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LETTER TO THE EDITOR

Forest fire risk estimation in a typical temperate forest in Northeastern China using the Canadian forest fire weather index: case study in autumn 2019 and 2020

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Abstract

China's forest cover has increased by approximately 10% as a result of sustainable forest management since the late 1970s. The forest ecosystem area affected by fire is increasing at an alarming rate of approximately 600,000 ha per year. The northeastern part of China, with a forest cover of 41.6%, has the greatest percentage of acres affected by forest fires. This study combines field and satellite weather data to determine factors that influence dead fuel moisture content (FMC). It assesses the use of the Canadian forest fire weather index to determine the daily forest fire danger in a typical temperate forest in Northeastern China during autumn. Based on the Wilcoxon test for paired samples, the observed and predicted values of FMC showed similar variation in eight of eleven sampling sites (72.7%), with a p value > 0.05. Three sampling plots presented lower predicted values of FMC than observed values (27.3%), with a p value < 0.05. The calculation of fire risk using the Canadian Forest Fire Weather Rating System (CFFDRS) in Maoer Mountain forest ecosystems presented low, medium or high risk; thus, the CFFDRS is suitable for determining fire danger in our study region. Along with these results, this study served to compare the use of FMC-metre field data and China Weather Station data to evaluate fire danger. The results of this study led us to suggest the multiplication of meteorological stations in fire-prone regions.

Keywords Fuel moisture content · Weather · Fire risk · Ecosystems: temperate

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1 Introduction

Forest fires are the most widespread and critical disturbance in boreal and temperate forest ecosystems (Ying et al. 2018). While China's forest cover has increased by approximately 10% as a result of sustainable forest management since the late 1970s (Nöchel and Svennin 2017), the forest area ecosystems affected by fire are increasing at an alarming rate of approximately 600 thousand hectares per year (Yang et al. 2010). Climatic conditions and forest composition in Northeastern China, much like those in the United States of America, Canada, Australia, and Mediterranean Europe, are favourable to forest fires. The northeastern part of China (Heilongjiang, Jilin, and Liaoning provinces), with a forest cover of 41.59%, has the greatest percentage of acres affected by forest fires. Predictive climate models in China suggest that from 2041 to 2080, the climate will be characterized by higher temperatures (Wu et al. 2020). Accordingly, a high priority for forest protection in China is required (Thomas 1990), and there is an imperative need for China to develop its national forest fire danger rating system (Yang and Di 2011).

Wildfires are influenced by many factors, including vegetation, topography, weather, human behaviour, and ignition sources (Flannigan et al. 2005). It is very important to improve fire risk forecasting and reduce potential fire hazards. Therefore, it is particularly important to strengthen forest fire management and improve forest fire prediction capabilities. The ignition, spread and development of forest fires are strongly affected by the moisture content of forest fuel (Rothermel 1972; Dimitrakopoulos and Papaioannou 2001). In particular, the frequency of forest fires is directly affected by the moisture content of dead fuel on the ground. Therefore, accurately predicting the moisture content of dead fuel on the forest surface is the key for forecasting forest fire risk and fire behaviour. The dead fine fuel moisture content varies both spatially and temporally as a function of microclimate and fuel properties (Cawson et al. 2020). Temperature, relative humidity, precipitation, wind velocity and solar radiation determine the moisture vapour differential between the dead fuel and atmosphere (Matthews 2014). The prediction model of fuel moisture content using the gravimetric method is often considered the gold standard approach (Matthews 2010). Nevertheless, this approach has limited use, as it cannot provide continuous or real-time moisture data when desired and needs continuous equipment and workers in the field (Cawson et al. 2020). Alternatively, the FMC-metre can be used to collect instantaneous measurements in any place but also requires manual measurement before or after the experiment (Masinda et al. 2021).

The prediction of forest fires has been studied for decades using different forest rating systems, such as the Canadian Forest Fire Danger Rating System (CFFDRS), U.S. Forest Service National Fire Danger Rating System (NFDRS), and McArthur Forest Fire Danger Index (FFDI) (Di Giuseppe et al. 2016). Although a wide range of indices have been developed to calculate fire risk (Bett et al. 2020), many are limited to specific areas, while some indices are valid on a large scale, such as the fire weather index (FWI). The CFFDRS has, since the early twentieth century, involved an extensive network of weather observations, FMC field sampling, and ignition sustainability investigations (Fujioka et al. 2008). The FWI system is a subsystem of the CFFDRS (de Groot and Groot 1987). The FWI was established by Van Wagner (1974) and is more efficient than other forest fire indices (Schunk et al. 2017; Tremblay et al. 2018). It predicts the FMC by relying on meteorological variables from different global regions. It then combines these variables to analyse fire behaviour in terms of spread and intensity (Vitolo et al. 2019). It also determines the effects of meteorological variables on forest fuel and forest fires by providing a relative numerical rating of fire danger over a given area. However, it is not able to describe a complete picture of daily wildfire danger with a single number (Stocks et al. 1989). Initially developed for use in Canadian pine stands, the FWI sees widespread use in other forest stands due to its simplicity of fit. The FWI system is widely approved by many fire and land management agencies, which use it to issue fire warnings and assign resources in the field (Dimitrakopoulos et al. 2011; Vitolo et al. 2019), but it only offers a qualitative overview of predicted fire regimes. Many studies have established a strong relationship between FWI codes/indices and fire occurrence and behaviour (Papagiannaki et al. 2020). Simpson et al. (2014) argued the necessity of evaluating the suitability of applying the FWI system to regions other than the one in which it was originally established. Which weather variables greatly influence the fuel moisture content? Does the relationship between the moisture of the FMC metre and CWS change by forest type and time?

This study aims to determine the main meteorological factors influencing FMC in a typical temperate forest in Northeastern China and to assess the potential use of the Canadian Forest Fire Weather Index as a decision-support tool in fire hazard management.

2 Material and methods

2.1 Study location

This study was conducted in a typical temperate forest on Maoer Mountain in Northeastern China (45° 43′ N, 126°37′ E; average elevation is 255 m). The surface area of the Maoer Mountain forest ecosystem is 21813.1 ha. The region has a cold, temperate climate with rainy summers. It receives an average annual rainfall of 649 mm. The hottest month in the study area is July, with an average temperature of 21.8 °C, while January is the coldest month, with an average temperature of − 19.9 °C. The annual thermal amplitude is 41.7 °C, and the rainfall amplitude is 171 mm. The bedrock is granite, and the soil is mainly dark brown forest soil (Wang 2006). Since the beginning of the twentieth century, the primary forest has been gradually degraded by large-scale industrial logging by Russian and Japanese invaders, as well as by the Chinese government. The primary forest, which was dominated by *Pinus koraiensis* Siebold and Zucc. mixed with deciduous species such as *Betula platyphylla* Sukaczev, *Larix gmelinii* L., *Populus davidiana* Dode, *Quercus mongolica* Fisch., and *Fraxinus mandshurica* Rupr., has been replaced by a secondary forest and mostly by *L. gmelinii* plantations (Chen et al. 1982). Currently, there are three main types of secondary forest distributed at various sites characterized by different conditions. These forests include *Quercus mongolica* forest on steep arid infertile upper slopes, mixed deciduous forest located on well-drained gentle fertile mid-slopes and deciduous forest on gentle moist fertile slopes. There are also two dominant plantations: pine and larch plantations (Wang 2006).

In terms of seasons, Heilongjiang Province has more rainfall and humid air in summer. In the winter, the temperature is low, the snow is frozen, and there are no burning conditions; therefore, forest fires are registered during these periods. In autumn, the temperature decreases rapidly, often with cold waves and frosts; thus, leaves of trees begin to fall and wither in autumn, and the forest becomes sparse, making fires less likely to spread; therefore, the number of fires is relatively reduced compared with that in spring (Yuhong 2002). The mean annual area of burnt forest in Heilongjiang Province varies between 500 and 2500 km^2 (Li et al. 2015). These averages represent 0.25–1.2% of the total forest cover

(205,328 km^2) of Heilongjiang Province as estimated on the China Forest Administration website (12 December 2019).

2.2 Meteorological data acquisition and use

In this study, in combination with FMC metre data that provide weather variable measurements and fuel fresh weight on the ground surface, we used China Weather Station (CWS) data, as the installation of FMC metres in forests requires many resources (material, cost, time and personnel):

(1) The first series of data was acquired from FMC metres in the field. FMC metres were set in the Maoer Mountain forest ecosystem to track the change in dead fuel moisture content in relation to variations in air temperature, relative humidity, solar radiation, wind speed, and rainfall. We used this series of data to develop the FMC patterns and to calculate the FWI indices (noon temperature, relative humidity, wind speed, and total daily rainfall);

(2) We acquired the second series of data from the China Weather Station (http://cdc.cma.gov.cn/, station id: 50,953, 45.45° N and 126.46° E), which included temperature, relative humidity, wind speed and total daily rainfall. The temporal and spatial resolutions of CWS data are 1 h and 71 kms, respectively.

2.3 Sampling

In 2019, the data collection was carried out in one month, and the sampling period at the different sites had a deviation of one, 2, or 3 days following the installation of the machines (FMC metres). In 2020, data collection started late because the research team was prevented from going early in the field due to COVID-19, which is why data were collected for a half-month. It is rarely practical to measure the dead fuel moisture content directly in the field; thus, it is generally estimated. It is possible to use either real or predicted values of air relative humidity and temperature to reasonably estimate FMC (De Melo-Abreu et al. 2010). In this study, we used a fuel moisture content metre, which is a device consisting of an automatic balance and a mini weather station (Masinda et al. 2021). It automatically measures the fuel mass, air temperature, relative humidity, wind speed, solar radiation, and rainfall reaching the fuel on the ground surface (as well as soil moisture and temperature) at instantaneous time intervals (30 min for this study). Data were collected at 11 sampling points: sampling was conducted at points 1–5 in 2019 and at points 6–11 in 2020, arranged on four linear transects (Table 1). Transects were separated by 1.11 km, or 0.01° of latitude, and sampling points on each transect were distant from one another by 0.788 km, corresponding to 0.01° of longitude at 45° of latitude. Around each sampling point, we plotted a quadrant with the 50 m per side, which was used to describe the vegetation around the sampling point. In each quadrant, we manually gathered samples of dead fine surface fuel over an area of 30 cm × 30 cm along the transect, equivalent to the FMC basket metre. Samples were composed of twigs with a 1-hour time lag and freshly fallen nonwoody material, which included leaves, cones, and pollen cones (Keane 2015). We then oven-dried our samples at 105 °C for 24 h and determined the gravimetric water content as the fraction of water mass (W_f) to oven-dry fuel mass (W_d):

Table 1 Local field sampling characteristics

Site	Longitude	Latitude	Tree species composition	Aspect	Slope	*D*	TH
1	127.65	45.40	*Betula platyphylla* Sukaczev*, Populus davidiana* Dode and *Fraxinus mandshurica* Rupr	North	15	0.7	18
2	127.69	45.41	*Betula platyphylla, Populus davidiana, Tilia mandshurica* Rupr. and Maxim. and *Juglans mandshurica* Maxim	West	10	0.8	17
3	127.66	45.41	*Fraxinus mandshurica, Juglans mandshurica*, *Phellodendron amurense* Rupr., and *Ulmus pumila* L	Northwest	15	0.7	16
4	127.67	45.40	*Fraxinus mandshurica*, *Juglans mandshurica*, *Tilia mandshurica*, *Populus davidiana*, *Betula costata* Trautv, *Ulmus pumila*, etc.	Northwest	15	0.6	17
5	127.68	45.41	*Populus davidiana*, *Tilia mandshurica*, *Juglans mandshurica*, *Betula costata* and *Fraxinus mandshurica*	Southeast	15	0.8	18
6	127.66	45.43	*Fraxinus mandshurica*, *Juglans mandshurica*, *Phellodendron amurense* Rupr., *Betula platyphylla*	North	14	0.7	17
7	127.66	45.42	*Larix gmelinii* and *Ulmus propinqua*	Southeast	10	0.7	18
8	127.66	45.40	*Quercus mongolica* Fisch. and Ledeb	South	11	0.8	14
9	127.70	45.41	*Pinus sylvestris*, *Betula platyphylla* and *Ulmus propinqua*	Southeast	9	0.6	15
10	127.67	45.41	*Ulmus propinqua*, *Juglans mandshurica*, *Quercus mongolica*	Northeast	12	0.7	16
11	127.67	45.42	*Ulmus propinqua*, *Fraxinus mandshurica*, *Phellodendron amurense*	Northwest	13	0.8	17

In this table, *D* denotes the depression, while TH represents the tree height

$$\mathrm{FMC}_{(1)} = \left[\left(W_{\mathrm{f}} - W_{\mathrm{d}}\right)/W_{\mathrm{d}}\right] \times 100 \tag{1}$$

To estimate the moisture content of fine dead fuel using the FWI system (Wotton 2009), we deduced the predicted values of the FMC using the Fine Fuel Moisture Code (FFMC) according to the following formula:

$$\mathrm{FMC}_{(2)} = 147.2 \times (101 - \mathrm{FFMC})/(59.5 + \mathrm{FFMC}) \tag{2}$$

2.4 Modelling with data from FMC metres

We used half-hour data to develop models of daily and diurnal FMC models, while FMC models fitted with both FMC metre and CWS data were developed with daily averages. To assess the FMC variation, we fitted general linear models to select variables that have a strong effect on FMC. The FMC metre dataset consisted of air temperature, relative humidity, wind velocity, solar radiation and fresh fuel weight. The China Weather Station (CWS) dataset included the temperature on the ground surface, temperature at 10 m height, sunshine-hours, relative humidity, rainfall and wind velocity. Before computing FMC models, variable importance was first determined using the random forest method and was presented by a graph. Collinearity was checked for each model; thus, FMC models were developed.

2.5 FWI codes/indices prediction and correlation

Estimation of FWI indices and codes was obtained using the *fwi-function* with the cffdrs-R package based on noon local standard time weather observations, including temperature, relative humidity, wind speed, 24-h rainfall, and the previous day's fuel moisture conditions (Wang et al. 2019). These codes and indices include the fine fuel moisture code (FFMC), duff moisture code (DMC), drought code (DC), build-up index (BUI), and initial spread index (ISI). The daily severity rating (DSR) is an additional component of the FWI system, planned to be more directly related to the probable effort required for wildfire suppression, and it is a power conversion of the FWI that underlines high FWI values (Tsinko et al. 2018). We used the qualitative Forest Fire Danger Rating System established by Van Wagner (1987) to describe fire danger as very low, low, moderate, high, very high, or extreme (Table 2). We compared the observed values (obtained after oven-drying) of FMC with the estimated values (obtained with CFFDRS) using the Wilcoxon signed-rank test for paired samples.

Table 2 Fire danger rating scale

Danger classes	FWI range
Very low	00–01
Low	02–04
Moderate	05–08
High	09–16
Very high	17–29
Extreme	30 +

3 Results

3.1 Response of FMC variation to weather factors

Our results showed that, relatively, the FMC was more sensitive to rain, less sensitive to relative humidity and temperature, and insensitive to wind speed (Fig. 1a, h). In addition, the FMC response to rainfall of 2–4 mm during a good drying day took 2–3 days for the FMC to recover to pre-rain values. These results highlight the strength of the relationship between rain and FMC variation.

3.2 Comparison among noon FMC

In this section, we compare the changes in FMC with field measurements, predicted field FMC and predicted CWS FMC. The results are shown in Fig. 2a–e. In 2019, the period from 11 to 25 October presented low FMC values (Fig. 2). On the other hand, the first and last weeks of the month presented high FMC values, mainly due to rain. In 2020, the results in Fig. 3a–f show that the predicted (FMC metre and CWS) FMC varied at the same rate as the measured FMC, although a rapid increase in FMC was observed after the rain on October 20. The maximum FMC value approached 325% (Fig. 3e), while the minimum FMC value was 7.4% (Fig. 3b).

3.3 Patterns of fuel moisture content

3.3.1 Predicted model with both data sources

The general linear model developed with both FMC metre and CWS variables showed that rain and relative humidity influence on FMC were stronger than the influence of temperature, wind speed, solar radiation and sunshine time. All models presented a good predictive power. In the fitted models (Table 3), *T, H, W, Rn,* and *R,* denote temperature, relative humidity, wind speed, rain and solar radiation, respectively, from the FMC metre and *SS* is the sunshine timing and T_h is the temperature at a 2 m height for the CWS data source.

3.3.2 Predicted model with FMC metre data

Apart from the developed models in the above section, we computed daily and diurnal models of FMC to observe whether the effect of sunlight would increase the quality of the model. Thus, at each site, FMC models were developed in 2019 and 2020 with diurnal or daily data. Developed models in 2019 showed that relative humidity, temperature, wind speed and solar radiation influenced the water content of fuel at site 1. At site 2, humidity, temperature and wind speed were the influential factors. At sites 3, 4 and 5, wind speed and rain did not result in a substantial improvement in model efficiency. A general overview of the daily developed FMC models proved that relative humidity, temperature, solar radiation and wind velocity greatly influenced the FMC. The integration of rain (p value > 0.05) did not result in a substantial improvement in model efficiency. Out of five sampling sites, one was characterized by a high predictive power model: R^2 (adj.) = 0.70. The other four sites were characterized by models with medium

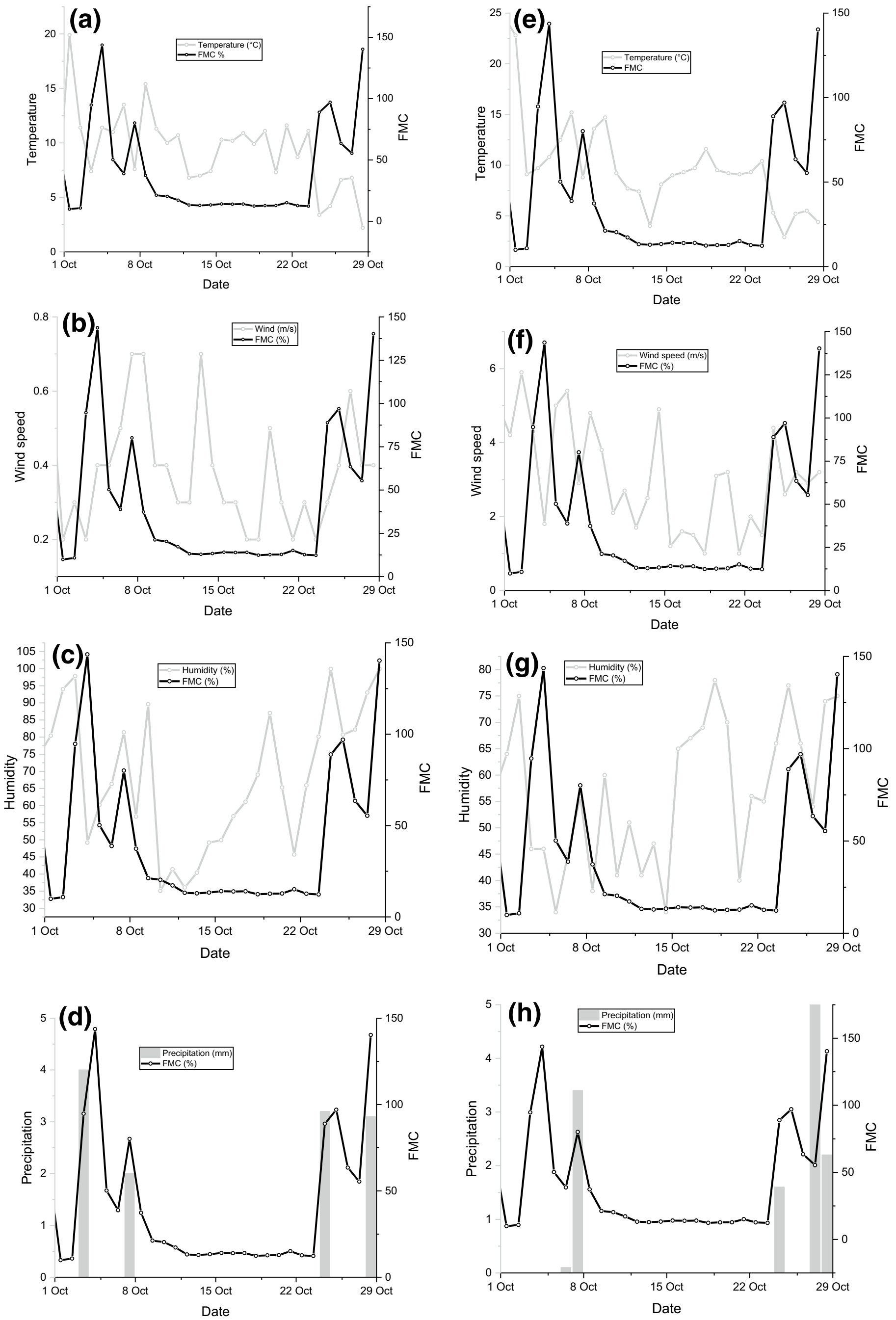

Fig. 1 Variation of FMC based on FMC metre (**a**–**d**) and China weather station databases (1-e; 1-h)

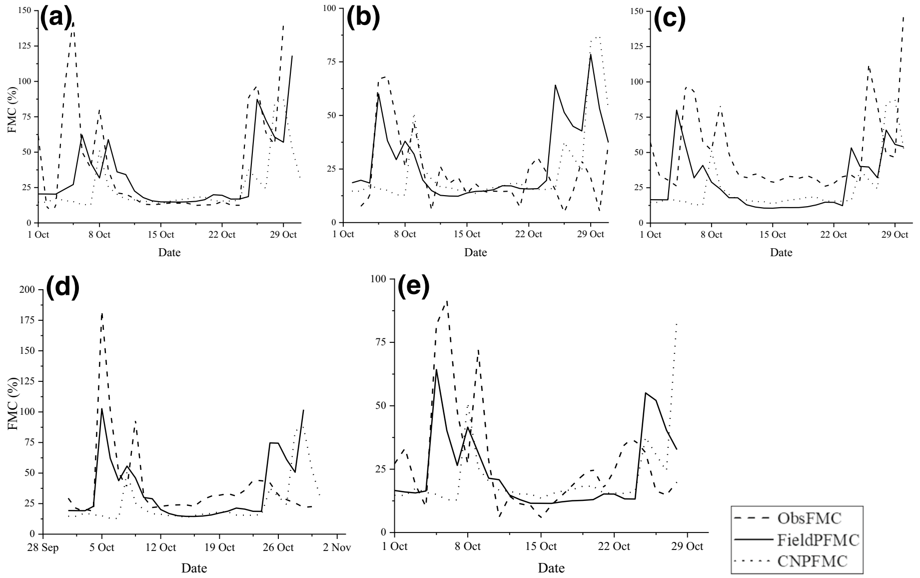

Fig. 2 **a–e** Observed versus FMC metre and CWS predicted FMC values in 2019

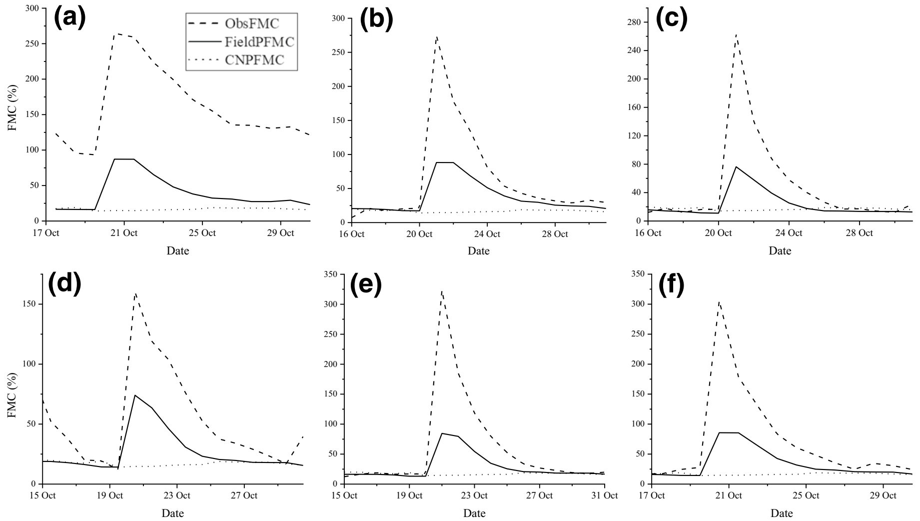

Fig. 3 **a–f** Observed versus FMC metre and CWS predicted FMC values in 2020. *Note* that ObsFMC represents the FMC value calculated after oven-drying the fuel, FieldPFMC represents the predicted FMC value developed using field data, and CNPFMC denotes the predicted FMC using China Weather Station data

predictive power: $0.52 \leq R^2$ (adj.) ≤ 0.64 (Table 4). Developed models with diurnal data showed that relative humidity, temperature and solar radiation had a strong effect on FMC. The influences of wind velocity and rain were not noticeable. The results in Table 5 show that sites 1, 2 and 3 were characterized by models with high predictive

Table 3 FMC models fitted with FMC metre and CWS data

Model	Equation	R^2 (adj.)	F
1	$FMC = 25.29\ Rn + 3.77\ SS$	0.70	34.28
2	$FMC = 2.989\ SS$	0.71	74.15
3	$FMC = 1.165\ H - 4.536\ T + 0.180\ R$	0.88	73.56
4	$FMC = 0.491\ H + 0.130\ Rn^5$	0.72	40.39
5	$FMC = 2.647\ T_h + 0.235\ Rn^4$	0.76	44.20

Table 4 Daily developed FMC models in 2019

Model	Equation	R^2 (adj.)	F
1	$FMC = 0.648\ H - 2.491\ T + 30.119\ W + 0.043\ R$	0.64	343.3
2	$FMC = 0.130\ H + 1.241\ T + 1.543\ W$	0.57	427.5
3	$FMC = 0.008\ H - 0.007\ T + 0.0004\ R$	0.70	678.3
4	$FMC = 0.347\ H + 0.003\ R$	0.61	787.6
5	$FMC = 0.237\ H + 1.243\ T + 0.001\ R$	0.52	337.6

Table 5 Diurnal developed FMC models in 2019

Model	Equation	R^2 (adj.)	F
1	$FMC = 0.979\ H - 1.735\ T$	0.72	599.9
2	$FMC = 0.134\ H - 0.156\ T^2 + 4.915\ T - 0.029\ T{\cdot}H$	0.72	277.4
3	$FMC = 0.013\ H - 0.010\ T + 0.00023\ R$	0.80	664.1
4	$FMC = 0.456\ H + 0.019\ R$	0.55	334.9
5	$FMC = 0.481\ H + 2.620\ T - 0.046\ T{\cdot}H$	0.50	138.3

Table 6 Daily developed FMC models in 2020

Model	Equation	R^2 (adj.)	F
1	$FMC = 1.982\ H - 2.499\ T + 59.368\ W + 85.949\ Rn$	0.83	848.4
2	$FMC = 0.808\ H - 1.132\ T^2 + 54.249\ Rn^2$	0.63	420.0
3	$FMC = 0.882\ H - 2.968\ T + 46.989\ Rn + 0.044\ T{\cdot}H$	0.65	402.1
4	$FMC = 0.722\ H + 22.438\ Rn$	0.73	1220.0
5	$FMC = 0.952\ H^2 + 64.02\ Rn$	0.52	550.2
6	$FMC = 0.830\ H + 54.805\ Rn$	0.66	715.8

power: $0.72 \leq R^2$ (adj.) ≤ 0.80, while sites 4 and 5 were characterized by models with medium predictive power: $0.50 \leq R^2$ (adj.) ≤ 0.55.

Daily developed FMC models in 2020 indicated that relative humidity, rain and temperature were the most important factors influencing the water content of fuel at all sampling sites. The effect of wind on water content was significant at site 1, and the effect of solar

Table 7 Diurnal developed FMC models in 2020

Model	Equation	R^2 (adj.)	F
1	FMC = 2.288 H – 2.866 T	0.82	529.3
2	FMC = 1.164 H – 3.647 T + 48.114 Rn	0.64	151.3
3	FMC = 1.165 H – 7.686 T + 0.159 $T{\cdot}H$	0.74	245.9
4	FMC = 0.959 H – 1.102 T	0.76	475.4
5	FMC = 1.257 H – 3.757 T + 62.70 Rn	0.61	143.4
6	FMC = 1.219 H – 2.260 T + 46.572 Rn	0.66	162.3

Table 8 Wilcoxon test results for paired samples between the observed and predicted FMC

Sites	Estimated parameter (V)	p value	Sites	Estimated parameter (V)	p value
1	248	0.311	1	101	< 0.001
2	206	0.598	2	134	< 0.001
3	465	< 0.001	3	59	0.669
4	129	0.056	4	109	0.317
5	122	0.110	5	100.5	0.266
–	–	–	6	105	0.011

radiation was only influential at site 3. Two of six sampling sites were characterized by models with high predictive power: $0.73 \leq R^2$ (adj.) ≤ 0.83. The other four sites were characterized by models with medium predictive power: $0.52 \leq R^2 \leq 0.66$ (Table 6). In addition, developed models with diurnal data showed that relative humidity, temperature and rain were the influencing drivers of FMC. Three sites were characterized with models with high predictive power, R^2 (adj.) > 0.70 and three others with medium predictive power: $0.61 \leq R^2$ (adj.) ≤ 0.66 (Table 7).

3.4 Adequacy of the FWI system in predicting the FMC in a Maoer mountain forest ecosystem

The Wilcoxon signed-rank test for paired samples showed that the observed and predicted values of FMC in 2019 were similar at sites 1, 2, 4 and 5 (p value > *0.05*) and different at sites 3 and 4 (p value < *0.05*). Note that the predicted FMC values were calculated with the FWI function. In 2020, the Wilcoxon signed-rank test for paired samples showed that the moisture content predicted with FMC metre data was significantly different from the moisture content predicted with CWS data at sites 1, 2 and 6 (p value < 0.05). At sites 3, 4 and 5, both moisture contents were similar (p value > 0.05). The difference between the observed and estimated FMC at sites 1, 4 and 6 could have been influenced by canopy density, altitude, slope, and aspect or may have been related to sampling facts rather than to real variance in moisture content (Table 8).

3.5 Fire danger estimation

The value of the FWI varied across the study period (October 2019) and was low from October 1st to 12th, moderate from October 13th to 18th, very high from October 19th to

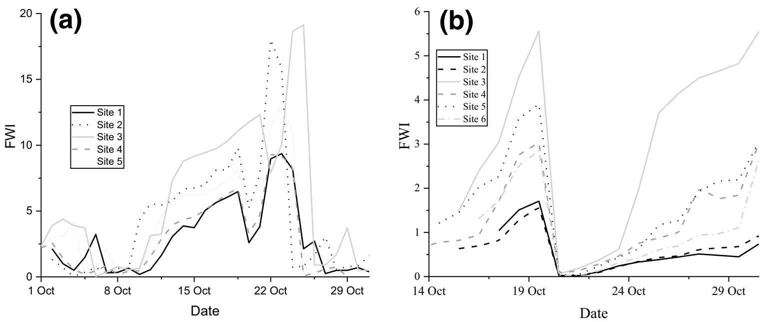

Fig. 4 Variation of the FWI in 2019 (**a**) and 2020 (**b**)

26th, and low from October 26th to 31st. It rained only during the first and last weeks of the study period. The lack of rain was mainly responsible for the high fire danger ratings. Figure 4a shows that the FWI values at sites 2 and 3 from October 21st to 25th reached a high or a very high level of fire danger, while the FWI values at sites 1, 4, and 5 varied between the very low and moderate fire danger levels. The results in Fig. 4b illustrate that from 14 to 31 October 2020, the FWI oscillated between 0 and 5.56. Unfortunately, the value of the FWI from 14 to 31 October 2020 was lower than that in 2019 in the same time interval.

4 Discussion

In this paper, we analysed the FMC variation and fire danger in typical temperate forests to (1) identify the most significant variables affecting FMC changes and (2) evaluate the skill of the FWI system in predicting forest fire risk in temperate forest stands in Northeastern China.

4.1 Variation of FMC as a function of meteorological factors

There were large increases in FMC during rainfall (Fig. 1a, b). Although there were some divergences in FMC presentation, all data sources displayed similar FMC changes and provided the same information to researchers and fire managers. The difference between field (45.41° N, 127.67° E) measurements and those obtained from the CWS (45.45° N, 126.46° E) was presumably related to the distance between the station and experimental area. Thus, an increase in the number of weather stations in fire-prone regions is needed, as suggested by Chuvieco et al. (1999, 2002) and Zhang et al. (2011).

4.2 Prediction models of fuel moisture content using FMC metre data and satellite data

Different sites revealed variability in the accuracy of FMC predictors. Relative humidity, temperature and/or solar radiation had a significant effect on FMC at these sites. These results parallel those in other regional studies that reported that relative humidity and temperature have a significant effect on FMC. Diurnal models were more accurate than daily models; however, FMC drivers were the same in both models. After a 2–4 mm rainfall event, the FMC needed 2–3 days to recover to its pre-rainfall values. Thus, we hypothesized that firefighters could spend 2–3 days without raids in the field, as dead fuel would be too wet to burn for approximately 2–3 days after a rainfall event. During this period, the fuel water content exceeded the ignition and fire spread threshold of all types of fuel in the region (Masinda et al. 2020).

A comparison of FMC after FMC metre measurement and estimated FMC with the FWI system showed that FMC metre measurement was slightly greater, but not significantly (Fig. 2a–e). Only the results of one site (Fig. 2d) revealed a significant difference between the calculated and estimated FMCs ($V=465$, p value <0.001). The results in 2019 and 2020 allowed us to adopt the use of both data sources to predict the moisture content of dead fine surface fuel in the Maoer Mountain forest ecosystem because at eleven sampling sites, the predictions were statistically similar at eight sites, i.e. 72.7%. These results indicated that the FWI system underestimated the FMC values compared with field-experimental observations. The disparity between the observed and predicted values may have been a result of the height at which wind speed was sampled, which differed between the field measurements and estimated values. Tree canopy may also have played a role in this difference. We measured temperature and wind speed at 0.3 m above the ground under tree cover, while the FWI system measured temperature at 2 m and wind speed at 10 m in an open area (Field 2020). Accordingly, previous studies showed that tree canopies reduce solar radiation and wind flow on the ground surface and have an effect on dead fuel moisture content (Zylstra 2011; Estes et al. 2012; Zhang et al. 2017).

4.3 Validity of the FWI system for fire risk management in typical temperate forests in China

Our FWI values were similar to those of other Chinese provinces where the FWI values were linked to fire (Lynham and Stocks 1989; Tian et al. 2011, 2014; Yang and Di 2011). Many studies have found a strong relationship between the FWI and wildfire occurrence in other regions, such as the Mediterranean, south-eastern and central Europe (Good et al. 2008; Dimitrakopoulos et al. 2011; De Jong et al. 2016; Bedia et al. 2018; Lahaye et al. 2018; Fernandes 2019), Russia (Tosic et al. 2019), Australia (Dowdy et al. 2010), and on a global scale (Field et al. 2015). Our results show that the FWI value in the interval from October 21 to 28 exceeded 13.95 and approached 20.67, which corresponds to more than 30 and 170 ha of burnt forest, respectively, according to the Xanthopoulos et al. (2014) scale. The FWI system produced valuable insight for fire management by determining very low, low, medium, high and very high levels of fire danger in the Maoer Mountain forest ecosystems. It improves the accuracy of fire hazard assessment in the study area by informing the public of imminent fire hazards; thus, it is a useful tool for regulating access to forest ecosystems during the fire season.

The spatial distribution of FWI indices differs considerably across the globe. Although FWI values can be calculated at any location based on weather variables, they are only useful where fuel is available (Vitolo et al. 2019). Considering the heterogeneity of forest ecosystems and the uncertainty of future trends in fire severity and intensity, which is largely due to complex, nonlinear interactions among weather, forest, and anthropogenic factors, specific information regarding vegetation type vulnerability is needed at both local and global scales (Flannigan et al. 2009; Papakosta and Straub 2017; Fernandes 2019).

4.4 Implication for wildfire management

The FMC metres serve to track the moisture content of dead fuel over time in a range of landscape locations without the need for frequent study area visits. They are more precise than distant weather stations, particularly in different locations with different forest ecosystems. However, they should be used in concert with other tools, as sometimes they cannot track data when their batteries are discharged. Many humidity models used by fire managers have been established with data from weather stations remote from sampling sites; therefore, FMC metres are valuable in this regard. The challenge we have is to equip the FMC metre with all components necessary to collect all useful data, even remotely.

5 Conclusion

This study evaluated the ability of the Canadian Forest Fire Weather Index to estimate fire danger in typical temperate forest stands in Northeastern China. Before evaluation, we developed FMC models with FMC metre and CWS data. From this dataset, we determined the most important weather variables responsible for changes in fuel moisture content. Field data variables were more accurate in estimating fire danger than CWS data variables, suggesting that more local meteorological stations in fire-prone regions would be beneficial in fire-risk assessment. In four of five models, rain had a strong effect on FMC variation. Relative humidity, temperature, and solar radiation also had a relative effect on FMC. Among models built from field data, there was variation in factors affecting FMC. Relative humidity was the most important factor, followed by radiation, temperature, and rainfall. The calculation of fire risk using the CFFDRS in Maoer Mountain forest ecosystems presented low, medium or high risk. It is obvious that the Canadian Forest Fire Danger Rating System is suitable for fire management in temperate forest ecosystems of China, according to Wagner (1987) fire danger. Along with these results, this study served to compare the use of FMC-metre field data and China Weather Station data to evaluate fire danger. The results of this study led us to suggest the multiplication of meteorological stations in fire-prone regions.

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Declarations

Conflict of interest The authors declare that there are no competing interests.

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