Forest Ecology and Management 496 (2021) 119379

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Soil moisture influences on Sierra Nevada dead fuel moisture content and fire risks

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ARTICLE INFO

Keywords:
Wildfire
Sierra Nevada
Fuel moisture
Soil moisture
Fire season

ABSTRACT

Dead fuel moisture influences the risk of fire ignition events, with implications for fire hazards, risk mitigation, and the design of prescribed burning activities. Because direct fuel moisture measurements are rarely available, fuel moisture must be estimated when evaluating fire risks. Most estimates rely primarily on atmospheric conditions and ignore the interaction of fuels with the soil surface with which they are in hydraulic contact. In this study we explore whether dead fuel moisture predictions can be improved with information about surface soil moisture. Despite the likelihood that dead fuels would exchange water with underlying soil, the influence of soil moisture on fuel moisture has been poorly studied. An analysis of 202 observations of co-located soil moisture, 1 and 10 h fuel moisture measurements, with environmental and meteorological covariates, showed that soil moisture had a small but significant effect on fuel moisture across all sampled conditions. The influence of soil moisture on fuel moisture was the most important among all other environmental factors for wet soil conditions and 10-h fuels, where a 1% increase in soil moisture content led to approximately a 0.6% increase in fuel moisture. The effect of soil moisture on 1-h fuel moisture although significant was small. Incorporating spatio-temporal variability of soil moisture into time-series or spatial predictions of fuel moisture tended to (i) reduce the seasonal duration in which fuels had a high probability of ignition by an average of 52–60 days across the tested years, and (ii) increased the heterogeneity of the probability of ignition through space, compared with similar models that did not incorporate soil moisture information.

1. Introduction

Fire behavior is strongly dependent on the availability and quality of living and dead fuels. Amongst dead fuels, which comprise duff, litter, dry grasses, and non-living woody material, the moisture content (Fuel Moisture Content or FMC) has a profound influence on the probability of ignition, a fire's rate of spread, and its burn intensity (Renkin and Despain, 1992; Chuvieco et al., 2004; Rothermel, 1983; Larjavaara et al., 2004; Fernandes et al., 2008). In fact, Van Wagtendonk (1977) cited dead fuel moisture to be "the principal factor influencing fire characteristics and subsequent effects on fuel and vegetation". Consequently, FMC is widely used as an input into fire risk assessment and fire modeling applications. Fine FMC is conventionally reported for fuels of two distinct sizes (1-h and 10-h fuels), corresponding to fuels with diameters of <0.64 cm and 0.64–2.54 cm, respectively. The size class names refer to the timescales over which the fuel moisture equilibrates with changing atmospheric conditions (Schroeder and Buck, 1970): finer fuels desorb and absorb moisture more rapidly than coarser fuels, resulting in distinct timelags (Cochrane, 2009). These fine dead fuel size classes are associated with the initial ignition and spread of fires, such that their moisture content is particularly relevant to the risk of fire occurrence (Bennett et al., 2010).

FMC for dead fuels is measured at numerous points across the United States - for example, ~ 60% of the 2,400 Remote Automated Weather Stations (RAWS) nationwide, and 85% of the 470 located in California, include continuous FMC readings of 10-h wooden dowels. Moisture data from these readings form the main input to the US National Fire Danger Rating System (NFDRS). Measured fuel moisture is interpolated to a 10 km grid over the continental US using atmospheric data to inform the interpolation (Wildland Fire Assesment System). These stations measure FMC using a standard 100 g pine dowel installed 10–12 inches above the ground (National Wildfire Coordinating Group, 2019). However, a study

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https://doi.org/10.1016/j.foreco.2021.119379
Received 11 March 2021; Received in revised form 13 May 2021; Accepted 16 May 2021
Available online 11 June 2021

by Bovill et al. (2015), concluded that 10-h fuel sticks were only able to accurately describe burning conditions (assuming that true burning conditions were represented by surface fuel measurements) about 50% of the time. Cawson et al. (2020) concluded that elevated fuel sticks report FMC values 3-fold lower than surface measured FMC. These findings suggest that RAWS stations on their own may not be sufficient for making FMC predictions, and that there may be important processes occurring at the ground surface that alter FMC. Field-sampled FMC is reported by the National Fuel Moisture Database (National Fuel Moisture Database, 2020), but mostly on sparse (e.g. bi-monthly) time intervals, and at limited locations. For example, only 31 sites in California have 10-h FMC records, and only 13 report 1-h FMC. This suggests that no datasets in the U.S. have appropriate measurements on suitable temporal and spatial resolutions to accurately predict the FMC of surface fuels.

This relatively sparse measurement network means that fire predictions mostly rely on a range of empirical and mechanistic models to estimate FMC (Matthews, 2014). One of the most complete and widely used is the Nelson Dead Fuel Moisture Model (Nelson, 2000), a process-based model that forms a component of the FlamMap, BEHAVEPlus, and NFDRS fire behavior and management models used throughout the USA.

(https://www.firelab.org/applications). The Nelson model is forced using precipitation volume and time since precipitation, in conjunction with environmental conditions to describe heat and moisture transfer for an idealized 10-h stick. The Nelson model performs well in many environmental conditions, but underestimates dead FMC predictions under wet conditions, when field sampled FMC exceeds 20% (Estes et al., 2012; Carlson et al., 2007). Errors in estimated FMC have real-world consequences: over-predicting FMC can result in escaped prescribed fires, higher severity fires, and less predictable fire behavior. Under-predicting FMC may cause unsuccessful prescribed fires (for example, 41% of interrupted burns in Portugal were due to high FMC, Fernandes and Botelho, 2004), due to exaggerated perceptions of risk (Quinn-Davidson and Varner, 2012; Bovill et al., 2015), or in failing to meet intended objectives, such as fuel hazard reduction or ecosystem restoration (Bovill et al., 2015; Johnson and Miyanishi, 1995; Fernandes and Botelho, 2004). In the context of modeling, reported uncertainty in FMC of $+/-$ 50% (that is, ± 2 percentage points around a mean of 4 percent FMC) can produce errors of up to 80% in output variables such as the rate of fire spread (Trevitt, 1988).

One possible explanation for errors in FMC, including the observed bias under wet conditions, is that soil moisture is excluded from model formulations predicting FMC (Hiers et al., 2019). Although FMC models attempt to account for antecedent wetness using precipitation data, these data may poorly represent soil moisture in topographically complex landscapes (Berryman et al., 2015; Holsinger et al., 2016), in snowmelt dominated systems where snowpack decouples the timing of precipitation from the input of moisture to soil (Harpold and Molotch, 2015; Williams et al., 2009; Bales et al., 2011), or in other areas with heterogeneous moisture environments (McLaughlin et al., 2017; Thompson et al., 2011; Kreye et al., 2018). Since surface fuels are often in direct contact with soil, heterogeneous soil moisture environments could produce variations in FMC - indeed, such variations are often implicitly assumed in fire management approaches when planning prescribed burns (Robert York, personal communication October 1, 2020).

Improved understanding of SMC - FMC relationships could be valuable for better interpolating FMC observations, for example using downscaled (e.g. Mascaro et al., 2019) remotely sensed observations of surface soil moisture from the Soil Moisture Active Passive (SMAP) radar (Chan et al., 2016) or NOAA's Soil Moisture Operational Products System (SMOPS) soil moisture product. The global availability of such products and a growing field of downscaling methodologies, coupled with *in situ* soil moisture measurements, would enable soil moisture to be viably used for continental-scale fuel moisture estimates.

To date, only a handful of studies address the relationship between fuel moisture and soil moisture, but all suggest that FMC is likely to be related to underlying soil moisture. For example, Hatton et al. (1988) and Rothwell et al. (1991) found that soil moisture was a significant determinant of litter moisture content in Eucalyptus and Aspen forests. Zhao et al. (2021) concluded that litter moisture models coupled to soil moisture perform better under wet soil conditions than models uncoupled from soil moisture. Pook and Gill (1993) showed that predictions of litter FMC were improved when incorporating soil moisture information, while Samran et al. (1995) concluded that precipitation and soil moisture account for 41–59% of the moisture content in the portion of the fuel bed in direct contact with soil.

Water transport processes in unsaturated soils include the flow of liquid water and the diffusion of water vapour. Both processes could transport water from the soil to fuels. This transport would be expected to slow down under dry soil conditions which suppress hydraulic conductivity in both mineral soil and organic materials (e.g. $\approx 10^{-4}$ cm^{-1} for duff with $\approx$ 20% water content, Raaflaub and Valeo, 2009), and also impeded evaporation fluxes (Gardner and Hillel, 1962; Kondo et al., 1990; Han et al., 2017). Consistent with these expectations, hydrologic modeling suggests dry conditions decouple surface organic layers from underlying soil moisture content. This coupling was restored by increased liquid and vapour fluxes when soils became wetter (Keith et al., 2010; Zhao et al., 2021). We, therefore, expect that FMC is likely to vary in how closely it is coupled to soil moisture content depending on how dry soils are, and that statistical models aiming to characterize SMC-FMC relationships might need to be structured in such a way as to account for this variation.

In this study, we aim to expand the body of work addressing the connections between SMC and FMC by exploring the relationships between SMC and the FMC of fine (1-h and 10-h) woody fuels in the Sierra Nevada. We use the results to quantify the potential importance of accounting/failing to account for soil moisture variations when estimating fuel ignition probability in the mid-elevation mixed-conifer forests in the Sierra Nevada. Three research questions (RQs) guide the study:

(i) Is soil moisture content a significant driver of variation in fuel moisture content for 1-h and 10-h fuels?
(ii) How do predictions of 1-h and 10-h fuel moisture vary when soil moisture is included or excluded from predictive models?
(iii) What are the practical implications of inclusion or exclusion of soil moisture on the timing and spatial variation in ignition probability?

Throughout, we quantify soil moisture using the volumetric water content of the soil. This choice of a soil moisture metric is not necessarily obvious: arguably, if SMC-FMC relationships are primarily driven by fluxes of water from soil to fuels, soil water potential might provide a more direct physical control on FMC. Volumetric water content, however, offers several advantages over water potential, including spatially-scalable data (from remote sensing and geophysical models) and ease of field-sampling; soil water potential estimates require knowledge of soil textural properties and thus require much more extensive soil sampling. On the other hand, volumetric water content can be easily approximated using a portable TDR with minimal soil disturbance. Since either metric can introduce error into the inference of the SMC-FMC relationship, we have elected to work with water content as the independent variable throughout due to its ease of sampling and data availability.

2. Methods

2.1. Study site

2.1.1. Blodgett research forest: data collection

Fuel moisture, soil moisture, and other covariates were sampled from the 1,763 ha Blodgett Research Forest (lat: 38.91, lon: −120.66, elev: 1,200–1,500 m), located in the foothills of the Sierra Nevada. Tree species in this area include sugar pine (*Pinus lambertiana*), ponderosa pine(*Pinus ponderosa*), white fir (*Abies concolor*), incense-cedar (*Calocedrus decurrens*), Douglas-fir (*Pseudotsuga menziesii*), California black oak (*Quercus kelloggii*), tanoak (*Lithocarpus densiflorus*), bush chinkapin (*Chrysolepis sempervirens*), and Pacific madrone (*Arbutus menziezii*). Soils are well-draining, deep, weathered, sandy-loams overlaid by an organic forest floor horizon. Common soil depths range from 85–115 cm (Moghaddas and Stephens, 2007).

A variety of research activities take place within different compartments of this forest. Sampling took place in 15 out of 110 compartments (Appendix Figure A.1). Because some treatments associated with each compartment (treatments listed in Appendix Table A) had the potential to alter soil or fuel structure, which could bias the study results, we confined the sampling to locations in which no soil disturbance or recent prescribed fires had occurred. We selected compartments for sampling to get a wide representation of overstory cover, slope, aspect, and soil wetness conditions. Soil type (sandy loam), forest species composition (mid-elevation Sierra Nevada conifers), and fuel depths (0–10 cm) were comparable across locations. Because of similarities in soil texture, we were confident that soil moisture (rather than water potential) could be reasonably used as a fuel moisture predictor variable.

Blodgett Forest receives an average of 1340 mm of precipitation each year (2006–2019) of which 340 mm is snowfall. Average daily summer maximum temperatures are 30 °C, and average daily minimum winter temperatures are 2.6 °C. A meteorological station (CDEC station BMT) located 2 km from the Blodgett Research Forest perimeter measures wind speed, relative humidity, and temperature.

2.2. Data collection

One hundred and one 1 and 10-h fuel samples were taken in daylight hours between May 7th and May 12th, 2019. This data collection window corresponds to the post-snowmelt period, during which we expected the variability in soil moisture within the landscape to be maximised, allowing us to test hypotheses about its effects on fuel moisture. Sampling locations are plotted in the Appendix Figure A.1. A single 1-h and 10-h fuel sample was taken at each sampling site between May 7th and May 12th. Weather was sunny and clear throughout the sampling period, with an average wind speed of 4–6.5 km/h. The last precipitation events prior to sampling were 13 mm on April 15th and 20 mm on April 8th. At the time of sampling, the accumulated water-year precipitation was 1320 mm. Fuels were collected sufficiently late in the morning that no dew was observed on the fuel surface. Within a sampling compartment, fuels were collected along an elevation gradient or in transects following the profile of a stream. Samples were taken on slopes 0–35%. All topographic aspects were sampled, but south-facing aspects were most represented (54% of all samples).

At each sampling location, an average of 39 grams of 1-h and 109 grams of 10-h fuels were collected and weighed using a scale with a 0.01 gram resolution, then stored in paper bags. A standard fuel sizing gauge (<0.64 cm for 1-h fuels, and 0.64–2.54 cm for 10-h fuels) was used to standardize fuel collection. At the end of each day, fuels were oven-dried at 105 °C for 24 h (Matthews, 2010). Dry fuel weight was recorded and FMC was calculated as the ratio of the difference between wet and dry fuel weight and dry fuel weight (Pollet and Brown, 2007). During sampling, temperature (*T*) and relative humidity (*RH*) were measured on 1 min intervals using a HOBO U23 Pro v2 data logger mounted at the top of a 2 m staff, which was moved to each sampling location. Temperature and humidity were reported as the 5-min average around sampling time. Vapor pressure deficit (*VPD*) was calculated as the difference between saturation vapor pressure (e_{sat}, computed following Buck, 1981) and vapour pressure of water in air ($e_a = e_{sat}*RH/100$). The presence/absence of wind was reported as a binary variable. Volumetric soil moisture was measured with a CS HydroSense II handheld probe across the top 12 cm of the mineral soil profile. At each sample site, 3 soil moisture readings were taken within 1-m radius of the fuel sampling location. Any duff and litter were cleared before measuring soil moisture.

Because fuels are known to have a lagged response to atmospheric conditions we also collected temperature and humidity data over the full course of the sampling dates from a stationary weather station (CDEC station BMT; 2 km west of the Blodgett Research Station border). We developed additional weather datasets including (i) Time lagged (1, 2, and 10-h) relative humidity and temperature, and the associated VPD, and (ii) 'composite' VPD measures, in which the lagged humidity and temperature were averaged with the point measurements, and result used to compute VPD. We refer to these as the 'composite' VPD measurements using 1, 2, or 10 h lags.

To account for differences in fuel shading, at each sampling location, we took photographs of the canopy at the ground level using a phone camera (12 megapixel resolution). Canopy cover was calculated by binarizing photographs into canopy vs open sky by applying greyscale thresholds using *imager* library (Barthelme, 2021) in *RStudio*, and the percentage canopy coverage was computed as the number of canopy pixels over the total number of pixels. Across the different sampled compartments, canopy cover ranged from 0–67% (Table 1). Additionally, we noted if fuel samples were shaded or in direct sunlight at the time of sampling. The time of day for each fuel collection was translated to solar elevation angle (sun angle from the horizon) using The National Renewable Energy Laboratory's Solar Position and Solar Intensity calculator (https://midcdmz.nrel.gov/solpos/solpos.html). Elevation, slope, aspect and topographic wetness index (*TWI*, Beven and Kirby, 1979) were calculated for all sampling locations using a 1/3 arc-second DEM (10 m by 8 m) obtained from USGS (https://www.sciencebase.gov/catalog/item/5aea899ee4b0860c0f70ed94). *TWI* quantifies topographic controls on landscape wetness. Table 1 summarizes collected data and sampling ranges.

Table 1
Summary of both field collected and topographically-derived variables collected across one hundred and one sampling sites within the Blodgett Research Forest. Both 1-h and 10-h fuels were collected at each location.

Continuous			
Variable	Abr.	Range	Unit
1-h Fuel Moisture	FMC_{1-hr}	2.8–22	%
10-h Fuel Moisture	FMC_{10-hr}	4.5–46	%
Soil Moisture	*SMC*	6.3–53	%
Relative Humidity	*RH*	10–70	%
Temperature	*T*	14–27	°C
Canopy Cover	*C*	0–67	%
Solar Elevation Angle [a]	*SE*	0–68	deg
Vapor Pressure Deficit[b]	*VPD*	0.6–3.0	kPa
Elevation[c]	*Elev*	1216–1382	m
Topographic Wetness Index[c]	*TWI*	3.7–17	–
Distance to stream		1–220	m
Slope[c]		0–34	%
Aspect[c]		0–360	deg
Discrete			
Wind	*W*	1 if there is wind/breeze; 0 = otherwise	
Shade	*Sh*	1 if fuel is in shade; 0 = otherwise	

[a] Calculated based on latitude/longitude and time of day

[b] Calculated from temperature and relative humidity

[c] Derived from 1/3 arc-second (10 by 8 meter) spatial resolution digital elevation model.

2.3. Data analysis

Statistical modeling was used in all analyses. Before developing statistical models, all data were scaled to have a mean of zero and a standard deviation of 1, the form of the SMC-FMC relationships for both 1-h and 10-h fuels was visually inspected. Data was scaled to facilitate the comparison between different drivers of FMC. We expected that the SMC-FMC relationship would have nonlinear form, weak under dry soil conditions, and stronger under wet soil conditions. As shown in Fig. 1 such non-linearity was obvious in the 10-h fuels, and weakly present for the 1-h fuels. The sampled soil saturated at SMC of $\sim$ 53%. Only limited FMC samples (n = 3) were collected under saturated soil conditions. We also looked for evidence of any non-linearity in the relationship between VPD and FMC, but found that the VPD-FMC relationship was linear across all VPD values (results not shown).

To reduce the dimensionality of the statistical models we checked the collinearity of all field variables (see Appendix Figure B.1). Where field variables were correlated, we retained for analysis the variable with the greatest partial correlation with FMC. To select the VPD metric to be used in the regression (locally measured, lagged or a composite metric), we tested models using each of these VPD measures. For both 1-h and 10-h fuels we found that measured FMC was best explained by the 1-h lagged composite VPD metric described in Section 2.2. In the remainder of this manuscript, where we refer to 'VPD', we are describing this composite measure.

We then developed linear and piecewise linear models for FMC. Linear models for FMC were heteroscedastic when applied to 10-h fuels, but homoscedastic when applied to 1-h fuels, as assessed by the Breusch–Pagan (BP) test on studentized residuals (Bischoff et al., 2006). We used a weighted least squares (WLS) regression to account for the heteroscedasticity and non-linearity in the SMC-FMC relationship. Other statistical methods to address heteroscedasticity produce similar results to WLS and are presented, for completeness, in Appendix B.3.

Linear models were developed using backward stepwise selection (Chambers, 1992, *step.model* in *RStudio*) in order to identify the model with the lowest Akaike Information Criterion (Akaike, 1987, AIC). Weights for the 10-h FMC WLS were assigned iteratively to maximise normality and homoscedasticity of the resulting model, measured with Shapiro-Wilk (SW Shapiro and Wilk, 1965) and Breusch–Pagan (Breusch and Pagan, 1979, BP) tests respectively.

The weighting scheme was applied separately to low values of SMC (where residual variance in the unweighted model was relatively low) and to high values of SMC (where residual variance was higher), using a SMC of 20.9% as a threshold. The weighting for low SMC was 1/exp $(FMC)^{0.5}$ and for high SMC, $1/\exp(FMC)^{1.3}$.

The linear models (OLS for 1-h fuels and WLS for 10-h fuels) did not exhibit spatial autocorrelation (Moran's I test), or multicollinearity (variance inflation factor), and satisfied assumptions of linearity, normality (SW), and homoscedasticity (BP). Relevant test statistics are shown in Table 2. Goodness-of-fit was assessed with root mean square error (RMSE).

Additionally, a piecewise linear regression was fit for the 10-h fuels only, using a single break-point based on SMC. The purpose of this model aimed to describe the non-linear responses to SMC observed in the 10-h FMC. In the piecewise model, we allowed the coefficient and the intercept for SMC to change at the break-point. All other variables had a single coefficient across the full SMC range and did not change at the break-point. With these specifications, we repeatedly fit the piecewise model with different break-point locations, and selected the one that minimized AIC, which was used to specify the final model. To allow significance testing in the presence of heteroscedasticity, we calculated robust errors (White, 1980; Huber, 1967). All model summaries are provided in Appendix B.2.

Table 2
Scaled regression coefficients for 1-h FMC regression (top), and 10-h FMC regression (bottom). Where α is the linear regression intercept, *SMC* is soil moisture content, *VPD* is vapor pressure deficit, *C* is canopy cover, *SE* is solar elevation angle, and *W* is the binary for presence of wind/breeze. Regression intercept is α and regression residuals are represented by ϵ. The significance level of each coefficient is reported using p-values. Normalized partial r^2 (sum of all partial r^2 coefficients = 1) values are used to assess relative importance of each variable. Model performance is assessed by AIC and RMSE. P-values of the homoscedasticity test (BP) and residuals' normality (SW) test are provided, where the null hypothesis is the assumption of homoscedasticity and normality of the studentized residuals.

Coefficient (β)	Estimate	p-Value	Partial r^2	Significance
$FMC_{1-hr} = \alpha + \beta_{SM}SM + \beta_{VPD}VPD + \beta_C C + \beta_{SE}SE + \beta_W W + \epsilon$				
α	−0.000	1.000		
SMC	0.146	0.032	0.058	*
VPD	−0.329	0.000	0.258	***
C	0.580	0.000	0.560	***
SE	0.189	0.005	0.099	**
W	−0.089	0.167	0.024	
AIC = 199RMSE = 0.61				
SW: p-value = 0.70BP: p-value = 0.85				
$FMC_{10-hr} = \alpha + \beta_{SMC}SMC + \beta_{VPD}VPD + \beta_C C + \beta_{SE}SE + \beta_W W + \epsilon$				
α	−0.098	0.009		**
SMC	0.109	0.018	0.098	*
VPD	−0.126	0.001	0.173	**
C	0.290	0.000	0.629	***
SE	0.071	0.071	0.057	·
W	−0.086	0.167	0.045	
AIC = 117 RMSE = 0.76				
SW: p-value = 0.40BP: p-value = 0.24				

Significance Level: ·0.1, * 0.05, ** 0.01, *** 0.001

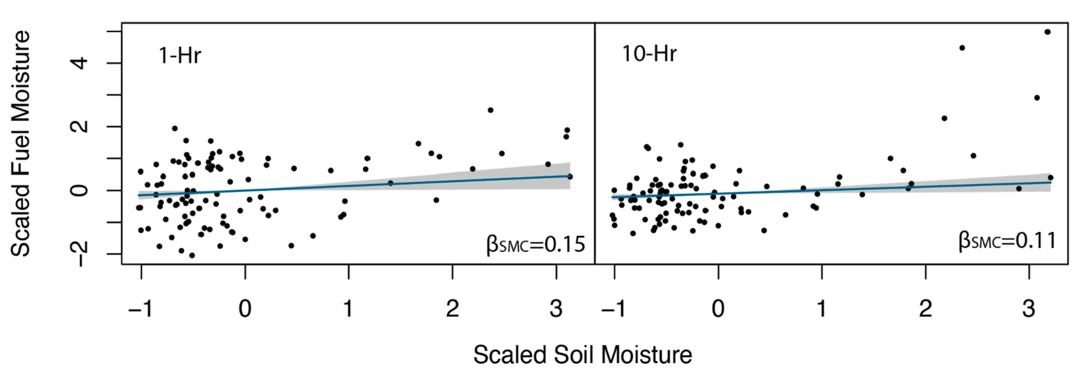

Fig. 1. Relationship between field sampled SMC and FMC for 1-h fuels (left) and 10-h fuels (right). Regression fit between SMC and FMC is shown as a blue line. SMC coefficient, β_{SMC}, is the line's slope. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.4. Research Question 1: Is soil moisture content a significant driver of variation in fuel moisture content for 1-h and 10-h fuels?

To answer this research question we first considered the significance and strength of the coefficients on SMC in the FMC prediction relative to other predictor variables. We did this directly within the 1-h FMC model, where inter-comparison is straightforward given the apparently linear relationship of FMC to all predictors. For the 10-h FMC OLS model, the non-linear SMC-FMC relationship made this direct comparison challenging. We therefore consider also the variable significance and strength within the piecewise linear function (Toms and Lesperance, 2003).

Separately from the variable significance and strength within the model fits, we also evaluated the importance of SMC on the model performance by comparing the error statistics for the models fit with and without SMC, as described above.

To test the impact of including/excluding SMC on the FMC predictions, we refit the 10-h piecewise regression and the 1-h OLS with and without soil moisture. To enable a like comparison between the piecewise regression with and without SMC, we refit the model for data with high/low SMC separately. We anticipated that this would increase the performance of the models without SMC, generating a more rigorous model comparison.

2.5. Research Question 2: How do predictions of 1 and 10-h fuel moisture vary when soil moisture is included or excluded from the predictive model?

To answer this question, we applied 1-h OLS and 10-h piecewise models with/without soil moisture to an environmental dataset obtained from the Upper Providence CZO weather station network in the Southern Sierra Nevada (Bales et al., 2011, data: https://eng.ucmerced.edu/snsjho/files/MHWG/Field/Southern_Sierra_CZO_KREW). To obtain soil moisture at 10-cm depth (the shallowest measured), we selected a node located on a flat aspect with an open canopy (elevation: 1982 meters, lat: 37.0626 N, lon: −119.1823E). For other environmental variables such as snowpack depth, temperature, relative humidity, and wind speed, we obtained data from the nearby base-station (data: https://www.fs.usda.gov/rds/archive/catalog/RDS-2018-0028). The base-station is located 40 meters from the soil moisture node and is also under an open canopy. Other nodes in the CZO network were used for data gap-filling, which was minimal.

We used the models to estimate FMC for each hour of the data record in three ways: (i) using daily soil moisture, (ii) using models that include soil moisture, but holding SMC constant at its seasonal average value, and (iii) using the models that exclude soil moisture. We excluded periods when air temperature was below freezing, snow depth exceeded 1 cm, or solar angle was lower than 45 degrees in the morning and 1 degree in the evening - during these periods, the environmental conditions were too distant from the field sampled range for model validity. Given these constraints, we used the regressions to identify the lowest normalised fuel moisture for 1-h and 10-h daily FMC values for each of the three prediction models and each prediction day. To convert the normalised FMC values to absolute FMC estimates, we transformed the unit-less predicted to have the Blodgett field-collected statistics (mean and standard deviation of 11.3% and 4.2% for 1 h fuels; 13.4% and 6.6% for 10-h fuels, respectively). These experiments enable the evaluation of the consequences of including/excluding soil moisture on temporal variability when predicting FMC.

2.6. Research Question 3: What are the practical implications of inclusion or exclusion of soil moisture on the timing and spatial variation in ignition probability?

2.6.1. Temporal variation in ignition probability

Because of the long temporal weather and soil moisture record, we used the Upper Providence CZO weather station data to explore the temporal fire risk dynamics at a single point and how they might be influenced by including or excluding soil moisture from the FMC predictions.

We estimated FMC with each of the three regression models described in Section 2.5 for the January 1, 2008 to January 1, 2018 period. We then used the probability of ignition tables adapted by Pat Andrews (Rothermel, 1983), derived from a mechanistic model developed by Schroeder (1969), and are used in the field by fire managers to classify fire risk from FMC. We made these predictions on hourly timescales and reported the daily maximum probability of ignition. The probability of ignition values were converted into an estimate of fire season start and end by finding the 5th and 95th percentile of all recorded days for each season with a probability of ignition of 30% or above, respectively. This threshold is partially based on the field sampled fuel moisture range, where relatively high minimum 10-h FMC (4.5–46.1%) results in a small number of days with high probabilities of ignition. Sampling during the entire growing season may provide a greater range in FMC variability, and thus a different probability of ignition threshold might be more appropriate. Though the specific timing of the start and end of the fire season varies with the selected probability of ignition threshold, the relative relationship between predictions of fire season among different SMC models remained the same across different tested thresholds. We summarize the start and end of the fire season over a 10-year record using box and whisker plots (range, mean, and 90th percentile) for each model and fuel category. We compare the 10-year fire season start and end means derived from each model to determine the effect of SMC inclusion/exclusion on the fire season statistics.

2.6.2. Spatial variation in ignition probability

To assess the spatial variation in ignition probability, we used a soil moisture model for the Illilouette Creek Basin (ICB) developed by Boisramé et al. (2017) to explore spatial variations in fire risk at two points in time (spring and fall), again when including/excluding SMC from FMC predictions. ICB was chosen for spatial analysis of fire risk, because of extensive soil moisture measurement campaigns across many years and vegetation types in addition to having a fine weather station record. This weather record spans four years, which is why we did not use it for the temporal assessment of fire risk described in Section 2.6.1.

We compare the effect of SMC inclusion/exclusion on the spatial distribution of fire probability in the ICB over a snapshot in time in the spring and fall of 2017. ICB is a well characterized 150 km^2 basin located in Yosemite National Park, USA, spanning elevations of 1,270–3,600 meters. Like Blodgett Research Forest, the soils are sandy and well-drained and vegetation is a mix of coniferous forest. ICB also has large areas of shrub/grassland and meadow vegetation (Boisramé et al., 2017). Although we do not alter the SMC-FMC model for different vegetation cover types, we use a percent canopy map for ICB from LANDFIRE for 2016 (USGS, 2016) to separately estimate percent canopy for forest and shrubland. We set percent canopy for non-forest landcover to 0%, because we do not expect sufficient shading to affect FMC. A spatial 30 m resolution SMC map of the top 12 cm soil profile was derived using the random forest model developed by Boisramé et al. (2017). The SMC values in this map are representative of a two week interval close to the dates of field sampling of SMC used to train and cross-validate the random forest model (May 23–24th in the spring and August 5-9th 2017 in the fall). Three temporary weather stations are installed in ICB (lat −119.57, lon 37.68, elevation 2,136 m) recording volumetric SMC at 10 cm depth along with climatic variables at 10-min resolution for years 2016–2020. We used the weather station record to determine a data point at the lowest VPD within each two week period. We use this lowest VPD value to make spatial FMC predictions which represent high fire risk periods, meteorologically, for both fall and spring seasons. Temperature (used to calculate VPD) was spatially scaled from the weather station location to the rest of the basin based on a temperature lapse rate of $-0.0007^{0}C/m$ of elevation (following

Boisramé et al., 2019). The actual vapor pressure was not scaled in calculating VPD. The wind binary was set to 1 (presence of wind) for the entire basin, and the solar angle determined from the weather station time, day, and location. Solar angle was not corrected for slope. We then calculated FMC at all 30 m pixels in the basin using the changing SMC model and the no SMC model for 10-h fuels only, and converted these to probability of ignition (Rothermel, 1983) as described in Section 2.6.1. We report the differences in the probability of ignition between the two models for the spring and fall soil moisture scenarios.

3. Results

3.1. Research Question 1: Is soil moisture content a significant driver of variation in fuel moisture content for 1-h and 10-h fuels?

Table 2 summarizes the fitted regression coefficients for 1-h OLS regression and 10-h WLS regression, while Table 3 summarises the piecewise regression. In these tables, the importance of each variable in terms of SMC can be measured by the statistical significance (p-Value), the partial r^2, which measures how much the variation in FMC is influenced by each variable, and in terms of the coefficients directly - with the last comparison being enabled by the use of scaled variables in the models: all coefficients in Table 2 are unitless, with a mean of zero and a standard deviation of 1, facilitating such comparisons.

The results indicate that soil moisture content is a *significant* but not important driver of FMC variation for 1-h fuels (Table 2, top section), a significant and some important driver of FMC variation for 10-h fuels across the full range of soil moisture conditions explored (Table 2, lower section), and is the most important contributor to variations in FMC for 10-h fuels under wet soil conditions (Table 3, $SMC_{\geqslant b}$ estimate).

For the 1-h OLS regression, the coefficient on soil moisture content was 0.146, which is lower in magnitude than the coefficients on canopy coverage (0.58), VPD (−0.329), and solar elevation angle (0.189). These coefficients were all significant ($p<0.05$), and the partial r^2 values follow the same rank order as the coefficients. The analysis here suggests that SMC has a statistically significant, but in practice marginal influence on 1-h FMC (Table 2).

For the 10-h WLS regression, the coefficient on soil moisture content was 0.109, which was also lower in magnitude than the coefficients on canopy coverage (0.29) and VPD (- 0.126). Again all coefficients were statistically significant, and the rank order of coefficients and partial r^2 was identical. Additionally, the model fits (in terms of identifying the most important parameters) were robust to the methodology used to remove heteroscedasticity (Appendix B.3). Note, however, the under-prediction of FMC by the WLS model for high SMC conditions, which can be visually seen in Fig. 1, which shows the 1-h and 10-h SMC-FMC data and the fitted OLS and WLS models.

The piecewise regression model for 10-h FMC addresses this under-prediction. The model fit for the piecewise regression is presented in Table 3. The breakpoint used in the piecewise regression (20.9% SMC) minimizes AIC (AIC = 206), and can be physically interpreted as a measure of how wet soil must be to enable hydraulic continuity between soil and fuels, as shown in Fig. 2. Below the breakpoint, SMC has a minimal (0.26) and non-significant influence on FMC. For wet soils, however, SMC has a large (0.85) and significant influence on FMC. In physical terms, for dry soils, a +1% increase in SMC increases FMC by +0.18%, compared to a +0.58% increase above the breakpoint. By comparison, the VPD coefficient is −0.15, which physically interpreted means that a 1 kPa increase in VPD, decreases FMC by −1.6%.

The findings in research question 1, therefore, suggest that SMC has a significant but unimportant influence on 1-h FMC and 10-h FMC under dry conditions - but a significant and large influence on FMC under wet soil conditions, when it is the most important predictor of 10-h FMC variation.

Table 3
Scaled regression coefficients for 10-h piecewise FMC regression with a breakpoint (b) at scaled SMC value of 0.29 (or non-scaled 20.1%). Where α is the linear regression intercept, *SMC* is soil moisture content, *VPD* is vapor pressure deficit, *C* is canopy cover, *SE* is solar elevation angle, and *W* is the binary for presence of wind/breeze. Upper and lower bound estimates provide a 95% confidence interval for the slope coefficients. Confidence intervals are calculated using robust standard errors which can be trusted in the presence of heteroscedasticity in the residuals. The significance level of each coefficient is based on p-values. Model performance is assessed by AIC.

Coefficient (β)	Estimate	p-Value	Significance
$\alpha_{<b}$	−0.016	0.024	*
$\alpha_{\geqslant b}$	−0.868	0.010	*
$SMC_{<b}$	0.263	0.089	.
$SMC_{\geqslant b}$	0.835	0.006	**
VPD	−0.153	0.004	**
C	0.431	0.000	***
SE	0.102	0.058	.
W	−0.121	0.72	

AIC = 206 RMSE = 0.63
SW: p-value = $4.8e^{-8}$ BP: p-value = $3.8e^{-7}$

Significance Level: ·0.1, * 0.05, ** 0.01, *** 0.001

3.2. Research Question 2: How do predictions of 1 and 10-h fuel moisture vary when soil moisture is included or excluded from the predictive model?

We first address this question in the context of model fit and coefficient values, before turning to the implications in terms of predicted FMC time-series based on observational data. We consider only the OLS model for 1-h fuels and the piecewise model for 10-h fuels. We consider the effects of the model change on adjusted r^2 and RMSE only, as there is not a direct way of comparing AIC across different model forms (which are imposed by the way we removed soil moisture from the piecewise model).

Excluding SMC from predictions of the linear models for 1-h fuels slightly worsened the model fit (the adjusted r^2 dropped slightly by 0.015; and the RMSE increased by 0.1 which is equivalent to 0.04% FMC). The linear model continued to meet all linear regression assumptions (homoscedasticity, normality, and with the residual expectation of ~ 0). In the absence of SMC, the coefficients on the other predictor variables all increased, and the significance of the variables was unchanged. This suggests that in the absence of SMC, 1-h OLS model accounts for temporal changes in FMC primarily by increasing the sensitivity to VPD (since percentage canopy is static). The summary of the linear model fit without SMC is provided in Appendix B.2.

The piecewise model with SMC was compared to a model that fit linear regressions on the other variables separately below and above

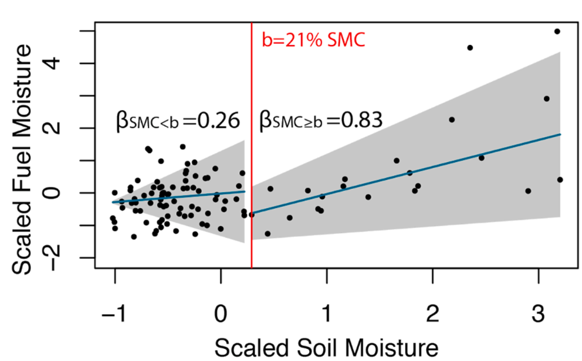

Fig. 2. Relationship between field sampled SMC and FMC of 10-h fuels. Piecewise regression fit between SMC and FMC is shown as a blue line, 95% confidence interval around SMC/FMC slope coefficients is shown in gray. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

20.9% SMC. Removing SMC from the 10-h FMC model decreased the adjusted r^2 by 0.11, and increased RMSE by 0.63 (equivalent to a 1.5% FMC) under dry conditions. Under wet conditions, removing SMC decreased the adjusted r^2 by 0.18, and increased RMSE by 0.29 (equivalent to a 5.5% FMC). These metrics suggest that exclusion of SMC from 10-h FMC model negatively impacts model fit and increases prediction error. Under dry soil conditions and without SMC, the scaled VPD coefficient was unchanged, while at higher SMC, the scaled VPD coefficient was −0.42 rather than −0.153 (implying that a 1 kPa decrease in VPD decreases FMC by −4.4%). A full summary of the models fit without SMC is provided in Appendix B.2.

In summary, excluding SMC from the 1-h FMC model slightly worsens model fit and slightly increases the model sensitivity to VPD. Excluding SMC from the 10-h FMC model has little impact on predictions during dry conditions or the sensitivity of other parameters. Under wet conditions, however, excluding SMC means the model relies more heavily on VPD to approximate the changes in FMC. However, since the correlation coefficient, r, between scaled SMC and VPD under wet soil conditions is 0.38, this worsens the model fit relative to incorporating SMC directly.

The effects of including/excluding SMC as a predictor of FMC based on observational data from the Upper Providence CZO are summarized in Fig. 3. Panels A-F of this figure show predicted 1-h (left-hand column) and 10-h (right-hand column) FMC time-series using 1) daily observed SMC (A, D), 2) season-averaged SMC (B,E) where the average was taken over the snow-free period within which the fire season could feasibly occur, and 3) regressions excluding SMC (C,F). At this site, SMC is >20.9% for approximately 8.3% of the data record, and these wet conditions are responsible for the elevated predictions of 10-h fuel moisture at the beginning and end of the snow-free period. We note that the high FMC predictions in the Fall are subject to an assumption of stationarity in the fitted SMC-FMC relationship under drying conditions (when measurements were made) compared to wetting conditions (when first winter rains arrive on a dry landscape), and may overestimate FMC during these periods.

For both 1-h and 10-h fuels, the inclusion of the daily SMC increases the variability in predicted FMC, although this is much more pronounced for 10-h than 1-h fuels. Comparing Panels F and E in Fig. 3 shows that where soil moisture is included but held constant, the other variables produce little FMC variability. Because seasonally averaged SMC is <20.9%, only the dry-soil regression values are being used to predict 10-h FMC. Unsurprisingly, this means that the predictions do not indicate increases in 10-h FMC during early spring and late fall. Comparing Panels D and F indicates that when daily SMC is included, both the predicted peak FMC and the within-season variability in predicted FMC is greater. Additionally, the predicted decline in early season FMC, and increase (where present) in late season FMC is less dramatic for the model including SMC (panel F) vs the one that excludes FMC (panel D).

We conclude that the use of SMC in FMC predictions marginally improves model fit using the Blodgett Forest data and marginally increases predictions of peak FMC and within-season FMC variability for 1-h fuels, relative to models that omit SMC when fitting, or that hold SMC constant. The use of SMC in FMC predictions for 10-h fuels has a large impact on the model fit of Blodgett Forest data and increases predicted FMC peaks in spring and fall based on the 10-year Providence Creek CZO data.

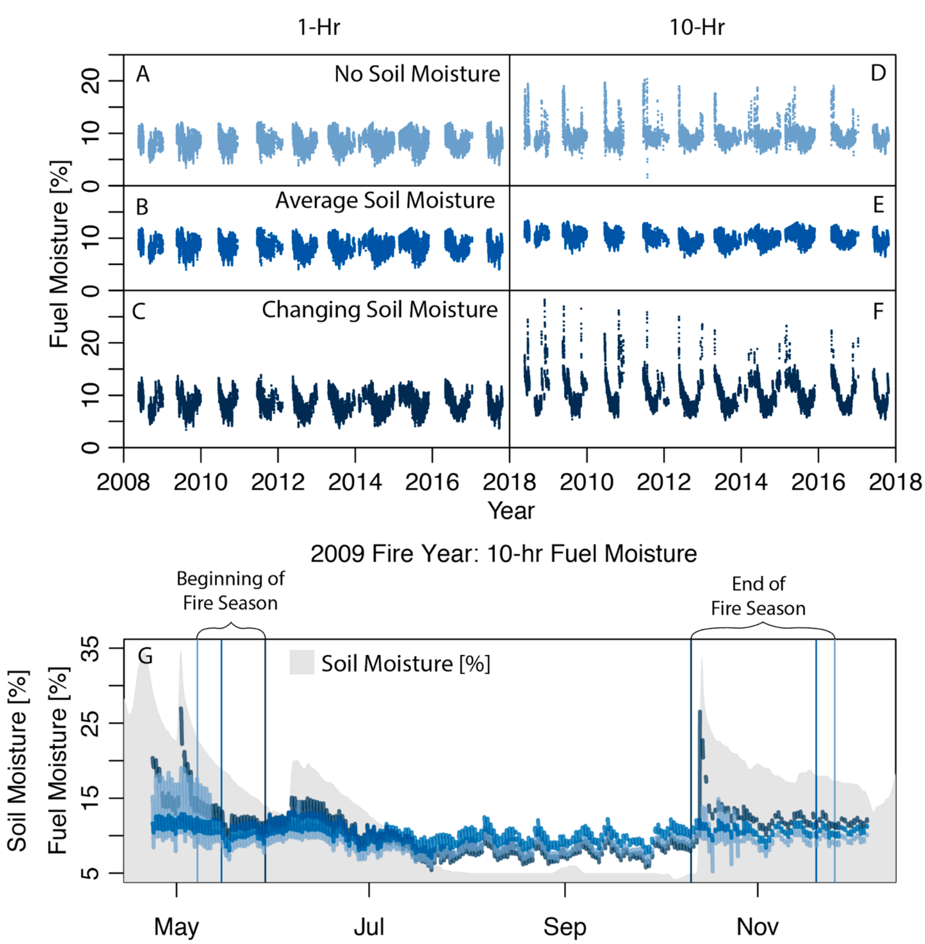

Fig. 3. 1-h FMC at Upper CZO Providence site from 2008–2018 predicted by: A) linear regressions trained on data without SMC; E) OLS regression with season-averaged SMC values, and F) OLS regression with daily soil moisture values. 10-h FMC at Upper CZO Providence site from 2008–2018 predicted by: D) two linear regressions trained on data points below and above fuel moisture content of 20.9%, but excluding soil moisture; E) segmented linear regression with season average soil moisture values, and F) segmented linear regression with daily soil moisture values. G) Ten-hour FMC, SMC, start, and end of the 2009 fire season (vertical lines) are shown in dark blue based on changing soil moisture model, blue for average soil moisture model, and light blue for the model that excludes soil moisture. The start of the fire season was determined as the 5th percentile of days of the year with the recorded probability of ignition of 30% or greater. The end of the fire season corresponds to the 95th percentile. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. Research Question 3: What are the practical implications of inclusion or exclusion of soil moisture on the timing of fire season and spatial variation in fire risk?

3.3.1. Temporal effects of including soil moisture on predicted fire season timing

First, we consider the implications of SMC variations on the yearly timing of the season when ignition probabilities are > 0.3 for each fuel type. In our results we refer to this as the 'fire season', recognizing that this is somewhat arbitrary, but is useful for analysis. Associating a 'fire season' with 1-h and 10-h FMC reflects their high surface area to volume ratio, which promotes ignition, fire spread, and propagation (Bennett et al., 2010; Gould, 2003).

Fig. 3-G illustrates how the dates associated with the start and end of the fire season varied in 2009 depending on the use of daily SMC, or season-averaged SMC, or the complete exclusion of SMC from the FMC model. As illustrated, the higher FMC in the early spring and late fall greatly curtail the period of time of elevated ignition probabilities for the 10-h fuels. Meanwhile the predictions based solely on weather/topographic variables or season-averaged soil moisture only, tend to predict lower FMC during these times, and thus earlier starts and later ends to this fire season. Notice, however, that during the height of the fire season (August - October), the predicted FMC is actually lowest in the daily SMC model, illustrating the potential for FMC predictions based on SMC inclusion to also be lower than those that exclude SMC as a predictor variable. If dry conditions arrive in the early spring or late fall, it is possible that SMC based predictions could extend the fire season relative to predictions that fix or neglect SMC.

Indeed, as summarized in box-and-whisker plots for both 1-h and 10-h fuels in Fig. 4, the shrinking of the fire season is not universal; the inclusion of soil moisture barely alters the timing of the fire season for 1-h fuels (which starts 4 days later and ends 2 days earlier if SMC is considered in the regression, compared to the other models), but tends to significantly delay the onset of the fire season and the timing of its end for the 10-h fuels. In particular, dry soil conditions may prolong the fire season, even when meteorological conditions suggest fire risks are lower (whisker on the end of fire season changing soil moisture plot extends beyond the whiskers on the other models). At this site, snowmelt saturates spring soils and retains wet soil conditions well into the warm season, accounting for soil moisture significantly delays the predicted timing of the season start, by approximately 35 days. Although there is more variation at the end of the dry season, accounting for soil moisture increases FMC enough to lower ignition probabilities some 2–3 weeks earlier than predictions based on average or lack of SMC. The total length of the predicted fire season in any specific year, however, can be greater or lesser when SMC is included in predicting FMC (data not shown). Furthermore, the predicted fire season may also change depending on the probability of the ignition threshold chosen to represent fire risk conditions.

3.3.2. Spatial effects of including soil moisture on predicted ignition probabilities

Spatially distributed probability of ignition maps for the Illilouette Creek Basin were derived for 10-h fuels in the spring and fall of 2017 using the changing soil moisture FMC model and the no SMC model (see Appendix C). Differences in the resulting predicted probability of ignition for both periods are shown in Fig. 5. In this map, red colors indicate that the probability of ignition is higher at a given location if the model accounts for SMC, and blue colors mean that the probability of ignition is lower if the model accounts for SMC (Fig. 5).

During spring conditions, including SMC in predictions tends to reduce predicted ignition probability in mid-elevations of the basin, particularly along the riparian areas, meadows, and creeks. Even during spring, however, low elevation areas in the basin, particularly those with no shading, and some higher-elevation locations with high slope gradients, had sufficiently low soil moisture and/or warm temperatures,

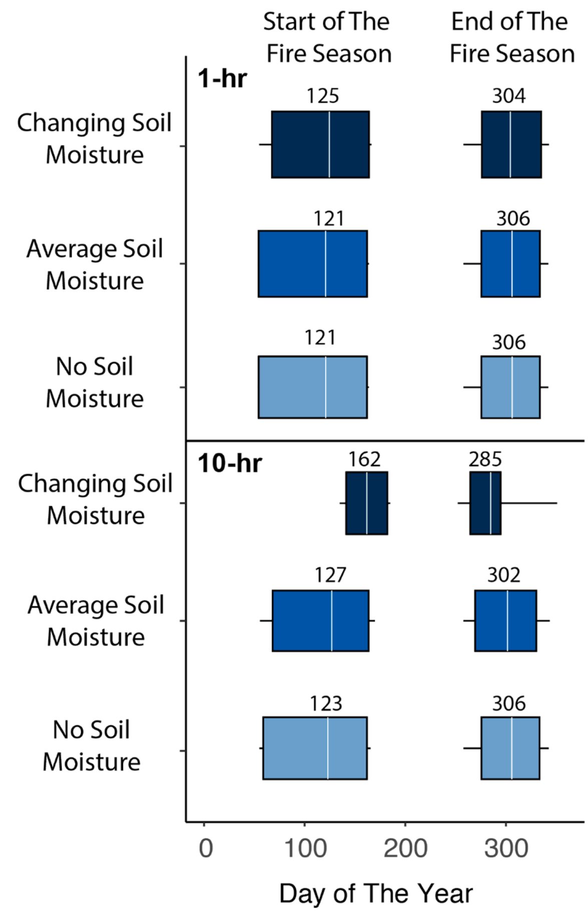

Fig. 4. Box-and-whisker plot of the start and end of the fire season based on 1-h (top) and 10-h (bottom) FMC. The min and max of the start and end of the fire season are summarized as vertical lines, 25th and 75th percentiles as boxes, and mean as vertical white line with a numerical summary above. Fire season was calculated as a function of air temperature, shading, and fuel moisture. The beginning and end of the fire season is defined as the 10th and 90th percentiles of the number of days since January 1st of each year where the probability of ignition is greater or equal to 30%.

that the model including SMC predicted high ignition probability than SMC-excluding models. In the fall, areas predicting a lower probability of ignition if SMC is included expand around riparian corridors which retain elevated soil moisture conditions into the fall. Though the difference between fire ignition probabilities (with SMC and without SMC) is less drastic than in the spring. Some high elevation and steep-slope areas predict a higher probability of ignition when SMC is accounted for.

These temporal (Providence Creek) and spatial (Illilouette Creek) analyses indicate that including SMC variability in FMC predictions can have large impacts on how models might predict the probability of ignition through time and space, in response to heterogeneous soil moisture conditions.

4. Discussion

Using field sampled weather and soil moisture conditions, we have fit regression models to predict 1-h and 10-h FMC. During dry soil moisture conditions, atmospheric and shading conditions explain FMC best. For 1-h FMC, canopy percentage explains most (56%) of the variation in FMC, followed by VPD which explains 26% of the variation in FMC. The remaining variation is then explained by solar angle (10%), SMC (6%), and binary presence of breeze/wind (2%).

For coarser, 10-h fuels, the relationship between SMC and FMC appears to be segmented; during dry soil conditions, SMC has little effect

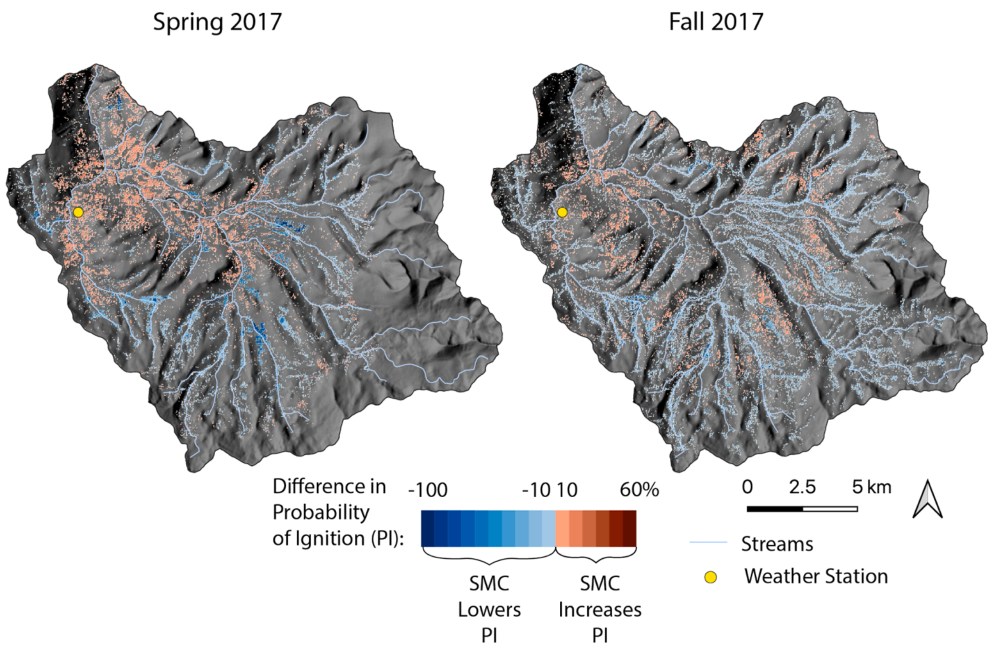

Fig. 5. The difference in the probability of ignition between regression model trained with soil moisture and model that was trained without soil moisture. VPD (one of the FMC predictors) is calculated using a temperature lapse rate of −0.007 °C/m. Temporal weather station (yellow dot) record was used to calculate VPD. Soil Moisture was calculated based on Boisramé et al. (2017). Canopy cover was obtained from LANDFIRE for year 2016 (USGS, 2016). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

on FMC (explains 24% of variation in FMC though not significant at 0.05 level), however during wet soil conditions, SMC explains 84% of the variation in FMC (significant at 0.01 level) When soil moisture conditions are dry, canopy percentage and VPD remain strong drivers of FMC, explaining 40% and 14% of the variation in FMC. Solar elevation and wind binary explain the other 10% and 11% of variation respectively.

Much of this study has focused on the effects of SMC on 10-h FMC, rather than emphasizing results for 1-h fuels. This focus is intended to explore the most interesting implications of the study findings, but should not be interpreted as an exaggeration of the importance of SMC for predicting fire risks. Clearly, where 1-h fuels are more significant drivers of fire risk than 10-h fuels, SMC variations will be relatively unimportant in determining fire risk by comparison to meteorological variables.

However, our 10-h fuel findings on the effect of shading and atmospheric variables on FMC are consistent with work by Ray et al. (2010) who found VPD and leaf area index to be significant predictors of surface leaf moisture content. When soil moisture was not available, Masinda et al. (2021) found that temperature and relative humidity best explained FMC in North China pine forest. However when soil moisture was measured, it was the most important predictor of FMC. In most models that exclude soil moisture, authors reported bias towards underestimating fuel moisture for wet fuels (Ray et al., 2010; de Dios et al., 2015). Our finding that SMC is an important driver of FMC during wet soil conditions may partially explain this bias.

The data from Blodgett Forest suggest that both 1-h and 10-h fuel moisture contents vary with soil moisture, but with different sensitivities which we attribute to differences in the rate at which these fuels dry out via evaporation. In this interpretation, the relatively weak response of 1-h fuels to SMC reflects the larger surface-to-volume area of these finer fuels, which enables rapid loss of water in response to increasing atmospheric water demand. The flow of water from wet soils to fuels is expected to be comparatively slow, meaning that atmospheric and radiative conditions impose a stronger influence on the variation in FMC than does the soil water - that is, FMC in the 1-h fuels appears to be mostly controlled by the ‘demand’ for evaporation. By contrast, the smaller surface-to-volume area of coarser fuels slows the rate of drying due to evaporation (Nelson, 2000; Matthews, 2014), reducing the sensitivity of 10-h FMC to atmospheric and radiative conditions, and increasing the importance of slower and more consistent water fluxes provided by soil moisture. FMC in the coarser fuels therefore seems to be more controlled by water ‘supply’ than demand. A dependence on supply would be consistent with the observed increase in sensitivity of FMC to SMC under wet soil conditions, which would tend to increase the rate of supply.

The sensitivity of 10-h FMC to wet soil conditions is likely to be important under a variety of conditions. In the snow-driven Mediterranean climates of the Sierra Nevada, wet soil conditions following spring snowmelt can co-exist with other-wise fire-prone atmospheric conditions. Excluding soil moisture from FMC predictions could result in an under-estimation of FMC and over-estimation of fire risk at these times. Similar effects could take place following fall rainfall. That said, it must be recognised that the measurements made in this study took place in the context of a wet landscape that was drying in the spring. There is a potential for the SMC-FMC relationships to be hysteretic (to differ under wetting versus drying conditions), which may alter the non-linearity or strength of the SMC-FMC relationship. Further field and laboratory experimentation to better characterise the SMC-FMC relationship in drying versus wetting conditions would be useful to resolve this issue. It would also be valuable to increase the observations made in wet soil conditions from the $n = 22$ obtained in this analysis.

The time-series analysis of the SMC and meteorological data from the Upper Providence CZO suggests that changes in the inferred fire season attributable to the inclusion of SMC were greatest under drying conditions in the spring. Unsurprisingly, the impacts of SMC inclusion on FMC predictions were minimal for 1-h fuels (shortening the fire season by 6 days overall). However, for the 10-h fuels, the greatest impact was to shorten the fire season on average by 39 days. Impacts in the fall were smaller, with the fire season predicted to end 21 days earlier - assuming that the association between FMC and SMC was the same under wetting conditions in the fall as it was under drying conditions in the spring. While it is difficult to anticipate how much the FMC-SMC relationship might change when fuels and soils were both originally dry, we would expect originally dry conditions to weaken the relationship between FMC and SMC, so that the regression model would overestimate the reduction in fire season length in fall. However, even discounting the SMC-FMC behavior in fall, inclusion of SMC in the models increases FMC and is likely to reduce ignition probability in the shoulder seasons. The specifics of how much ignition probabilities change are specific to the minimum FMC used to scale the time-series of FMC from the regression model predictions. If local FMC observations were lower than the minimum observed during field observations at Blodgett, predicted FMC would be lower overall, and the inclusion of SMC would result in a less dramatic change in ignition probabilities.

Spatially, SMC influences the distribution of 10-h FMC as well. Inclusion of SMC in the models caused both increases and decreases of the probability of ignition relative to a model that excludes SMC completely. In the spring, there are areas that predict a much lower probability of ignition (relatively to models that exclude changing SMC) around riparian areas due to heightened SMC. These wet areas may be crucial as fire-breaks by preventing extensive fire spread throughout the landscape, an inference supported by observations that early spring prescribed fires in the Sierra Nevada produced only patchy fuel consumption (Knapp et al., 2005). However, in mid summer when soil moisture is at its lowest, these dry soils tend to lower FMC predictions, increasing the predicted probability of ignition in some areas of the landscape.

While this study suggests that there is potential to improve the understanding of the spatial and temporal variations in fire risk by incorporating observations/predictions of SMC into FMC predictions, many challenges remain before SMC-FMC relations could be generalised for the purpose of such predictions. These challenges include: (i) characterising SMC-FMC relations across different soil types, which are expected to influence the strength and non-linearity of the SMC-FMC relation, (ii) characterising SMC-FMC relationships for other fine fuel types, notably litter, which often comprises the bulk of fuel loads (Burrows et al., 2006) and could have a different dependence on soil moisture than fine woody fuels (Keith et al., 2010; Raaflaub and Valeo, 2009). In the present study, sampling was confined to locations with low litter content. However, in areas with heavy litterfall and accumulation, it is likely that soils, litter, and woody fuels could interact to modify evaporation and water fluxes, and consequently litter and fuel moisture content (Mahdavi et al., 2017; Matthews, 2005). Additionally, (iii) the physical processes associated with the movement of water from wet soils to woody fuels remain poorly characterised, and could be productively explored in a laboratory setting. Potentially, such process characterisation could enable physical modeling of the water and energy balance of the surface soil, litter and fuel layers, which could be helpful for generalising relationships across distinct soil and vegetation conditions. Additionally, (iv), one of the most powerful avenues for incorporating SMC into FMC predictions at landscape scales is the growing number of satellite remote sensing products that are sensitive to soil moisture (i.e. SMAP, SMOS, MWRI, AMSR-E, AMSR2, and many others Kim et al., 2019). However, the spatial resolution of these products is considerably coarser than the point measurements used to derive the current relationship. Resolving these scale mismatches for the purpose of FMC and fire risk prediction could usefully draw on recent advances in scaling of soil moisture observations (Montzka et al., 2018; Peng et al., 2017; Guevara and Vargas, 2019), but the optimal scale for FMC prediction, and how to inform such predictions with satellite SMC observation, remain essentially open questions. Finally (v), many existing FMC predictions adopt a two-stage approach in which environmental conditions are initially used to predict equilibrium moisture content (EMC) which is then combined with information about fuel characteristics to estimate the fuel moisture content (Matthews, 2014; Masinda et al., 2021; Nelson, 1984). This modeling procedure is quite different to that adopted in the statistical models here, and further research would be needed to establish how soil moisture variations might impact EMC, and whether modeling FMC from estimated EMC is operationally preferable to predicting FMC directly from environmental variables as was done in this study (de Dios et al., 2015).

5. Conclusion

This study demonstrated that under soil, weather, and vegetation conditions broadly representative of Sierra Nevada mixed conifer forests, fuel moisture covaries meaningfully with soil moisture, and that this covariation is particularly strong for 10-h fuels under wet soil conditions. Neglecting the relationship between soil moisture and fuel moisture when predicting fire risk is likely to over-estimate ignition probabilities under wet soil conditions, particularly in the spring, and to mis-characterise spatial patterns in ignition risk. More research is required to understand fuel moisture relations to soil moisture under: wet soil conditions specifically, wetting and drying conditions separately, different soil types, and in the presence of leaf litter layers. Such observational studies would be usefully complemented and informed by a better characterisation of the physical processes governing water and energy balances at the soil surface and between mineral soil, litter, and fuel layers. Nevertheless, the results, albeit preliminary, indicate that resolving the effects of soil moisture on fuel moisture could meaningfully improve fuel moisture predictions relative to the status quo of neglecting soil moisture variations. These improvements are most likely to arise under situations where soil moisture variations are not well correlated with variations in fire weather conditions - for instance in transitions between seasons, following snowmelt, and in wet locations in heterogeneous landscapes. With fire and water cycles both changing rapidly in mountainous areas like the Sierra Nevada, better characterising and understanding their influences on each other will be helpful for predicting and responding to changing risk profiles.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

National Science Foundation EAR grant 1013339 funded this work.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.foreco.2021.119379.

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