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Forest fire risk estimation in a typical temperate forest in northeastern China using the Canadian Forest Fire Weather Index, case of autumn 2019 and 2020

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Abstract

China's forest cover has increased by about 10% as a result of sustainable forest management since the late 1970s. The forest ecosystems area affected by fire is increasing at the alarming rate of roughly 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 (FWI) to determine the daily forest fire danger in a typical temperate forest in northeastern China in the fall season. Based on the Wilcoxon test for paired samples, the observed and predicted values of FMC showed similar variation in 63.6% of sampling sites, with p-value > 0.05; and 36.4 % of sampling sites presented lower predicted values of FMC than observed values, with p-value < 0.05. The Canadian Forest Fire Danger Rating System estimated the fire danger level as very low, low, moderate, high, or very high in our Maoer mountain forest ecosystems.

Keywords: fuel moisture content, weather, fire danger, Maoer mountain, forest ecosystems

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 about 10% as a result of sustainable forest management since the late 1970s (Nöchel and Svennin 2017), the forest area ecosystems affected by fire is increasing at the alarming rate of roughly 600 thousand hectares per year (Yang et al. 2010). Climatic conditions and forest composition in northeast 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, climate will be characterised by higher temperature (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). Great labours have been made around the world to lower the effects of wildfire including fuel diminution and alteration, prescribed burning, and firebreak contour (Zong et al. 2021). However, it is particularly important to strengthen forest fire management and improve forest fire prediction capabilities in regions where the forest fire danger rating system remains to be developed. Ignition, spread and development of forest fires are strongly affected by the moisture content of forest fuels (Rothermel 1972; Dimitrakopoulos and Papaioannou 2001). In particular, the frequency of forest fires is directly affected by the

moisture content of dead fuels on the ground. Therefore, accurately predicting the moisture content of dead fuels on the forest surface is the key for forecasting forest fire risk and fire behaviour. 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).

Aguado et al. (2007) have identified various methods estimating the FMC: the field sampling, standard fuels and meteorological indices. Prediction model of fuel moisture content by the gravimetric method is often considered as 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). The method that used standard fuels is based on monitoring weight changes of previously calibrated surface forest fuels that are presumed to be good representatives of certain fuel sizes. It reduces the effort of field sampling and provides an instant estimation of FMC. However, this method has a little spatial significance as the measurements are limited (Aguado et al. 2007). Meteorological danger indices method is often used to measure dead FMC. These indices depend on present and past meteorological conditions, since they try to evaluate the drought of different forest fuels. It leads to frequent updating and, in addition to estimating FMC, offers other critical variables for fire management. Based on the last method, this study used the FMC meter to evaluate the change of the FMC as it instantly evaluate the change of FMC in any place; however il also needs manual measurement before or after the experiment (Masinda et al. 2021).

Prediction of forest fire has been studied for decades using different forest rating systems like 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 has 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 like the fire weather index (FWI). The CFFDRS has, since the early 20th century, involved an extensive network of weather observations, FMC field sampling, and ignition sustainability investigations (Fujioka et al. 2008). The FWI system is a sub-system 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 fuels 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, 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. Accordingly, this work attempted to provide insights on the following questions: Which weather variables influenced much the fuel moisture content in Maoer mountain forest ecosystem? Does the relationship between the moisture of the FMC meter and China Weather Satellite Station (CWSS) change by forest type and time? What is the rating of fire danger in the fall fire-prone season? Thus, it aimed 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 method

2.1. Study location

This study was conducted in a typical temperate forest of Maoer mountain, in northeastern China (45°43'N, 126°37'E; average elevation is 255 m). The surface area of Maoer mountain forest ecosystem is 21813.1 ha. The region features a cold, temperate climate, with rainy summers. It receives an average annual rainfall of 649 mm. The hottest month in this 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 20th 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 in various sites characterised by different conditions. These forests are forest of *Quercus mongolica* on steep upper slope arid and infertile, the mixed deciduous forest located at well-drained fertile gentle mid-slope and the deciduous forest on gentle slope moist, and fertile. There are also two dominant plantations: *L. gmelinii* and *P. koraiensis* plantations (Wang 2006). In the winter, the temperature is low, the snow is frozen, and there are no burning conditions, so forest fires are registered during these periods. 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 estimated as in the China forest administration website (12 December 2019).

2.2. Meteorological data acquisition and use

This study used data from FMC meters which provide measurements of meteorological variables and the fresh weight of fuel on the ground surface (Masinda et al. 2021). It also used data from the CWSS as the installation of FMC meters over large areas of forest requires a lot of resources (material, financial, temporal and human). The first series of data was acquired from the FMC meters in the field. FMC meters were set in Maoer mountain forest ecosystem to track the change of dead fuel moisture content in relation to variations in air temperature, relative humidity, solar radiation, wind speed, and rainfall. We acquired the second series of data from the CWSS -Harbin Station- (http://cdc.cma.gov.cn/, station id: 50953, 45.45°N and 126.46°E), which included temperature, relative humidity, wind speed and total daily rainfall. The temporal and spatial resolution of CWSS are respectively one hour and seventy-one kilometres. These series of data served to develop the FMC patterns and to calculate the FWI indices (noon temperature, relative humidity, wind speed, and total daily rainfall).

2.3. Sampling

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 the FMC (De Melo-Abreu et al. 2010). In this study, we used the FMC meter which is a device consisting of an automatic balance and a mini weather station. It automatically measures the fresh fuel mass, air temperature, relative humidity, wind speed, solar radiation, and rainfall reaching the fuels on the ground surface (as well as soil moisture and temperature) at an instantaneous time interval. It supplies a continuous and automated measurement of the FMC that can be transferred from remote sampling site, reducing the manpower required to get information on the variation of the moisture content in the field.

Data were collected at 11 sampling points (5 and 6 sampling plots in 2019 and 2020, respectively) arranged on four linear transects (Table 1). Transects were separated by 1.11 km, or 0.01 degree of latitude and sampling points on each transect were distant one of the other of 0.788 km, corresponding to 0.01 degree of longitude at 45 degree of latitude. Around each sampling point, we had plotted a quadrant of 50 meters side which was used to describe the vegetation around it. In each quadrant, we manually gathered samples of dead fine surface fuels over an area of 30 cm × 30 cm along the transect, equivalent of the FMC basket meter. Samples were composed of twigs of one hour time-lag and freshly fallen nonwoody material which includes leaves, cones, pollen cones (Keane 2015). We then oven-dried our samples at 105°C for 24 hours and determined the moisture content as the fraction of water mass (W_f) to oven-dry fuel mass (W_d):

$$FMC_{(1)} = [(W_f - W_d) / W_d] \times 100 \quad (1)$$

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:

$$FMC_{(2)} = 147.2 \times (101\text{-}FFMC) / (59.5 + FFMC) \quad (2)$$

Table 1 Local field sampling characteristics

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

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	45.41	*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	127.67	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

2.4. Modelling with data from FMC meters

To assess the FMC variation, we fitted general linear models to select variables that have a strong effect on FMC. The FMC meter dataset consisted of air temperature, relative humidity, wind velocity, solar radiation and fresh fuel weight. The CWSS dataset included the temperature on the ground surface, temperature at 10 meters height, sunshine-hours, relative humidity, rainfall and wind velocity. Before computed 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. All models were computed in RStudio version 1.1.453.0 (RStudio Inc. 2018) and fuel moisture content variation was drawn with OriginPro2018 (Origin Lab, Northampton, MA, USA).

2.5. *FWI codes/indices prediction and correlation*

Estimation of FWI indices and codes was obtained using *fwi-function* with the cffdrs-R package (RStudio Team 2018; Integrated Development for RStudio, Inc., Boston, MA) based on noon local standard time weather observations, including temperature, relative humidity, wind speed, 24-hour rainfall, and the previous day's fuel moisture conditions (Wang et al. 2019). These codes and indices are respectively 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 FWI that underlines high FWI values (Tsinko et al. 2018). We used the qualitative Forest Fire Danger Rating System as established by Van Wagner (1987) to describe the fire danger as very low, low, moderate, high, very high, or extreme (Table 2).

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. 1- a, b). In addition, the FMC response to a rainfall of 2 - 4 mm during a good drying day took 2-3 days for the FMC to recover the pre-rain values. These results highlight the strength of the relationship between rain and FMC variation.

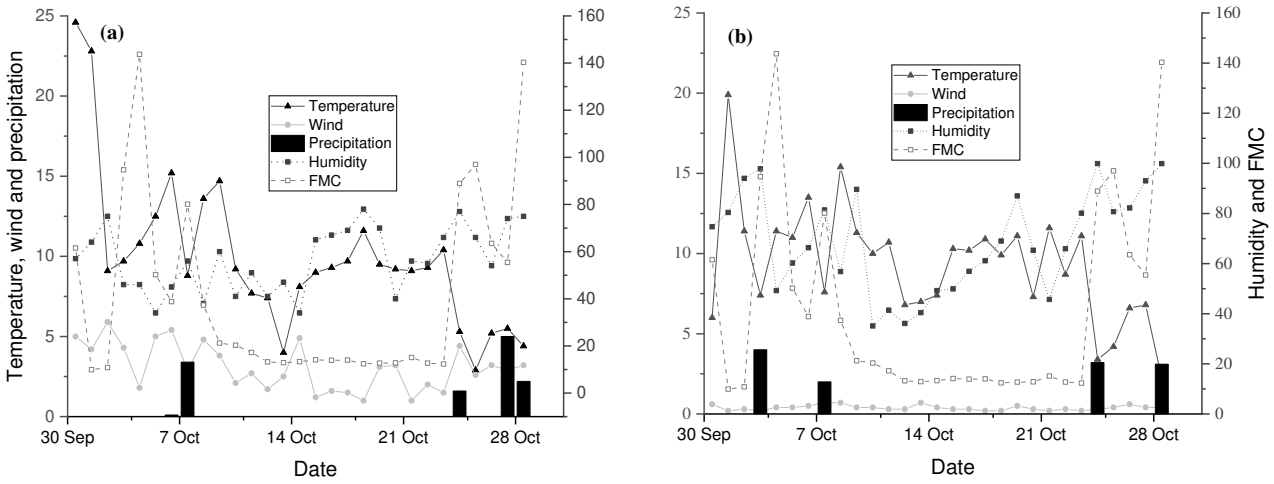


Fig. 1 Variation of FMC based on (a) FMC meter and (b) China Weather Station database

3.2. *Comparison among noon FMC*

In this paragraph, we compare the changes of FMC with field measurements, predicted field FMC and predicted CWSS FMC. Results are shown in Fig. 2-a, b, c, d, e. In 2019, the period from 11 to 25 October presented low FMC values (Fig. 2). On the other hand, the first and the last week of the month presented high values of FMC, mainly due to rain. In 2020, results in Fig. 3-a, b, c, d, e, f showed that the predicted (FMC meter and CWSS) FMC varied at the same rate as the measured FMC although, a dizzying increase in FMC was observed after the rain of October 20. The maximum value of FMC approached 325% (Fig. 3-e) while the minimum FMC value was 7.4% (Fig. 3-b).

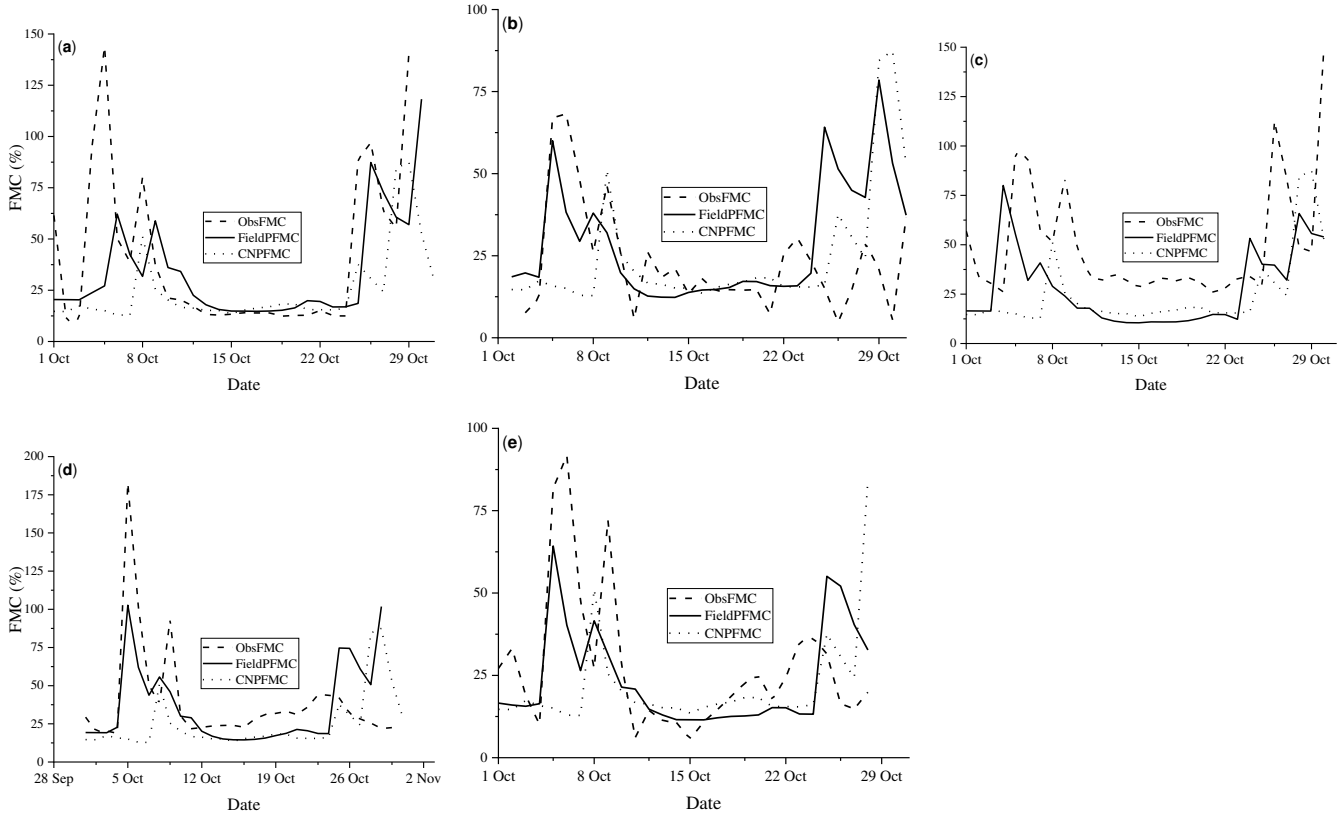
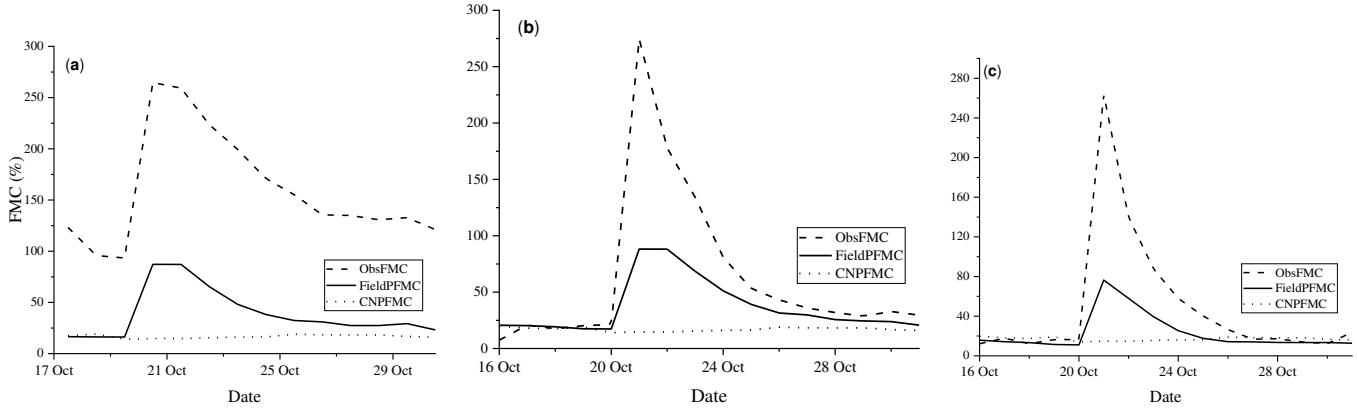


Fig. 2-a, b, c, d, e Observed versus FMC meter and CWS predicted FMC, in 2019



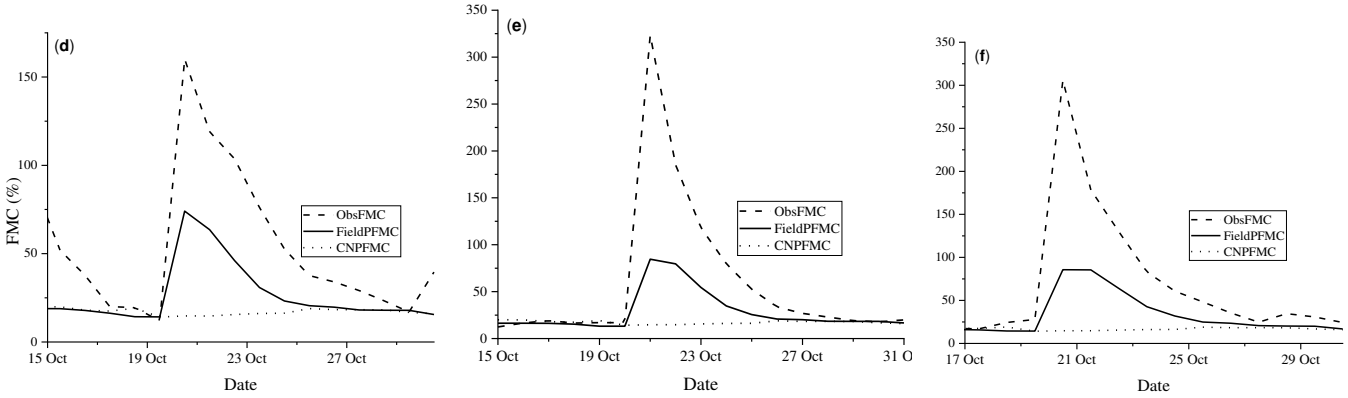


Fig. 3-a, b, c, d, e, f Observed versus FMC meter and CWSS predicted FMC, in 2020

3.3. Patterns of fuel moisture content

3.3.1. Predicted model with both data sources

The general linear model developed with both FMC meter and CWSS variables showed that rain and relative humidity influence on FMC were strong than the influence of temperature, wind speed, solar radiation and sunshine time. All models presented a good predive power (R-sq. adj.) > 70). In the fitted models (Table 3), *T, H, W, Rn, and R* respectively denote the temperature, relative humidity, wind speed, rain and solar radiation from the FMC meter and *SS* the sunshine timing and T_h the temperature at 2 m height for the CWSS data source. The residual standard error (RSE) varied from 15.72 to 31.17; the F-statistic varied between 34.28 and 74.15 while the degree of freedom (DF) oscillated between 26 and 29.

Table 3 FMC models fitted with FMC meter and CWSS data

Model	*Equation*	RSE	R-sq. (adj.)	F	DF
1	$FMC = 25.29\ Rn + 3.77\ SS$	31.17	0.70	34.28	27
2	$FMC = 2.989\ SS$	15.72	0.71	74.15	29
3	$FMC = 1.165\ H - 4.536\ T + 0.180\ R$	20.19	0.88	73.56	27
4	$FMC = 0.491\ H + 0.130\ Rn^5$	26.73	0.72	40.39	28
5	$FMC = 2.647\ T_h + 0.235\ Rn^4$	17.26	0.76	44.20	26

3.3.2. Predicted model with FMC meter data

Apart from developed models in the above section, we computed daily and diurnal models of FMC in order to observe if the effect of sun would increase the quality of the model. Thus, in 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 fuels in site 1. In site 2, humidity, temperature and wind speed are the influential factors. In sites 3, 4 and 5, wind speed and rain did not result in a substantial improvement in model efficiency. A general overview on daily developed FMC models proved that relative humidity, temperature, solar radiation and wind velocity influenced much 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 characterised by a high predictive power model: R-sq.(adj.) = 0.70. The other four sites were characterised by models with medium predictive power: 0.52 ≤ R-sq.(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 influence of wind velocity and rain were not noticeable. Results in Table 5 showed that sites 1, 2 and 3 were characterised by models with high predictive power: $0.72 \leq$ R-sq.(adj.) ≤ 0.80 while sites 4 and 5 were characterised by models with medium predictive power: $0.50 \leq$ R-sq.(adj.) ≤ 0.55. The residual standard error is RSE oscillated between 0.35 and 34.97 for daily developed models and 0.29 to 31.71 for diurnal developed models in Table 4. The F-statistic varied between 337.6 to 787.6 ($773 \leq DF \leq 1016$) for daily fitted models and F-statistic shifted between 138.3 and 664.1 ($408 \leq DF \leq 540$), etc.

Daily developed models of FMC in 2020 indicated that relative humidity, rain and temperature were the most important factors influencing the water content of fuels in all sampling sites. The effect of wind on water content was significant in site 1 and the effect of solar radiation was only influential in site 3. Two of six sampling sites were characterised by models with high predictive power: $0.73 \leq$ R-sq.(adj.) ≤ 0.83. The other four sites were characterised by models in medium predictive power: $0.52 \leq$ R-sq.(adj.) ≤ 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 characterised with models in high predictive power, R-sq.(adj.) > 0.70 and three others with medium predictive power: $0.61 \leq$ R-sq.(adj.) ≤ 0.66 (Table 7).

Table 4 Daily developed FMC models in 2019

Model	*Equation*	RSE	R-sq.(adj.)	F	DF
1	$FMC = 0.648\,H - 2.491\,T + 30.119\,W + 0.043\,R$	34.97	0.64	343.3	773
2	$FMC = 0.130\,H + 1.241\,T + 1.543\,W$	17.12	0.57	427.5	984
3	$FMC = 0.008\,H - 0.007\,T + 0.0004\,R$	0.35	0.70	678.3	880
4	$FMC = 0.347\,H + 0.003\,R$	25.27	0.61	787.6	1016
5	$FMC = 0.237\,H + 1.243\,T + 0.001\,R$	24.21	0.52	337.6	943

Table 5 Diurnal developed FMC models in 2019

Model	*Equation*	RSE	R-sq.(adj.)	F	DF
1	$FMC = 0.979\,H - 1.735\,T$	31.71	0.72	599.9	469
2	$FMC = 0.134\,H - 0.156\,T^2 + 4.915\,T - 0.029\,T{\cdot}H$	15.38	0.72	277.4	423
3	$FMC = 0.013\,H - 0.010\,T + 0.00023\,R$	0.29	0.80	664.1	496
4	$FMC = 0.456\,H + 0.019\,R$	31.68	0.55	334.9	540
5	$FMC = 0.481\,H + 2.620\,T - 0.046\,T{\cdot}H$	29.85	0.50	138.3	408

Table 6 Daily developed FMC models in 2020

Model	*Equation*	RSE	R sq.(adj.)	F	DF
1	$FMC = 1.982\,H - 2.499\,T + 59.368\,W + 85.949\,Rn$	87.97	0.83	848.4	692
2	$FMC = 0.808\,H - 1.132\,T^2 + 54.249\,Rn^2$	55.06	0.63	420.0	741
3	$FMC = 0.882\,H - 2.968\,T + 46.989\,Rn + 0.044\,T{\cdot}H$	42.56	0.65	402.1	857
4	$FMC = 0.722\,H + 22.438\,Rn$	35.18	0.73	1220.0	886
5	$FMC = 0.952\,H^2 + 64.02\,Rn$	81.29	0.52	550.2	1007
6	$FMC = 0.830\,H + 54.805\,Rn$	55.52	0.66	715.8	740

Table 7 Diurnal developed FMC models in 2020

Model	*Equation*	RSE	R sq.(adj.)	F	DF
1	$FMC = 2.288\ H - 2.866\ T$	82.41	0.82	529.3	230
2	$FMC = 1.164\ H - 3.647\ T + 48.114\ Rn$	53.25	0.64	151.3	251
3	$FMC = 1.165\ H - 7.686\ T + 0.159\ T{\cdot}H$	38.07	0.74	245.9	260
4	$FMC = 0.959\ H - 1.102\ T^2$	33.74	0.76	475.4	301
5	$FMC = 1.257\ H - 3.757\ T + 62.70\ Rn$	58.67	0.61	143.4	272
6	$FMC = 1.219\ H - 2.260\ T + 46.572\ Rn$	55.05	0.66	162.3	245

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

The *Wilcoxon test* for paired samples showed that the observed and predicted values of FMC in 2019 were similar in sites 1, 2, and 5 ($p\text{-value} > 0.05$) and different in sites 3 and 4 ($p\text{-value} < 0.05$). Note that the predicted FMC values were calculated with the FWI function. In 2020, the *Wilcoxon test* for paired samples showed that the moisture content predicted with FMC meter data were significantly different to the moisture content predicted with CWS data in sites 1, 2 and 6 ($p\text{-value} < 0.05$). In sites 3, 4 and 5, both moisture contents were similar ($p\text{-value} > 0.05$). The difference between the observed and estimated FMC in site 1, 4 and 6 would be influenced by canopy density, altitude, slope, aspect or may be related to sampling facts rather than to real variance in moisture content (Table 8).

Table 8 Wilcoxon's test result for paired samples between the observed and predicted FMC

Sites	***Estimated parameter (V)***	***p-value***	**Sites**	***Estimated parameter (V)***	*p-value*
1	*248*	*> 0.05*	**1**	*101*	*< 0.001*
2	*206*	*> 0.05*	**2**	*134*	*< 0.001*
3	*465*	*< 0.001*	**3**	*59*	*> 0.05*
4	*129*	*> 0.05*	**4**	*109*	*> 0.05*
5	*122*	*> 0.05*	**5**	*100.5*	*> 0.05*
-	-	-	**6**	*105*	*< 0.05*

3.5. Fire danger estimation

The value of FWI varied across the study period (October 2019) was low from October 1st-12th, moderate from October 13th-18th, very high from October 19th-26th, and low from October 26th-31st. It had rained only during the first and last week of the study period. The lack of rain was mainly responsible for the high fire danger ratings. Fig. 4-a depicts that the FWI values in sites 2 and 3 from October 21st-25th reached a high or a very high level of fire danger, while FWI values in sites 1, 4, and 5 varied between the very low and the moderate fire danger level. Results in Fig. 4-b illustrate that from 14 to 31 October 2020, the FWI oscillated between 0 and 5.56. Unfortunately, the value of FWI from 14 to 31 October in 2020 was lower than in 2019 in the same time interval.

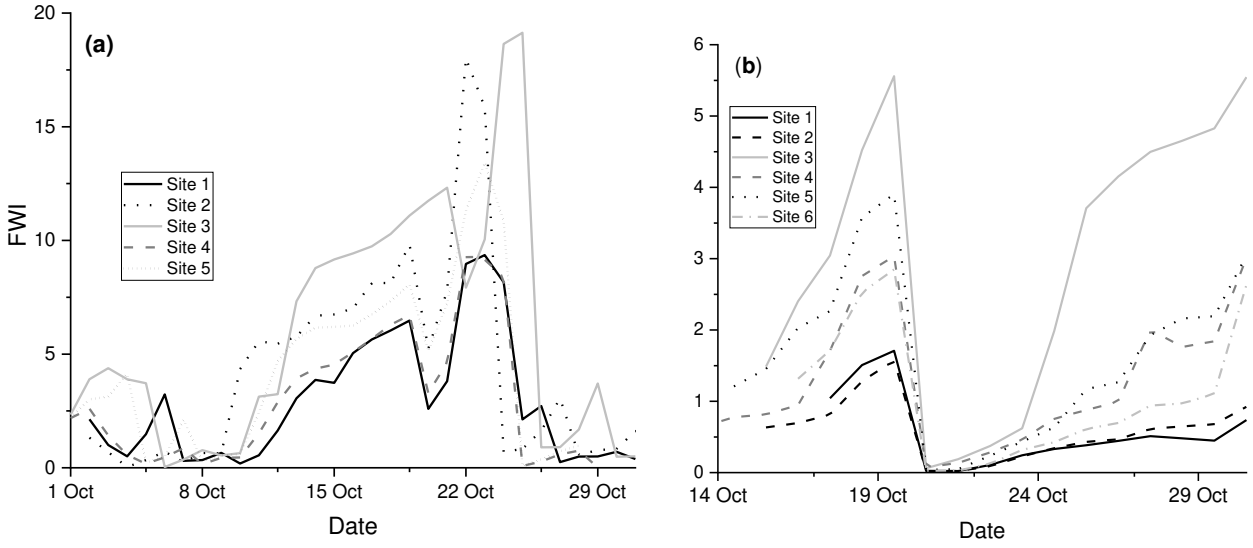


Fig. 4 Variation of FWI in 2019 (a) and 2020 (b)

4. Discussion

In this paper, we analysed the FMC variation and fire danger in typical temperate forests in order to (i) identify the most important variables affecting FMC changes and (ii) evaluate the skill of the FWI system in predicting forest fire risk in temperate forest stands, in northeastern China.

4.1. FMC changes

There were weighty increases in FMC during rainfall (Fig. 1- a, 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) measures and those obtained from CWSS (45.45°N, 126.46°E) is presumably related to the distance between the station and the experimental area. Thus, an increase in number of weather stations in fire-prone regions is needed as suggested by Chuvieco et al. (1999, 2002) and Zhang et al. (2011).

The FWI system underestimated the FMC values, compared to field-experimental observations (Fig. 2 and 3). The disparity between observed and predicted values may be a result of the height at which wind speed was sampled, which differed between the field measurements and the estimated values. Tree canopy may also play 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 measures temperature at 2 m and wind speed at 10 m in an open area (Field 2020). Accordingly, previous studies have shown that tree canopy reduces solar radiation and wind flow on the ground surface and has an effect on dead fuel moisture content (Zylstra 2011; Estes et al. 2012; Zhang et al. 2017).

4.2. FMC meter data prediction

Different sites revealed variability in the accuracy of FMC predictors. Relative humidity, temperature and/or solar radiation had a significant effect on FMC in these sites. Diurnal models were more accurate than daily models, however FMC drivers were the same in both models. After a 2 - 4 mm rainfall, the FMC needed 2 - 3 days to recover its pre-rainfall values. Thus, we hypothesised that firefighters could spend two to three days without raids in the field as dead fuels would be too wet to burn for approximately two to three days after the 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). Comparison between observed and predicted FMC showed that the observed values were slightly greater than the predicted values but were not significantly different (Table 8). Results of 2019 and 2020 allowed us to adopt the use of both data sources to predict the moisture content of dead fine surface fuels in Maoer mountain forest ecosystem because at eleven sampling sites, the predictions were statistically similar in seven sites, i.e. 63.6%.

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). More studies had found a strong relationship between FWI and wildfire occurrence in other regions, like the Mediterranean, south-east 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 the global scale (Field et al. 2015). Our results showed 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 Xanthopoulos et al. (2014) scale. The FWI system has produced valuable insight for fire management by determined very low, low, medium, high and very high level of fire danger in Maoer mountain forest ecosystem. 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 to regulate access to forest ecosystems during the fire-prone 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, however, they are only useful where fuels are 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, non-linear interactions among weather, forest, and anthropogenic factors, specific information about vegetation type vulnerability is needed on both local and global scales (Flannigan et al. 2009; Papakosta and Straub 2017; Fernandes 2019).

4.4. Implication for wildfire management

The FMC meters serve to track the moisture content of dead fuel over time in a range of landscape locations without the need of 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 can't track data when their batteries are discharged. Many humidity models used by fire managers had been established with data from weather stations remote from sampling sites, so FMC meters are valuable in this regard. The challenge we have is to equip the FMC meter with all its components necessary to collect all the useful data, even remotely.

5. Conclusion

This study evaluates the aptitude of the Canadian Forest Fire Weather Index in estimating fire danger in typical temperate forest stands in the northeast of China. Before evaluation, we developed FMC models with FMC meter and CWSS data. From this dataset, we determined the most important weather variables responsible for changes in fuel moisture content. FMC meter data were more accurate in estimating fire danger than CWSS data, suggesting more local meteorological stations in fire-prone regions would be beneficial in fire-risk assessment. In four of five models, rain had the strong effect on the variation of FMC. 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 Canadian Forest Fire Danger Rating System estimated the fire danger level as very low, low, moderate, high, or very high in our Maoer mountain forest ecosystems.

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Figures

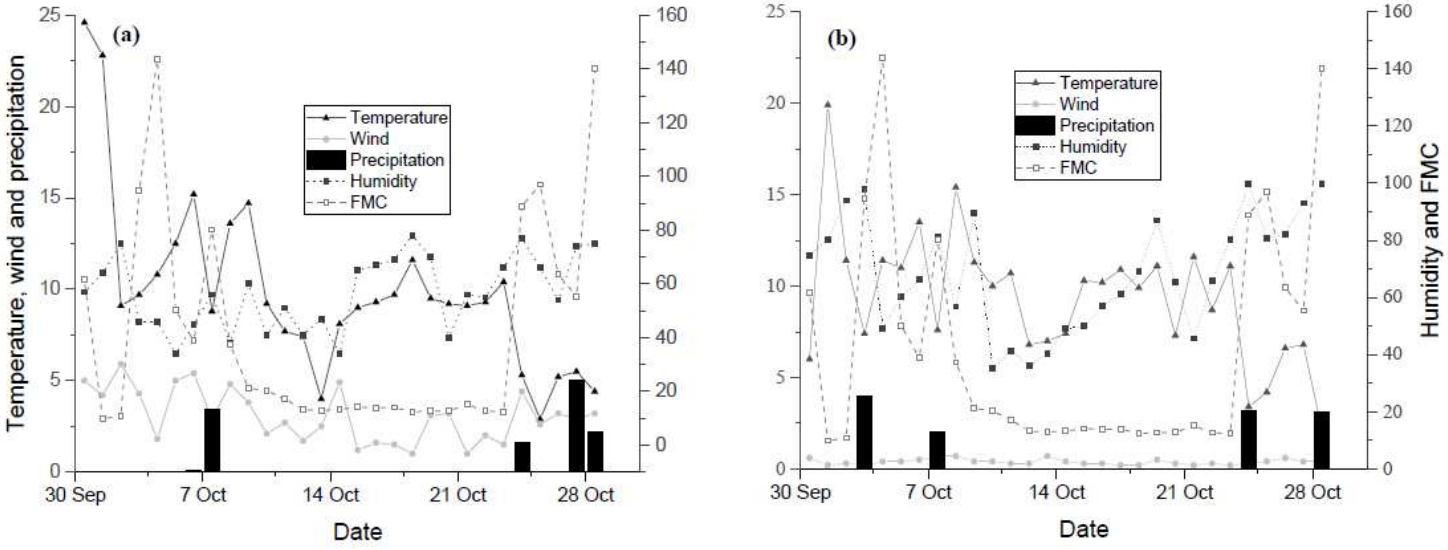

Figure 1

Variation of FMC based on (a) FMC meter and (b) China Weather Station database

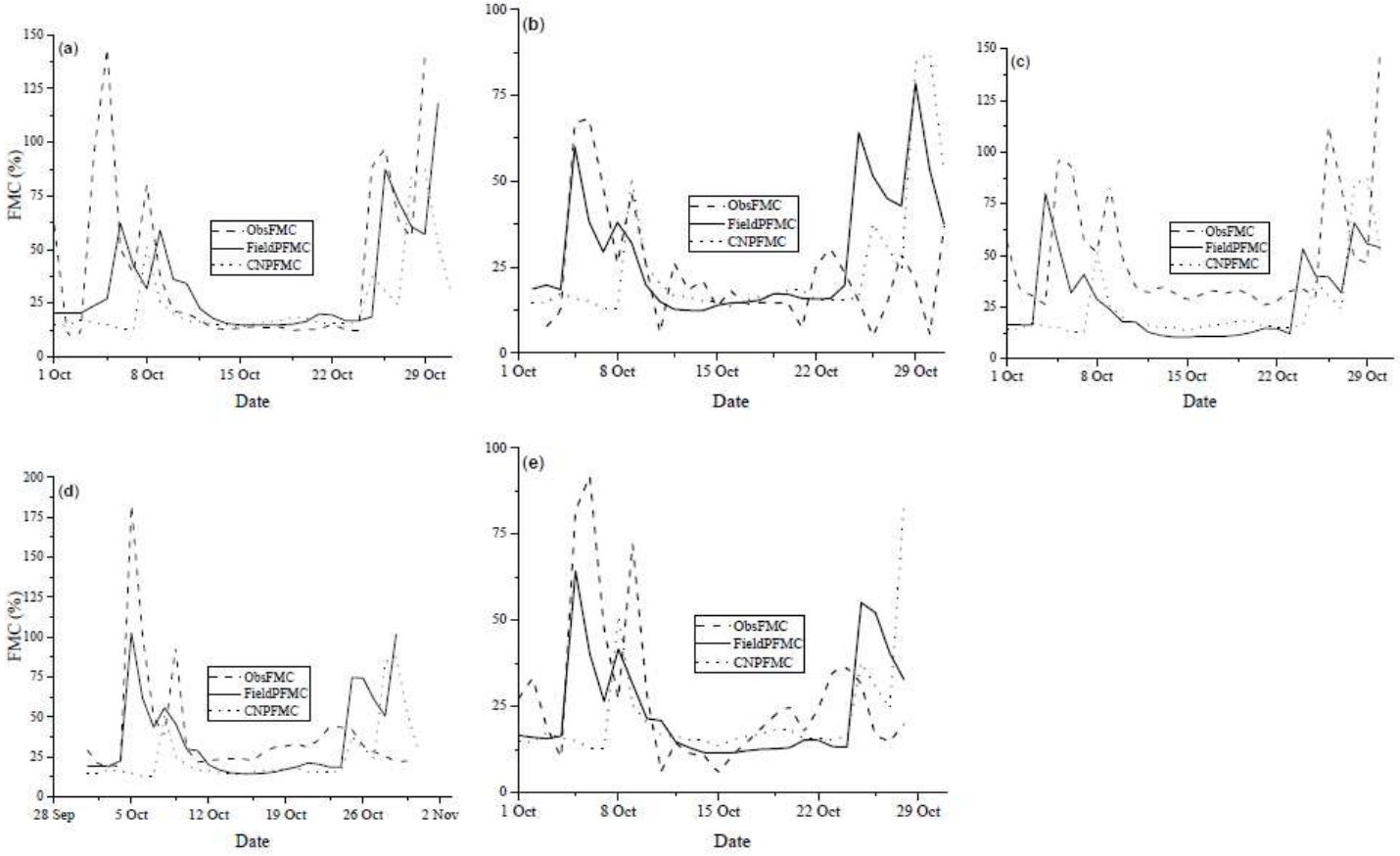

Figure 2

a, b, c, d, e Observed versus FMC meter and CWS predicted FMC, in 2019

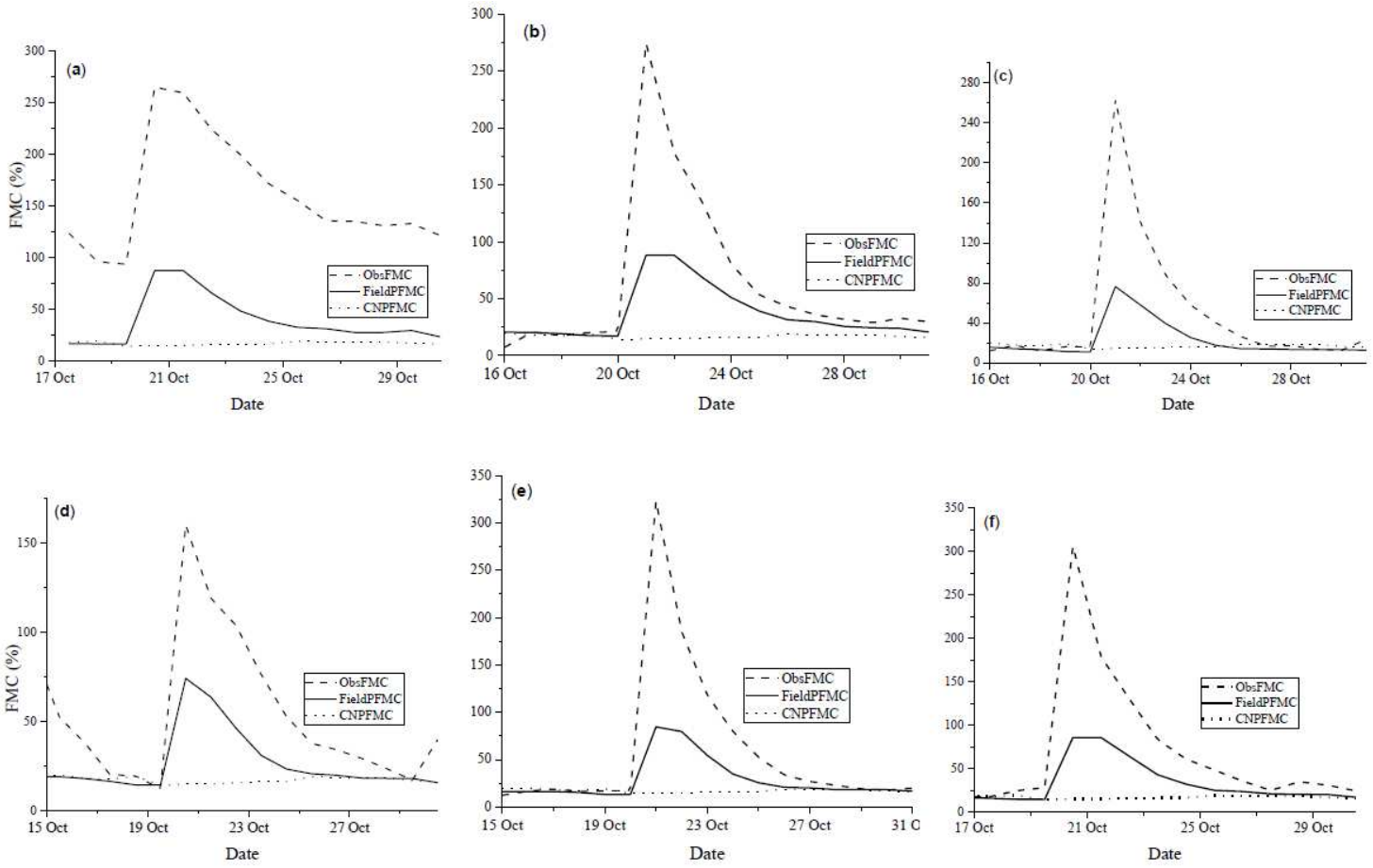

Figure 3

a, b, c, d, e, f Observed versus FMC meter and CWSS predicted FMC, in 2020

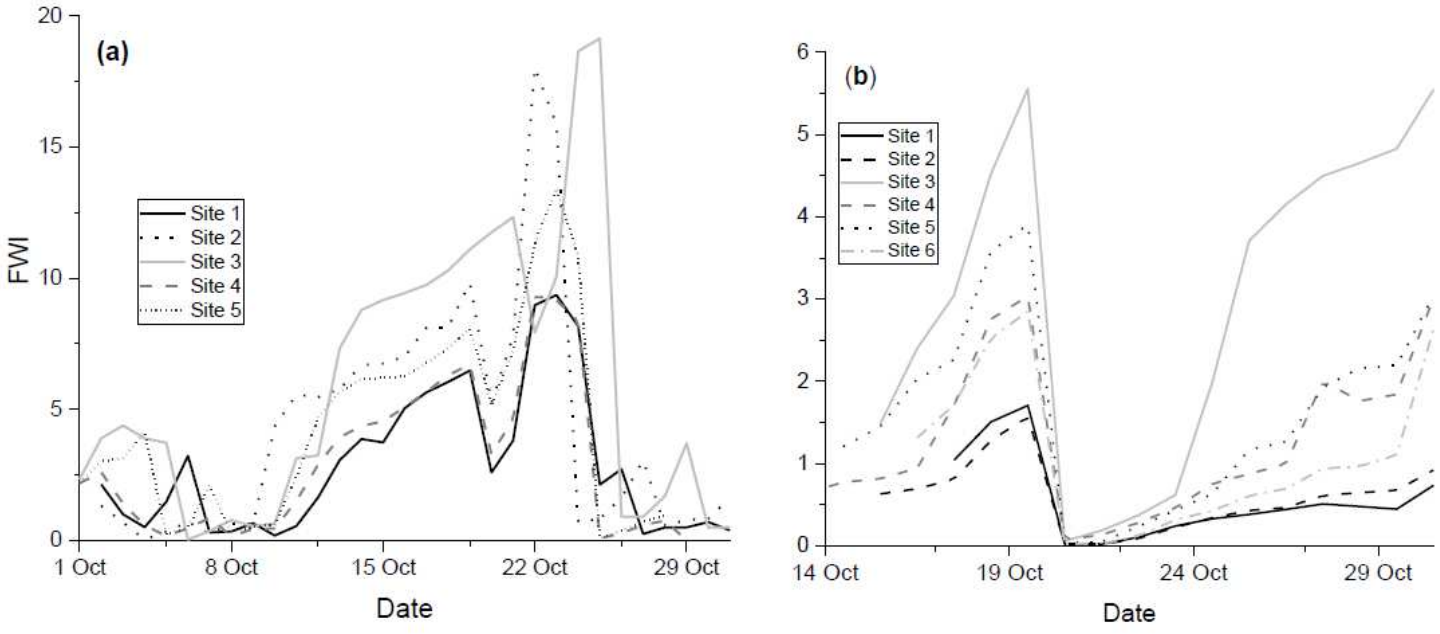

Figure 4

Variation of FWI in 2019 (a) and 2020 (b)