC_{max}, and TMC_{max}, respectively), today's mean, maximum and minimum shady slope FFMC ($\overline{TMC}_{mean}$, $\overline{TMC}_{max}$, and$\overline{TMC}_{min}$, respectively) tomorrow's mean, maximum and minimum temperature (NT_{mean}, NT_{max}, NT_{min}, respectively), tomorrow's mean, maximum and minimum relative humidity (NRH_{mean}, NRH_{max}, NRH_{min}), tomorrow's rainfall (*NR*), tomorrow's mean and maximum wind speed (NW_{mean}, NW_{max}, respectively), tomorrow's mean, maximum and minimum sunny slope

FFMC (NMC_{mean}, NMC_{max}, NMC_{min}, respectively), tomorrow's mean, maximum and minimum shady slope FFMC ($\overline{NMC}_{mean}$, $\overline{NMC}_{min}$, $\overline{NMC}_{max}$, respectively).

Correlation analysis was used to calculate coefficients between the variables and were used to analyse linear correlations between FFMC and meteorological variables. A shady slope mean FFMC prediction model was established and used to predict maximum and minimum moisture contents. In addition, tomorrow's mean, maximum, and minimum sunny slope FFMC were predicted using the relationship between mean sunny slope FFMC and mean shady slope FFMC. Interpolation theory was then used to establish diurnal variation curves for tomorrow's sunny slope and shady slope FFMC and the data used to test the accuracy of the models (Habermann and Kindermann 2007). The data were processed and analysed using STATISTICA 6.0 (Statsoft Inc., Tulsa, OK, USA). Pearson's correlation analysis was used for all correlation analyses, and all statistical analyses were performed using a significance level of 0.05. Variance inflation factor (VIF) tested for multicollinearity among variables. When VIF < 10, there was no multicollinearity between variables, and when VIF > 10, multicollinearity existed (Craney and Surles 2002).

Results

Diurnal variation in fine fuel moisture content

Mean, maximum, and minimum FFMC values were calculated for each day in the 51-day dataset (Figs. 2 and 3).

The average sunny slope FFMC was greater than the mean shady slope FFMC and accounted for 43.1% over the 51 days. The maximum sunny slope FFMC was greater than the maximum shady slope FFMC, accounting for 41.2% over the period. The minimum sunny slope FFMC was greater than the minimum shady slope FFMC and accounted for 51.0% over the 51 days. In addition, compared with the shady slope values, the average fine fuel moisture content was 12.5% lower than that of the sunny slope values. These results indicate that there were considerable differences between the FFMC values of sunny and shady slopes under the same meteorological conditions, and that slope strongly affected the moisture content of fine fuels.

Correlation analysis of FFMC and meteorological variables

The correlation of FFMC and meteorological factors are shown in Tables S1–3. Because some of the FFMC factors could not be obtained directly, they were estimated using the correlation results in Tables S1–3. $NMC_{mean} - TMC_{mean}$ was strongly correlated with NR, $NT_{\mathrm{max}} - TT_{\mathrm{max}}$, $NRH_{\mathrm{mean}} - TRH_{\mathrm{mean}}$, and $NT_{\mathrm{max}} - NT_{\mathrm{min}}$, and TMC_{mean} with TMC_{max} and TMC_{min} in both the sunny and shady areas (Table S1). Accordingly, NR, $NT_{\mathrm{max}} - TT_{\mathrm{max}}$, $NRH_{\mathrm{mean}} - TRH_{\mathrm{mean}}$, and $NT_{\mathrm{max}} - NT_{\mathrm{min}}$ could be used to predict TMC_{mean}, TMC_{max}, and TMC_{min}. Meanwhile, none of the wind factors (TW_{mean}, TW_{max}, NW_{mean}, and NW_{max}) were significantly correlated with the FFMCs of either the sunny or shady areas (Tables S2–3). Therefore, wind factors were not considered when constructing the prediction model for diurnal variation in fine fuel moisture content.

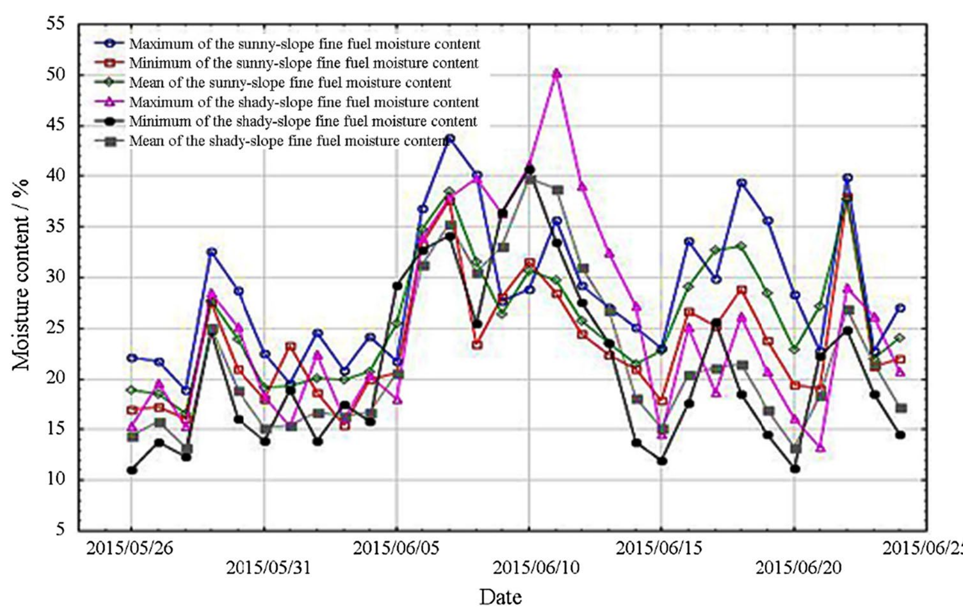

Fig. 2 Diurnal variation in the moisture content of fine forest fuel in sunny slope and shady slope (2015)

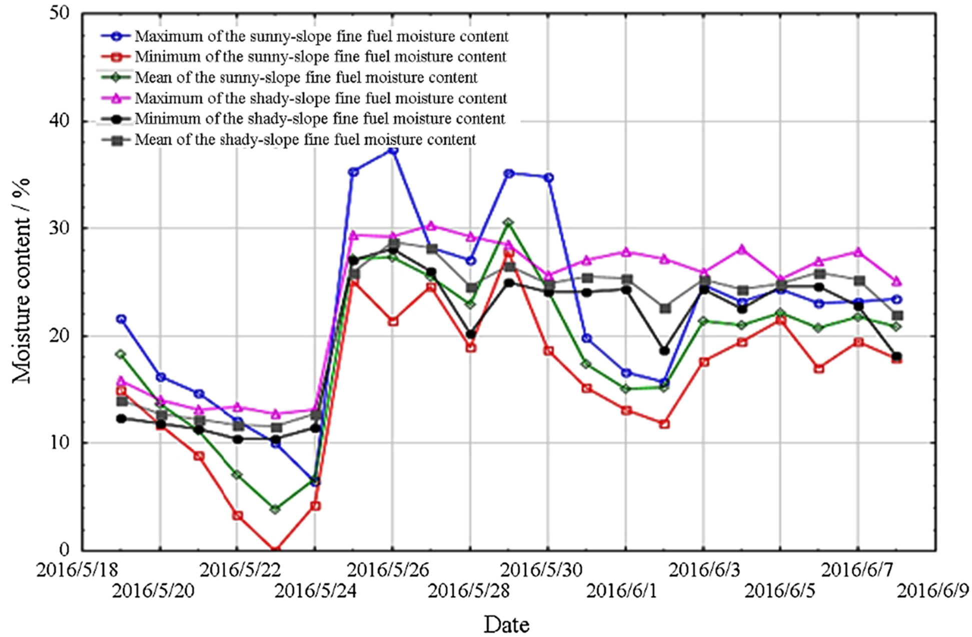

Fig. 3 Diurnal variation in the moisture content of fine forest fuel in sunny slope and shady slope (2016)

FFMC prediction model

The mean variance expansion factor of $TRH_{\max}$ and $TRH_{\min}$ ($\overline{\text{VIF}} = 1.19 < 10$) indicated that there was no collinearity. However, because the TRH_{mean} was significantly correlated with $TRH_{\min}$, a prediction model was established:

$$TRH_{\text{mean}} = a_1 TRH_{\max} + b_1 TRH_{\min} \tag{1}$$

Similarly, the mean variance expansion factor of TRH_{mean}, NR, $NT_{\max} - NT_{\min}$, and $NT_{\max} - TT_{\max}$ ($\overline{\text{VIF}} = 1.63 < 10$) indicated that there was no collinearity, and because the factors were significantly correlated with NRH_{mean}, a prediction model could be established:

$$\begin{aligned} NRH_{mean} = a_2 TRH_{mean} + b_2 NR + c_2(NT_{\max} - NT_{\min}) \\ + d_2(NT_{\max} - TT_{\max}) + e_2 \end{aligned} \tag{2}$$

In addition, the mean variance expansion factor of NR, $NT_{\max} - TT_{\max}$, $NRH_{\text{mean}} - TRH_{\text{mean}}$, $NT_{\max} - NT_{\min}$ ($\overline{\text{VIF}} = 1.39 < 10$; Table S1) indicated that there was no collinearity, and because the factors were significantly correlated with $NMC_{\text{mean}} - TMC_{\text{mean}}$, a prediction model was established:

$$\begin{aligned} NMC_{\text{mean}} - TMC_{\text{mean}} = a_3 NR + b_3\left(NT_{\max} - TT_{\max}\right) \\ + c_3\left(NRH_{\text{mean}} - TRH_{\text{mean}}\right) + d_3\left(NT_{\max} - NT_{\min}\right) \end{aligned} \tag{3}$$

finally the relationships between NMC_{mean} and both $NMC_{\max}$ and $NMC_{\min}$ were used to establish prediction models for both $NMC_{\max}$ and $NMC_{\min}$:

$$NMC_{\max} = a_4 + b_4 NMC_{mean} \tag{4}$$

$$NMC_{\min} = a_5 + b_5 NMC_{mean} \tag{5}$$

where a_i, b_i, $i = 1, 2\ldots, 5$, c_2, c_3, d_2, d_3, e_2 are the model parameters.

Prediction of maximum and minimum FFMC occurrence

Because the minimum and maximum fine fuel moisture content values occurred at different times each day, it was necessary to accurately estimate these to predict diurnal variation in FFMC. The timing of the minimum and maximum FFMC values on the sunny and shady slopes are summarized in Table 3.

The maximum sunny slope FFMC values occurred from 6:00 to 8:00 am on 92% of the 51 days (Table 3), whereas the minimum occurred from 16:00 to 19:00 am on 74% of the 51 days. The maximum shady slope FFMC values occurred from 5:00 to 8:00 am on 90.9% of the 51 days (Table 3), whereas the minimum occurred from 17:00 to 20:00 am on 83.6% of the 51 days. The maximum sunny slope moisture content values occurred earlier than the maximum shady slope values in 10.2% of the 51 days, at the same time in 28.6% of the 51 days, and later in 61.2% of the 51 days. The minimum sunny slope values occurred earlier than the minimum shady slope ones in 40.8% of the 51 days, at the same time in 20.4% of the 51 days, and later in 38.8% of the 51 days. The intervals between the minimum and maximum FFMC of the shady area were greater than that of the sunny area in 61.2% of the 51 days and less than that of the sunny area in 38.8% of the 51 days.

Table 3 Temporal distribution of maximum and minimum fine fuel moisture content

Slope	Max. fine fuel moisture content			Min. fine fuel moisture content		
	Time	Frequency	Percentage (%)	Time	Frequency	Percentage (%)
Sunny slope	5:00	2	4	16:00	8	16
	6:00	7	14	17:00	9	18
	7:00	24	48	18:00	9	18
	8:00	15	30	19:00	11	22
	Others	2	4	Others	13	26
Shady slope	5:00	8	14.5	17:00	11	20
	6:00	26	47.3	18:00	13	23.6
	7:00	11	20	19:00	10	18.2
	8:00	5	9.1	20:00	12	21.8
	Others	5	9.1	Others	9	16.4

Table 4 Correlations among factors affecting temporal distribution of minimum and maximum sunny slope fine fuel moisture content values

	$NMC_{max}-TMC_{min}$	$NMC_{max}-NMC_{min}$	$MC1$	$MC2$
$NMC_{max}-TMC_{min}$	1.00	0.22	0.99*	0.21
$NMC_{max}-NMC_{min}$	0.22	1.00	0.27	0.94*
$MC1$	0.99*	0.27	1.00	0.26
$MC2$	0.21	0.94*	0.26	1.00

*indicated the significant correlation between variables at $P = 0.05$ level

Table 5 Correlations among factors affecting temporal distribution of minimum and maximum shady slope fine fuel moisture content values

	$\overline{NMC}_{max}-\overline{TMC}_{min}$	$\overline{NMC}_{max}-\overline{NMC}_{min}$	$\overline{MC}1$	$\overline{MC}2$
$\overline{NMC}_{max}-\overline{TMC}_{min}$	1.00	0.15	0.97*	0.16
$\overline{NMC}_{max}-\overline{NMC}_{min}$	0.15	1.00	0.20	0.98*
$\overline{MC}1$	0.97*	0.20	1.00	0.20
$\overline{MC}2$	0.16	0.98*	0.20	1.00

*indicated the significant correlation between variables at $P = 0.05$ level

The differences between tomorrow's maximum FFMC and today's minimum FFMC ($MC1$) and between tomorrow's maximum FFMC and tomorrow's minimum FFMC ($MC2$) were calculated as follows:

$$MC1 = \frac{NMC_{max} - TMC_{min}}{24 - t_1 + t_2} \tag{6}$$

$$MC2 = \frac{NMC_{max} - NMC_{min}}{t_3 - t_2} \tag{7}$$

where t_1 is the time of today's minimum FFMC occurrence, t_2 the time of tomorrow's maximum, and t_3 the time of tomorrow's minimum.

Correlations among $MC1$, $MC2$, $NMC_{max}-TMC_{min}$, and $NMC_{max}-NMC_{min}$ are summarized in Tables 4 and 5.

Because $MC1$ was significantly correlated with $NMC_{max}-TMC_{min}$ and $MC2$ was significantly correlated with $NMC_{max}-NMC_{min}$ (Tables 4 and 5), prediction models were established for both $MC1$ and $MC2$:

$$MC1 = a_7 + b_7(NMC_{max} - TMC_{min}) \tag{8}$$

$$MC2 = a_8 + b_8(NMC_{max} - NMC_{min}) \tag{9}$$

where a_i, b_i, $i = 7, 8$ are the model parameters.

Models for tomorrow's maximum and minimum occurrence times were also established:

$$t_2 = t_1 - 24 + \frac{NMC_{max} - TMC_{min}}{a_7 + b_7(NMC_{max} - TMC_{min})} \tag{10}$$

$$t_3 = t_2 + \frac{NMC_{max} - NMC_{min}}{a_8 + b_8(NMC_{max} - NMC_{min})} \tag{11}$$

where t_1 is the time of today's minimum FFMC occurrence, t_2 is the time of tomorrow's maximum FFMC occurrence, and t_3 is the time of tomorrow's minimum FFMC occurrence.

Diurnal FFMC variation models

Based on the prediction models presented above [Eqs. 3–11], tomorrow's maximum FFMC (NMC_{max}) and its time of occurrence (t_2), tomorrow's minimum FFMC (NMC_{min}) and its occurrence time (t_3), the day-after-tomorrow's maximum FFMC ($NNMC_{max}$) and its time of occurrence (t_4), can be predicted and combined with today's minimum FFMC occurrence time (t_1). Finally, models for diurnal variation in FFMC were established using the spline interpolation method:

$$NMC = \begin{cases} TMC_{\min}(1 + 2\frac{t-(t_1-24)}{t_2-(t_1-24)})(\frac{t-t_2}{(t_1-24)-t_2})^2 + NMC_{\max}(1 + 2\frac{t-t_2}{(t_1-24)-t_2})(\frac{t-(t_1-24)}{t_2-(t_1-24)})^2 & 0 \le t < t_2 \\ NMC_{\max}(1 + 2\frac{t-t_2}{t_3-t_2})(\frac{t-t_3}{t_2-t_3})^2 + NMC_{\min}(1 + 2\frac{t-t_3}{t_2-t_3})(\frac{t-t_2}{t_3-t_2})^2 & t_2 \le t < t_3 \\ NMC_{\min}(1 + 2\frac{t-t_3}{(t_4+24)-t_3})(\frac{t-(t_4+24)}{t_3-(t_4+24)})^2 + NNMC_{\max}(1 + 2\frac{t-(t_4+24)}{t_3-(t_4+24)})(\frac{t-t_3}{(t_4+24)-t_3})^2 & t_3 \le t \le 24 \end{cases} \quad (12)$$

Equation 12 can be used to predict diurnal variation patterns in FFMC over the following day.

FFMC model prediction and validation

The parameter estimates of each model were determined by the least square method.

Today's maximum % relative humidity ($TRH_{\max}$) was determined by:

$$TRH_{mean} = 0.4029TRH_{\max} + 0.7889TRH_{\min}, R^2 = 0.825 \quad (13)$$

Tomorrow's mean % relative humidity (NRH_{mean}) was predicted by:

$$NRH_{mean} = 0.4768TRH_{mean} + 5.9198NR + 0.6646(NT_{\max} - NT_{\min}) - 1.1816(NT_{\max} - TT_{\max}) + 5.6178, R^2 = 0.615 \quad (14)$$

Tomorrow's mean sunny slope FFMC % (NMC_{mean}) was predicted using:

$$NMC_{mean} = TMC_{mean} + 0.2460NR - 0.1582(NT_{\max} - TT_{\max}) + 0.0750(NRH_{mean} - TRH_{mean}) - 0.1809(NT_{\max} - NT_{\min}) + 3.0681, R^2 = 0.629 \quad (15)$$

Tomorrow's maximum sunny slope FFMC % ($NMC_{\max}$) was predicted (Fig. 4) by Eq. 16:

$$NMC_{\max} = 2.7088 + 1.0641NMC_{mean}, R^2 = 0.880 \quad (16)$$

Tomorrow's minimum sunny slope FFMC % ($NMC_{\min}$) was predicted as follows (Fig. 5):

$$NMC_{\min} = -0.9650 + 0.8749NMC_{mean}, R^2 = 0.840 \quad (17)$$

Tomorrow's mean shady slope FFMC % ($\overline{NMC}_{mean}$) was predicted by:

$$\overline{NMC}_{mean} = \overline{TMC}_{mean} + 0.3971NR - 0.2556(NT_{\max} - TT_{\max}) + 0.0457(NRH_{mean} - TRH_{mean}) - 0.1209(NT_{\max} - NT_{\min}) + 1.4653, R^2 = 0.674 \quad (18)$$

Tomorrow's maximum shady-slope FFMC (%, $\overline{NMC}_{max}$) was predicted (Fig. 6) as follows:

$$\overline{NMC}_{\max} = 0.1941 + 1.1622\overline{NMC}_{mean}, R^2 = 0.926 \quad (19)$$

Tomorrow's minimum shady-slope FFMC (%, $\overline{NMC}_{min}$) was predicted (Fig. 7) using Eq. 20:

$$\overline{NMC}_{\min} = -0.5737 + 0.8260\overline{NMC}_{mean}, R^2 = 0.911 \quad (20)$$

The time of maximum sunny slope FFMC occurrence was determined by:

$$t_2' = t_1' - 24 + \frac{NMC_{\max} - TMC_{\min}}{0.0188 + 0.0722(NMC_{\max} - TMC_{\min})}, R^2 = 0.983 \quad (21)$$

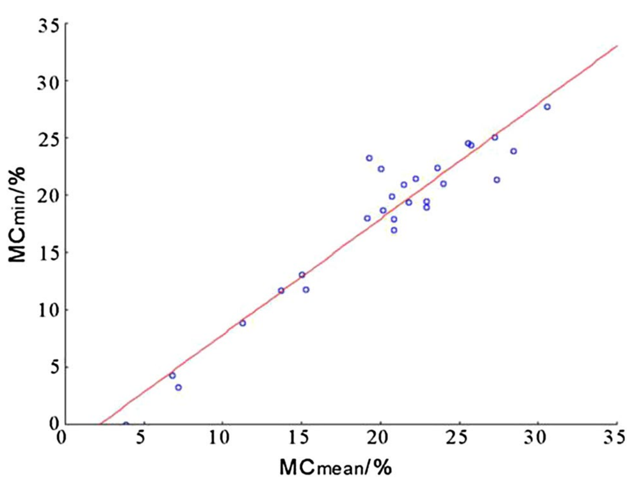

Fig. 5 Relationship between the mean and minimum sunny slope fine fuel moisture content

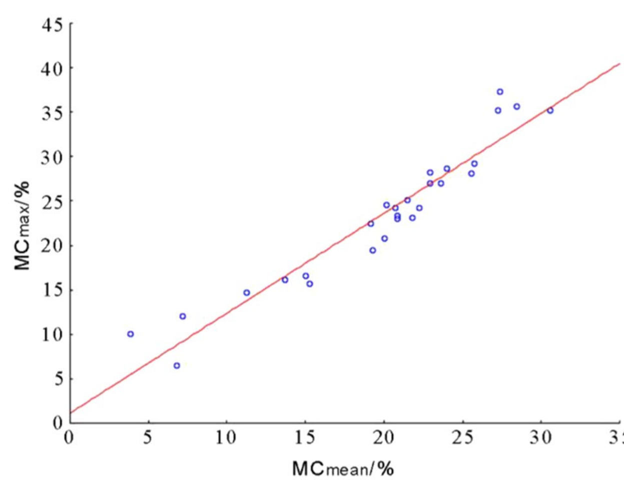

Fig. 4 Relationship between the mean and maximum sunny slope fine fuel moisture content

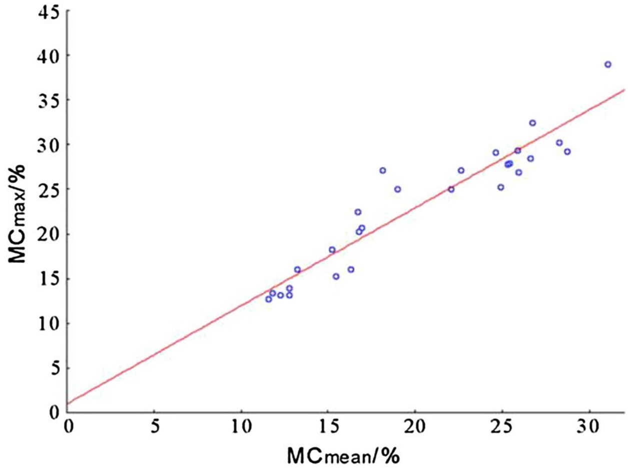

Fig. 6 Relationship between the mean and maximum shady slope fine fuel moisture content

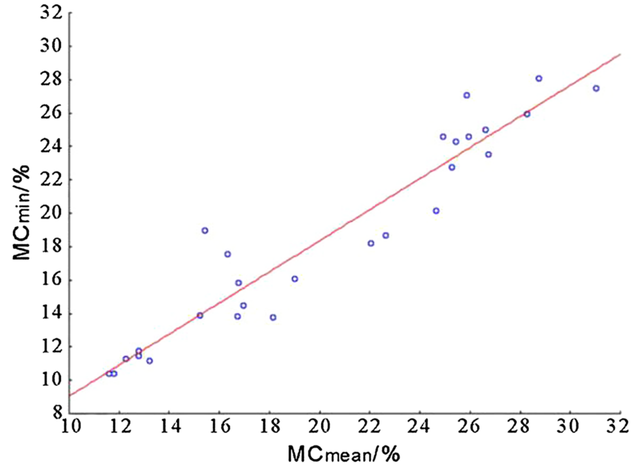

Fig. 7 Relationship between the mean and minimum shady-slope fine fuel moisture content

The time of minimum sunny slope FFMC occurrence was determined by:

$$t_3' = t_2' + \frac{NMC_{\max} - NMC_{\min}}{0.0407 + 0.0883(NMC_{\max} - NMC_{\min})}, R^2 = 0.886 \quad (22)$$

The time of maximum shady slope FFMC occurrence was predicted by:

$$t_2'' = t_1'' - 24 + \frac{\overline{NMC}_{\max} - \overline{TMC}_{\min}}{0.0287 + 0.0765(\overline{NMC}_{\max} - \overline{TMC}_{\min})}, R^2 = 0.939 \quad (23)$$

The time of minimum shady slope FFMC occurrence was determined by:

$$t_3'' = t_2'' + \frac{\overline{NMC}_{\max} - \overline{NMC}_{\min}}{0.0150 + 0.0790(\overline{NMC}_{\max} - \overline{NMC}_{\min})}, R^2 = 0.952 \quad (24)$$

The parameters estimated using these models all significantly passed the hypothesis test.

Moisture content values for fine fuel on sunny and shady slopes and meteorological data from June 12–14, 2015 were used to validate the FFMC prediction models. Equations 15 and 17 estimated the mean, maximum (29.3%), and minimum (20.9%) FFMC on sunny slopes for June 13 and to estimate the mean and maximum (26.2%) for June 14. Equations 21 and 22 estimated times of maximum (6.1 h) and minimum (17.2 h) sunny slope FFMC values for June 13, and maximum time (8.0 h) for June 14. In addition, the pattern of diurnal variation in sunny slope moisture content values on June 13, 2015 was estimated as follows (Fig. 8):

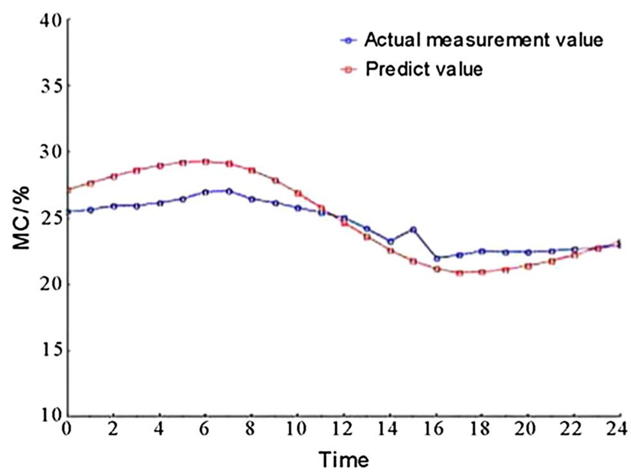

Fig. 8 Model validation for predicting fine fuel moisture content on sunny slopes

$$NMC = \begin{cases} 24.44(1+2\frac{t+7}{13.1})(\frac{t-6.1}{-13.1})^2 + 29.29(1+2\frac{t-6.1}{-13.1})(\frac{t+7}{13.1})^2 & 0 \le t < 6.1 \\ 29.29(1+2\frac{t-6.1}{11.1})(\frac{t-17.2}{-11.1})^2 + 20.89(1+2\frac{t-17.2}{-11.1})(\frac{t-6.1}{11.1})^2 & 6.1 \le t < 17.2 \\ 20.89(1+2\frac{t-17.2}{14.8})(\frac{t-32}{-14.8})^2 + 26.24(1+2\frac{t-32}{-14.8})(\frac{t-17.2}{14.8})^2 & 17.2 \le t \le 24 \end{cases} \quad (25)$$

Equations 18 and 20 estimated the mean, maximum (34.8%), and minimum (24.0%) moisture contents of fine fuels on shady slopes for June 13 and the mean and maximum (28.9%) for June 14. Equations 23 and 24 estimated times of maximum (7.4 h) and minimum (20 h) shady slope fine fuel moisture content for June 13 and the time maximum (7.2 h) for June 14. In addition, the pattern of diurnal variation in moisture content on shady slopes on June 13, 2015 was estimated as follows (Fig. 9):

$$\overline{NMC} = \begin{cases} 23.57(1 + 2\frac{t+5}{12.4})(\frac{t-7.4}{-12.4})^2 + 34.77(1 + 2\frac{t-7.4}{-12.4})(\frac{t+5}{12.4})^2 & 0 \le t < 7.4 \\ 34.77(1 + 2\frac{t-7.4}{12.6})(\frac{t-20}{-12.6})^2 + 24.00(1 + 2\frac{t-20}{-12.6})(\frac{t-7.4}{12.6})^2 & 7.4 \le t < 20 \\ 24.00(1 + 2\frac{t-20}{11.2})(\frac{t-31.2}{-11.2})^2 + 28.90(1 + 2\frac{t-31.2}{-11.2})(\frac{t-20}{11.2})^2 & 20 \le t \le 24 \end{cases} \quad (26)$$

The predicted mean, maximum, and minimum values for the sunny slope areas predicted for June 13, 2015, were 25.0%, 29.3%, and 20.9%, respectively, whereas the actual measurements were 23.6%, 27.0%, and 22.4%. The accuracies of the sunny slope model over 24 h were 100% and 84% when the absolute errors were < 3% and < 10%, respectively. Meanwhile, the predicted mean, maximum, and minimum FFMC values for the shady slope areas for June 13, 2015, were 29.8%, 34.8%, and 24.0%, respectively, whereas the actual values were 26.7%, 32.5%, and 23.6%. The accuracies of the shady slope model over 24 h were 72% and 76% when the absolute errors was < 3% and < 10%, respectively. The lower accuracy was mainly due to the relatively low FFMC. Overall, the model predicted diurnal variation of sunny slope FFMC better than shady slope FFMC, and validation confirmed that the developed models are suitable for describing and predicting diurnal variation in fine fuel moisture content.

Discussion and conclusion

In this study, models were developed for predicting the diurnal mean, the maximum, and minimum moisture content of fine fuels of boreal forests in China by investigating the relationships between fuel moisture contents and meteorological variables. The results provide a basis for forest fire danger prediction which is of considerable importance for scientific forest fire management in the context of global climate change.

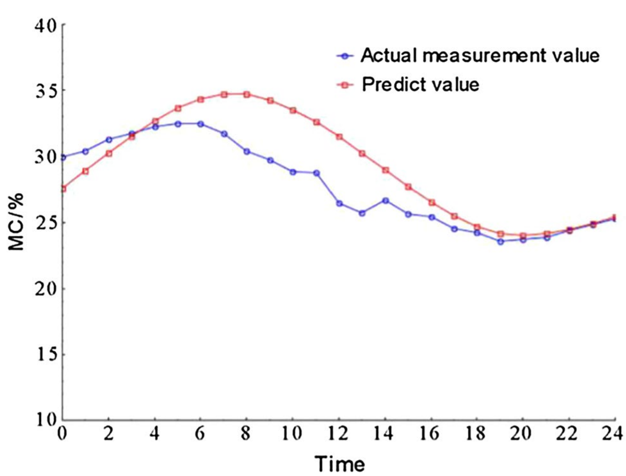

Fig. 9 Validation of model for predicting fine fuel moisture content on shady slopes

Even though the relationship between weather and fuel moisture content has been studied for nearly a century, reliable methods for predicting diurnal variations in fuel moisture have yet to be developed (Ralph and Nelson 1984). This study established fine fuel moisture content prediction models for a *B. platyphylla* and *L. gmelinii* mixed forest. The models considered mean, minimum, and maximum FFMC, as well as today's air temperature, relative humidity, and rainfall, and meteorological variables (maximum and minimum air temperature, and rainfall) for the following 2 days. The models could predict tomorrow's mean, minimum, and maximum moisture content, important parameters for describing the diurnal variation. Nelson and Ralph (2000) built a model to simulate diurnal changes in moisture content and temperature of 10-h time lag sticks, but the model did not consider rainfall, which leads to great discrepancies after rainfall. Viney and Catchpole (1991) proposed that the diurnal variation of fuel moisture content could be predicted using the sine function. If the maximum FFMCs of two consecutive days were significantly different, the prediction error of the model would be relatively high. In contrast, the model constructed during this study used a piecewise cubic function to describe the diurnal variation of FFMC, thereby reducing prediction error and improving prediction accuracy.

Soil moisture affects fuel moisture content via evapotranspiration. At sunrise or after rain, the soil releases some of its water by evaporation, part of which is sequestered by litter (Hatton et al. 1988). Subsequently, throughout the day, solar radiation and temperature gradually reduce the fuel moisture content, typically until minimum values are attained during the early afternoon, and the moisture content then increases after sunset. Solar radiation can affect fuel moisture content both directly and indirectly. With regards to direct effects, solar radiation increases air temperature, relative humidity, and fuel surface temperature. In short, the effect of solar radiation on the moisture content dynamics of fuels on the forest floor is not easily determined (Byram and Jemison 1943; Catchpole et al. 2001). Kreye et al. (2018) reported that exposure to solar radiation caused the dynamic drying of pine and oak litter, in spite of high relative humidity that generally exceeded 65%, and that the effect of heat radiation was more significant for fuel sources with high moisture contents. Therefore, future studies should improve the FFMC diurnal variation model by considering soil moisture and solar radiation.

Previous studies have reported that rainfall is the most important factor influencing fuel moisture content (Tolhurst and Cheney 1999; Slijepcevic and Anderson 2006). However, even though mean, minimum, and maximum rainfall were considered during the construction of the diurnal variation model, little attention was given to throughfall. This is the amount of rainfall to reach the duff layer after passing through various potential interceptors in the vertical forest profile, relative to the volume of rainfall that would have reached the stratum without interception (Ma et al. 2014). Potential interceptors include the canopy, subcanopy, exposed boles, branches, and herbaceous flora of the aerial component and the fallen dead wood and litter material of the forest floor component (Wotton et al. 2005). Throughfall describes how much rain reaches the ground surface, as well as how much is absorbed by the upper part of the organic layer, and greatly affects the diurnal variation of fuel moisture content and fire risk, especially after heavy rainfall (Wotton and Beverly 2007). Accordingly, the prediction models developed here should be applied cautiously in heavy rainfall conditions (Matthews et al. 2010). Future studies should also investigate several aspects of throughfall, for example, whether rainfall interception (water retention, deflection, dripping, and channelling) results in heterogeneous spatial distributions of throughfall. Future studies should also investigate the time over which throughfall absorption (into the upper 7 cm of the organic layer) affects fine fuel moisture content diurnal variations (Flannigan et al. 2016).

This study focused on the fine fuel moisture content of downhill slopes of *B. platyphylla* and *L. gmelinii* mixed forest. Diurnal variations of mid- and up-slope will differ, and diurnal patterns in fuel moisture content of different forest types will also vary (Holden and Jolly 2011; Rossa 2018). Future studies might adopt our models to investigate diurnal variations in fuel moisture content of different slope positions and forest types. Although our studies were underway to identify limitations and need to improve predictions, this study still provides a simple and useful tool for predicting diurnal variations of fine fuel moisture contents. The results provide an important theoretical basis for further improving diurnal variation models, thereby helping to improve the accuracy of forest fire prediction in the context of global warming, which is associated with increasing fire occurrence.

Acknowledgements We are also grateful to the staff of the Nanwenghe Forest Ecological Research Station for their assistance with fieldwork, and to both the Northern Forest Fire Management Key Laboratory (State Forestry and Grassland Bureau) and the National Innovation Alliance (Wildland Fire Prevention and Control Technology of China) for supporting this research.

References

Aguado I, Chuvieco E, Boren R, Nieto H (2007) Estimation of dead fuel moisture content from meteorological data in Mediterranean areas. Applications in fire danger assessment. Int J Wildland Fire 16:390–397

Anderson HE (1990) Moisture diffusivity and response time in fine forest fuels. Can J For Res 20:315–325

Beck JA, Armitage OB (2001) Diurnal fine fuel moisture characteristics at a northern latitude. Tall Timbers Fire Ecol Conf 15:211–221

Bradshaw LS, Deeming JE, Burgan RE, Cohen JD (1984) The 1978 national fire-danger rating system: technical documentation. General technical report, USDA, Forest Service, Ogden, Utah

Bradstock RA (2010) A biogeographic model of fire regimes in Australia: current and future implications. Glob Ecol Biogeogr 19:145–158

Byram GM, Jemison GM (1943) Solar radiation and forest fuel moisture. J Agric Res 67:149–176

Castro FX, Tudela A, Sebastià MT (2003) Modeling moisture content in shrubs to predict fire risk in Catalonia (Spain). Agric For Meteorol 116:49–59

Catchpole EA, Catchpole WR, Viney NR, McCaw WL, Marsden-Smedley JB (2001) Estimating fuel response time and predicting fuel moisture content from field data. Int J Wildland Fire 10:215–222

Craney TA, Surles JG (2002) Model-dependent variance inflation factor cutoff values. Qual Eng 14(3):391–403

De Dios VR, Fellows AW, Nolan RH, Boer MM, Bradstock RA, Domingo F, Goulden ML (2015) A semi-mechanistic model for predicting the moisture content of fine litter. Agric For Meteorol 203:64–73

Flannigan MD, Wotton BM, Marshall GA, De Groot WJ, Johnston J, Jurko N, Cantin AS (2016) Fuel moisture sensitivity to temperature and precipitation: climate change implications. Clim Change 134:59–71

Fulé PZ, Laughlin DC (2007) Wildland fire effects on forest structure over an altitudinal gradient, Grand Canyon National Park, USA. J Appl Ecol 44:136–146

Gisborne HT (1925) Using weather forecasts for predicting forest-fire danger. Mon Weather Rev 53:58

Habermann C, Kindermann F (2007) Multidimensional spline interpolation: theory and applications. Comput Econ 30:153–169

Hatton TJ, Viney NR, Catchpole EA, De Mestre NJ (1988) The influence of soil moisture on Eucalyptus leaf litter moisture. For Sci 34:292–301

Holden ZA, Jolly WM (2011) Modeling topographic influences on fuel moisture and fire danger in complex terrain to improve wildland fire management decision support. For Ecol Manag 262:2133–2141

Hu HQ, Wei SJ, Sun L (2012) Estimation of carbon emissions due to forest fire in Daxing'an Mountains from 1965 to 2010. Chin J Plant Ecol 36:629–644

Hu T, Sun L, Hu H, Weise DR, Guo F (2017) Soil respiration of the Dahurian Larch (*Larix gmelinii*) forest and the response to fire disturbance in Da Xing'an Mountains, China. Sci Rep 7:2967

Hu T, Hu H, Li F, Zhao B, Wu S, Zhu G, Sun L (2019) Long-term effects of post-fire restoration types on nitrogen mineralisation in a Dahurian larch (*Larix gmelinii*) forest in boreal China. Sci Total Environ 679:237–247

Jin S, Chen P (2012) Modelling drying processes of fuel beds of Scots pine needles with initial moisture content above the fibre saturation point by two-phase models. Int J Wildland Fire 21:418–427

Jonathan R, Dorrepaal E, Kardol P, Nilsson MC, Teuber LM, Wardle DA (2016) Understory plant functional groups and litter species identity are stronger drivers of litter decomposition than warming along a boreal forest post-fire successional gradient. Soil Biol Biochem 98:159–170

Kreye JK, Varner JM, Hamby GW, Kane JM (2018) Mesophytic litter dampens flammability in fire-excluded pyrophytic oak-hickory woodlands. Ecosphere 9:e02078

Li X, Fu G, Zeppel MJB, Yu X, Zhao G, Eamus D (2012) Probability models of fire risk based on forest fire indices in contrasting climates over China. J Resour Ecol 3:105–117

Liu X, Jin S (2007) Development of dead forest fuel moisture prediction based on equilibrium moisture content. Scientia Silvae Sinicae 43:126–133

Ma Y, Van Dam RL, Jayawickreme DH (2014) Soil moisture variability in a temperate deciduous forest: insights from electrical resistivity and throughfall data. Environ Earth Sci 72:1367–1381

Matthews SA (2006) Process based model of fine fuel moisture. Int J Wildland Fire 15:155–168

Matthews SA (2010) Effect of drying temperature on fuel moisture content measurements. Int J Wildland Fire 19:800–802

Matthews SA (2014) Dead fuel moisture research: 1991–2012. Int J Wildland Fire 23:78–92

Matthews S, Gould J, McCaw L (2010) Simple models for predicting dead fuel moisture in eucalyptus forests. Int J Wildland Fire 19:459–467

McArthur AG (1966) Fire weather and grass fire behaviour. Forests and Timber Bureau, Canberra, Australian Capital Territory, Leaflet 100: 23 pp

McCammon BP (1976) Snowpack influences on dead fuel moisture. For Sci 22:323–328

Meyn A, White PS, Buhk C, Jentsch A (2007) Environmental drivers of large, infrequent wildfires: the emerging conceptual model. Prog Phys Geogr 31(3):287–312

Nelson J, Ralph M (2000) Prediction of diurnal change in 10-h fuel stick moisture content. Can J For Res 30:1071–1087

Nolan RH, Boer MM, Resco de Dios V, Caccamo G, Bradstock RA (2016) Large-scale, dynamic transformations in fuel moisture drive wildfire activity across southeastern Australia. Geophys Res Lett 43:4229–4238

Page WG, Jenkins MJ, Alexander ME (2013) Foliar moisture content variations in lodgepole pine over the diurnal cycle during the red stage of mountain pine beetle attack. Environ Model Softw 49:98–102

Pellizzaro G, Cesaraccio C, Duce P, Ventura A, Zara P (2007) Relationships between seasonal patterns of live fuel moisture and meteorological drought indices for Mediterranean shrubland species. Int J Wildland Fire 16:232–241

Ralph M, Nelson JR (1984) A method for describing equilibrium moisture content of forest fuels. Can J For Res 14:597–600

Rossa CG (2018) A generic fuel moisture content attenuation factor for fire spread rate empirical models. For Syst 27:5

Rothermel RC, Wilson RA, Morris GA, Sackett SS (1986) Modeling moisture content of fine dead wildland fuels: input to the BEHAVE fire prediction system. USDA For Serv Intermt Res Stn Res Pap 11:1–61

Saglam B, Bilgili E, Kuçuk O, Durmaz BD (2006) Determination of surface fuels moisture contents based on weather conditions. For Ecol Manag 234:S75–S75

Santín C, Doerr SH, Merino A, Bryant R, Loader NJ (2016) Forest floor chemical transformations in a boreal forest fire and their correlations with temperature and heating duration. Geoderma 264:71–80

Schiks TJ, Wotton BM (2015) Modifying the Canadian Fine Fuel Moisture Code for masticated surface fuels. Int J Wildland Fire 24:79–91

Shan YL, Liu NA, Hu HQ, Zhang QC (2005) Moisture content of litter of principal fuel types in Liangshui Nature Reserve. J Northeast For Univ 35:41–43

Simard AJ (1998) The moisture content of forest fuels—A review of the basis concepts. Forest Fire 14:23–45

Slijepcevic A, Anderson WR (2006) Hourly variation in fine fuel moisture in eucalypt forests in Tasmania. For Ecol Manag 3:86–90

Slijepcevic A, Anderson WR, Matthews S (2013) Testing existing models for predicting hourly variation in fine fuel moisture in eucalypt forests. For Ecol Manag 306:202–215

Slijepcevic A, Anderson WR, Matthews S, Anderson DH (2015) Evaluating models to predict daily fine fuel moisture content in eucalypt forest. For Ecol Manag 335:261–269

Slijepcevic A, Anderson WR, Matthews S, Anderson DH (2018) An analysis of the effect of aspect and vegetation type on fine fuel moisture content in eucalypt forests. Int J Wildland Fire 27:190–202

Sun P, Yu HJ, Jin S (2015) Predicting hourly litter moisture content of larch stands in Daxinganling Region, China using three vapour-exchange methods. Int J Wildland Fire 24:114

Tolhurst KG, Cheney NP (1999) Synopsis of the knowledge used in prescribed burning in Victoria. Department of Natural Resources and Environment, Melbourne

Toomey M, Vierling LA (2005) Multispectral remote sensing of landscape level foliar moisture: techniques and applications for forest ecosystem monitoring. Can J For Res 35:1087–1097

Van Wagner CE (1969) Drying rates of some fine forest fuels. Fire Control Notes 30:5–12

Van Wagner CE (1972) Equilibrium moisture content of some fine forest fuels in eastern Canada. Can For Serv Inf Rep 2:56–78

Van Wagner CE (1987) Development and structure of the canadian forest fire weather index system, technical report. Canadian Forest Service, Ottawa, ON35

Van Wagner CE, Pickett TL (1985) Equations and FORTRAN program for the Canadian forest fire weather index system. For Tech Rep 2:33–38

Viegas DX, Viegas MT, Ferreira AD (1992) Moisture content of fine forest fuels and fire occurrence in central Portugal. Int J Wildland Fire 2:69–86

Viegas DX, Pinol J, Viegas MT (2001) Estimating live fine fuels moisture content using meteorologically-based indices. Int J Wildland Fire 10:223–240

Viney NR (1991) A review of fine fuel moisture modeling. Int J Wildland Fire 1:215–234

Viney NR, Catchpole EA (1991) Estimating fuel moisture response time from field observations. Int Wildland Fire 1:211–214

Wotton BM, Beverly JL (2007) Stand-specific litter moisture content calibrations for the Canadian Fine Fuel Moisture Code. Int J Wildland Fire 16:463–472

Wotton BM, Stocks BJ, Martell DL (2005) An index for tracking sheltered forest floor moisture within the Canadian Forest Fire Weather Index System. Int J Wildland Fire 14(2):169–182

Wotton BM, Nock CA, Flannigan MD (2010) Forest fire occurrence and climate change in Canada. Int J Wildland Fire 19:253–271

Xu H (1998) Da Xing'an mountains forests in China. Science Press, Beijing, pp 40–43

Yebra M, Chuvieco E, Riaoo D (2006) Investigation of a method to estimate live fuel moisture content from satellite measurements in fire risk assessment. For Ecol Manag 5:12–15

Yu HZ, Jin S, Di XY (2013) Prediction models for ground surface fuels moisture content of *Larix gmelinii* stand in Daxing'anling of China based on one-hour time step. Chin J Appl Ecol 24:1565–1571