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A semi-mechanistic model for predicting the moisture content of fine litter

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ABSTRACT

The moisture content of vegetation and litter (fuel moisture) is an important determinant of fire risk, and predictions of dead fine fuel moisture content (fuel with a diameter <25.4 mm) are particularly important. A variety of indices, as well as empirical and mechanistic models, have been proposed to predict fuel moisture, but these approaches have seldom been validated across temporally extensive datasets, or widely contrasting vegetation types. Here, we describe a semi-mechanistic model, based on the exponential decline of fuel moisture content with atmospheric vapor pressure deficit, that predicts daily minimum fuel moisture content. We calibrated the model at one site in New South Wales, Australia, and validated it at three contrasting ecosystem types in California, USA, where 10-h fuel moisture content was continuously measured every 30 min over a year. We found that existing drought indices did not accurately predict fuel moisture, and that empirical and equilibrium models provided biased estimates. The mean absolute error (MAE) of the fuel moisture content predicted by our model across sites and years was 3.7%, which was substantially lower than for other, commonly used models. Our model's MAE dropped to 2.9% when fuel moisture was below 20%, and to 1.8% when fuel moisture was below 10%. Our model's MAE was comparable to instrumental MAE (3.1–2.5%), indicating that further improvement may be limited by measurement error. The simplicity, accuracy and precision of our model makes it suitable for a range of applications, such as operational fire management and the prediction of fire risk in vegetation models, without the need for site-specific calibrations.

1. Introduction

Wildfires require four factors: (1) an ignition source; (2) 'fire weather' (favorable temperature, wind and relative humidity), (3) fuel load (sufficient combustible material to sustain fire); and (4) low fuel moisture (Bradstock, 2010). The moisture content of fine fuel, which is generally defined as litter and woody debris with a diameter less than 25.4 mm (Scott et al., 2014; Viney, 1991), is a particularly critical consideration in fire danger rating systems (Bradshaw and Deeming, 1983; McArthur, 1966; van Wagner, 1987). In turn, fire danger ratings are often used to make short-term decisions on staffing, movement of resources (from low to high risk areas) and restriction of activities (e.g: barbecues in wildland areas or operation of machinery). Dead fine fuel moisture is also an important component of basic fire science and ecological research, which require estimates that can be readily applied at large temporal and spatial scales using remote sensing or other techniques for scaling and, preferably, independent of site-specific calibrations.

A model of dead fine fuel moisture needs to provide accurate and precise estimates across ecosystem types, while maintaining simplicity with respect to input data and computation. Current methods for predicting fine fuel moisture can be broadly classified as drought indices, empirical models and mechanistic models. It is important to note that drought indices were not necessarily developed as dead fine fuel moisture models *per se*, though they are nonetheless used by agencies worldwide as indicators of fuel moisture. Dead fine fuel moisture is an important aspect for fire

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risk and fire propagation, and drought indices are therefore used as surrogates of dead fine fuel moisture.

Viney (1991) and Matthews (2013) reviewed 37 published models for predicting dead fine fuel moisture. A common theme across the reviewed models was a focus on hourly time scales and a paucity of models that operate at daily time steps, as well as a lack of long-term or multiple site validation (Slijepcevic et al., 2013). Studies on fire behaviour or propagation may require hourly model predictions, whereas daily values are required for most other operational and scientific purposes.

Here we test the applicability in the field of a novel, semi-mechanistic model of fuel moisture content that operates at daily time scales, and that is simple with respect to both inputs and computation. The model was designed to predict the daily minimum dead fuel moisture, as this is a key determinant of fire. The model is based on the diffusion of water vapor between hygroscopic dead plant tissue and the atmosphere. Model development and parameterization were performed at a temperate forest in SE Australia. The model was then tested with data from three contrasting Mediterranean ecosystem types in California (Table 1). The development of the model was originally motivated by the observation that drought indices and empirical models led to poor predictions of dead fine fuel moisture, and that mechanistic models are too complicated for many uses.

2. Methods

2.1. Model development

We developed a deterministic, steady-state model of minimum daily dead fine fuel moisture (FM) that operates at 24 h time-steps. The model assumes that: (1) fuel-to-air vapor pressure deficit (D_f, the difference between the saturation vapor pressure at the temperature of the evaporating surface of the fuel and the vapor pressure of the air) is the main driver of FM; (2) that the relationship between FM and D_f in the field is exponential; and (3) that equilibrium between FM and D_f is reached within one day:

$$\mathrm{FM}_{\mathrm{Df}} = \mathrm{FM}_0 + \mathrm{FM}_1 e^{(-\mathrm{m}D_f)} \quad (1)$$

where FM_0 is the minimum measured fuel moisture, $\mathrm{FM}_0 + \mathrm{FM}_1$ the maximum measured fuel moisture, and m defines the rate of moisture decay with increasing D_f (Motulsky and Christopoulos, 2003; Motulsky and Ransnas, 1987). We are interested in minimum daily fuel moisture; D_f indicates the maximum daily fuel-to-atmosphere vapor pressure deficit, and $\mathrm{FM}_{\mathrm{Df}}$ indicates the minimum daily fuel moisture modelled from D_f.

Fuel particles with diameters of 25.4 mm or less typically have a time-lag (time to reach 1/e of the final response) of 10 h or less (Viney, 1991), and so we assume that temporal auto-correlations between FM and D_f will be of less than one day. We further tested this assumption by examining the lagged correlation between field values of FM and vapor pressure deficit measured every 30 min.

Under field settings, an uncoupling between D_f and D could occur if the temperature at the evaporating site (fuel surface) is different from air temperature. To circumvent this problem, and to avoid needing to know the surface temperature, we followed Monteith (1965), where:

$$D_f = D + s(T_f - T_a) \quad (2)$$

with s, T_f and T_a indicating the slope of the saturation curve, and fuel and air temperatures, respectively. The difference in fuel to air temperature depends on the ratio between the sensible heat flux

Table 1
Site descriptions.

Site name	Dominant vegetation	Latitude (°)	Longitude (°)	Elevation (m)	Long-term			During data collection			
					Mean annual rainfall (mm)	Mean maximum temperature (°C)	Mean minimum temperature (°C)	Year	Duration of longest dry spell (days)	Maximum rain event (mm)	Maximum temperature (°C)
Cumberland Plains	Eucalypt and Melaleuca	−33.6153	150.7237	25	801	29.0	3.0	2013	38	109.8	45.5
SCCG Sonoran desert	Desert perennials and annuals	33.6518	−116.3721	275	129	28.8	12.9	2008	295	20.3	47.7
SCCG Pinyon/Juniper Woodland	Pinyon and Juniper	33.6049	−116.4547	1280	313	23.6	8.0	2007	109	28.5	35.6
SCCG desert Chaparral	Desert Shrubland	33.6100	−116.4502	1300	313	23.6	8.0	2007	89	44.4	38.2

(H) and the product of heat conductance (g_H) and the volumetric heat capacity of dry air (ρ_a and C_p)

$$T_f - T_a = \frac{H}{(g_H \rho_a C_p)} \quad (3)$$

g_H is readily available from the wood science literature (Glass and Zelinka, 2010) and H can be obtained from the energy balance of the fuel which, assuming negligible heat storage, is defined as:

$$H = \mathrm{Rn} - \mathrm{LE} \quad (4)$$

where Rn indicates the fuel's net radiation, and LE the latent heat lost from the fuel.

Combining Eqs. (3) and (4) with Eq. (2) leads to:

$$D_f = D + s\left(\frac{\mathrm{Rn} - \mathrm{LE}}{g_H \rho_a C_p}\right) \quad (5)$$

and combining Eq. (5) with Eq. (1) we obtain:

$$\mathrm{FM_{Df}} = \mathrm{FM_0} + \mathrm{FM_1} e^{\left(-m\left(D + \frac{s(\mathrm{Rn}-\mathrm{LE})}{g_H \rho_a C_p}\right)\right)} \quad (6)$$

Section 2.4 describes how Rn and LE were obtained. A practical limitation to this approach is that it requires knowledge of Rn and LE, which may limit the applicability of the model. Given the short-time lag of dead fine fuels, we expect D and D_f are coupled or, at least, correlated within the time-frame of interest. Thus, we also tested whether fuel moisture could be approximated by:

$$\mathrm{FM_D} = \mathrm{FM_0} + \mathrm{FM_1} e^{(-mD)} \quad (7)$$

where $\mathrm{FM_D}$ indicates fuel moisture is modelled from air D.

We ignored the effect of hysteresis in the relationship between FM and relative humidity, which has been reported in drying-wetting cycles (van Wagner, 1972), as will be described in more detail below.

$\mathrm{FM_D}$ implicitly incorporates the effects of new precipitation, as we discuss below. This model also assumes that seasonal changes in processes that affect the time lag of fuel moisture, such as litter depth, are negligible. Even if the relationship between dead fuel and time lag is considered as solely dependent on the thickness of the individual components of the fuel complex, the effective time-lag of the litter layer may change if, for instance, the depth of the litter layer increases with leaf fall in autumn. The model thus assumes that changes in litter depth, or other processes that affect the time to reach equilibrium, do not increase the time-lag of FM to the point where minimum daily FM is decoupled from maximum daily D. Unless otherwise noted, FM refers to daily minimum fuel moisture, D refers to daily maximum air D, and D_f refers to daily maximum fuel-to-atmosphere D.

2.2. Study sites

Initial model calibration and initial validation were performed at a site in the Cumberland Plain woodland in Eastern New South Wales, Australia (25 m above sea level, Table 1). The study was then expanded to include three sites across an altitudinal gradient (275–1300 m above sea level, Table 1) in Southern California, USA (Goulden et al., 2012). Each site was equipped with eddy covariance instrumentation to continuously measure meteorology and energy exchange. The instruments were mounted near the tops of towers that extended 5–10 m above the canopy. Temperature and relative humidity were measured with HMP probes (Vaisala, Helsinki, FI).

2.3. Fuel moisture measurements

Fuel moisture measurements were logged every 30–60 min (CR 1000 or 3000 or 5000, Campbell Sci Logan, UT, USA) with 19-mm diameter dowels connected to sensors (CS505, Campbell Sci Logan,

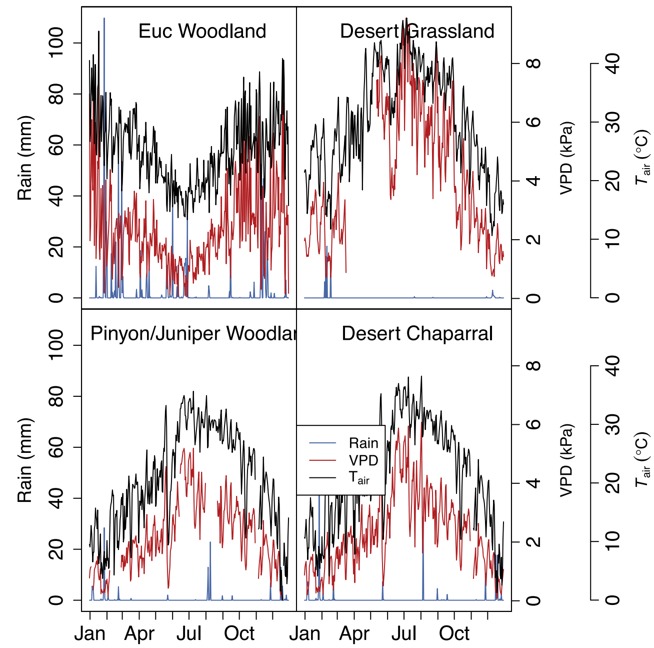

Fig. 1. Temperature, vapor pressure deficit (D) and rain during the study years and across sites. Intra-annual variation in these parameters was large enough to allow us to asses fuel moisture models under a broad range of ecosystem types and environmental conditions.

UT, USA). We refer to these observations as $\mathrm{FM_{CS505}}$. Each California site had 1 or 2 dowels placed at ground level. At the Australian site, we had 3 dowels that were placed 0.30 m above the ground facing North. There was always a very strong correlation between the different sensors within a site (R^2 = 0.97–0.99, data not shown), indicating that low replication within a site was not problematic. Our fuel moisture model should be relatively insensitive of sensor location provided the sensor is not buried under a deep litter layer, which might decouple its moisture from atmospheric conditions over 24-h period.

Data were continuously collected for one year at each site. The time series provided a diverse set of intra-annual environmental conditions, from 'very dry' to 'very wet', which allowed testing the model under a broad range of environmental conditions (Table 1, Fig. 1). All sites experienced prolonged dry periods: between 38 and 295 days without rain depending on the site, accompanied by occasional very hot days (as high as 47.7 °C). All sites experienced wet periods (>20.3–109.8 mm d^{-1}) that should have saturated the FM. Even small water inputs can saturate FM (Viney, 1991), and we conservatively defined rainy periods as days with 2 mm or more precipitation.

We performed an *a posteriori* cross-calibration of the sensors, using the Australian data as a benchmark, to ensure comparability across sites. We quantified instrument error by comparing the $\mathrm{FM_{CS505}}$ at the Cumberland Plain site with manual measurements of moisture content in 25.4–6.35 mm ('10-h') suspended fuel particles (theoretically equivalent to $\mathrm{FM_{CS505}}$), <6.35 mm ('1-h') suspended fuel particles and 1-h ground fuel particles (profile) at fortnightly to monthly intervals. Fifteen samples of each fuel type were collected on each sampling date, and the fresh and oven dry (105 °C for 48 h) weights recorded.

2.4. Model parameterization and validation

Model calibration (parameter m, Table 2) was performed using only 25% of the Australian dataset (the first 90 days of the year). The remaining 75% of the Australian data, and 100% of the Californian

Table 2
Initial model calibration and validation at the Cumberland Woodland Plains. The validation dataset is independent from the calibration dataset and includes 75% of the collected data (the parameterization dataset is comprised of the remaining 25%). FM_0 and FM_1 are the measured minimum fuel moisture and the maximum minus minimum fuel moisture, respectively. The only estimated parameter was the slope in the relationship between fuel moisture and *D*. Error intervals, when present, indicate 95% CI.

Model	Measured parameters	Estimated parameter		Validation					
	FM_0	FM_1	m	AIC	MBE	MAE	R^2	β_1	β_0
Eq. (1)	5.43	52.91	0.85 (±0.14)	480	5.35	5.93	0.69	0.90 (±0.08)	6.79 (±1.22)
Eq. (6)	5.43	52.91	1.14 (±0.14)	475	2.85	4.92	0.56	0.90 (±0.09)	4.28 (±1.60)
Eq. (7)	5.43	52.91	0.64 (±0.04)	461	2.39	4.53	0.59	0.91 (±0.09)	3.65 (±1.56)

data, were used for model validation. Model calibration was conducted by non-linear squares fitting using the base packages within the R software environment (R Development Core Team, 2013).

Rn in Eqs. (5) and (6) (Rn below canopy, Rn_{bc}) was calculated as:

$$Rn_{bc} = Rn_{ac} \times (1 - FAPAR) \tag{8}$$

where Rn_{ac} is above canopy Rn (NR01, Huskeflux, The Netherlands) and FAPAR the fraction of absorbed Photosynthetically Active Radiation (from MODIS). LE in Eqs. (5) and (6) was obtained from the evaporation rate (daily changes in fuel moisture content measured with the CS505).

The model was then validated by calculating mean absolute error (MAE), mean biased error (MBE, with positive and negative values indicating tendencies towards over- and under-prediction, respectively), the intercept (β_0), slope (β_1) and R^2 of the regression between predicted and observed values, as well as the Akaike Information Criterion (AIC):

$$AIC = n\log\left(\frac{RSS}{n}\right) + 2(p+1) \tag{9}$$

where n is the sample size, RSS the residual sum of squares and p the number of parameters. The model with the smallest AIC is considered the most parsimonious, with absolute differences of 8 indicating a significantly better model (Akaike, 1974; Burnham and Anderson, 2002). These metrics of model performance were computed over the entire dataset, and then additionally when FM_{CS505} was below 20% and 10%, as these are the critical ranges of fuel moisture for fire occurrence.

2.5. Model comparison

2.5.1. Comparison with drought indices

We compared our model with a suite of previously published models that were selected to represent a range of possible approaches. We compared the performance of our model against the drought index proposed by Keetch and Byram (1968; KBDI), and the drought factor (DF) in McArthur's Forest Fire Danger Index (McArthur, 1966; McArthur, 1967). These two indices, along with the Canadian Forest Fire Weather Index (van Wagner, 1987), are broadly used by agencies worldwide, with the latter providing very similar results to DF (Dowdy et al., 2009).

Additionally, we compared our results against the Fuel Dryness Index (F_d, (Snyder et al., 2006). F_d was additionally chosen as it provides an approach that is independent from other drought indices, empirical and mechanistic models, and because we are unaware of previous published studies that have validated it against field data. F_d was originally developed for grasslands, and depends on the ratio between sensible heat (H) and available energy (A):

$$F_d = \left(\frac{H}{A}\right) \times 100 \tag{10}$$

A was calculated as the sum of H + LE (latent heat flux) to minimise problems associated with energy balance closure. The flux data used in this study were processed and screened to ensure only high-quality data were used in this analysis (Goulden et al., 2012; Goulden et al., 2006).

2.5.2. Comparison with empirical models

As Matthews (2013) points out, all empirical models use a multiple linear regression of the form:

$$FM_{empirical} = a_0 + \Sigma a_i X_i \tag{11}$$

where a_i are fitting parameters, X weather variables, and the subscript empirical denotes that this is the value of FM derived from an empirical model. Empirical models typically use 2 to 4 weather variables. We built an empirical model that contained a relatively large number of weather variables for model comparison (maximum temperature, maximum wind speed, minimum relative humidity and days since last rain). Additionally, we compared our model against the fuel moisture index (FMI), an empirical model that has minimal computational and data demands (Sharples et al., 2009):

$$FMI = 10 - 0.25(T - RH) \tag{12}$$

where T and RH represent temperature and relative humidity. FMI was designed to provide a general 'rule of thumb' of the fuel moisture for operational purposes, although it was envisioned to be used with site-specific tables that relate FMI to actual FM. Despite its simplicity, the model performs well relative to comparatively advanced and mechanistic models of fuel moisture (Sharples and McRae, 2011; Sharples et al., 2009).

There are also a broad variety of mechanistic models of fuel moisture. Many of these models are difficult to implement as they require as many as 26 different parameters (Matthews, 2013). Most mechanistic models rely on Nelson's equilibrium moisture equation (e.g.: Matthews, 2006), based on Gibbs energy (Nelson, 1984b):

$$FM_{Nelson} = a + b\ln\left(\frac{-RT}{M\ln(RH/100)}\right) \tag{13}$$

where a and b are fitting parameters, R and M the universal gas constant and the molar mass of water, respectively. We calibrated all of these models with 25% of the Cumberland Plain dataset, and validated with the remaining 75% of the Australian dataset and 100% of the Californian dataset, following a parallel approach to the one we used for FM_D.

We also compared our model with two additional equilibrium moisture models that are broadly used in the literature. We used the model of Simard (1968) which, although originally developed for curing timber (Viney, 1991) has subsequently been applied within the US National Fire Danger Rating System (Bradshaw and Deeming, 1983):

$$\begin{aligned} &RH < 10\%;\ FM_{Simard} = 0.03 + 0.2626RH - 0.00104RHT \\ &RH \geq 10\%\& < 50\%;\ FM_{Simard} = 1.76 + 0.1601RH - 0.02660RHT \\ &RH \geq 50\%;\ FM_{Simard} = 21.06 - 0.4944RH + 0.00565RH^2 - 0.00063RHT \end{aligned} \tag{14}$$

Finally, we compared our model with the equilibrium fuel moisture model of van Wagner (1972), currently implemented in the Canadian Forest Fire Weather Index (van Wagner, 1987). This

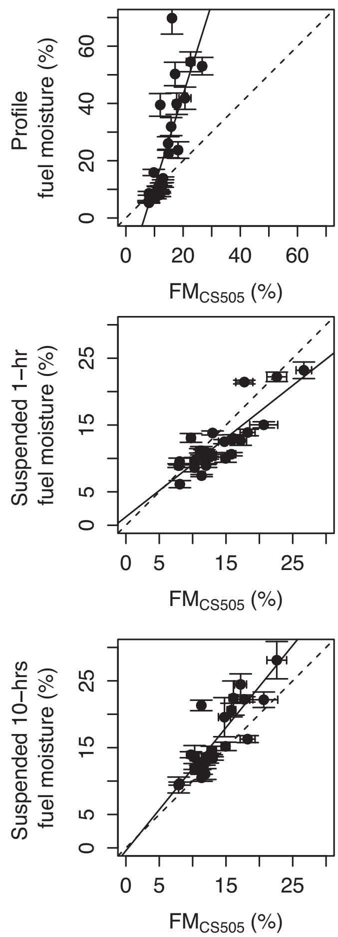

Fig. 2. Comparison between manual measurements of moisture in profile fuel particles (<6.35 mm ground fuel particles), '1-h' (<6.35 mm) suspended fuel particles and '10-h' (25.4–6.35 mm) suspended fuel particles (theoretically equivalent to FM_{CS505}), against FM_{CS505} measurements. The data validate the use of CS505 sensors as an unbiased measurement of suspended 1-h and 10-h fuel.

model takes into account the hysteresis in drying (d) and wetting (w) cycles:

$$FM_{\text{vanWagner},d} = 0.942RH^{0.679} + 0.000499e^{0.1RH} + 0.18(21.1 - T)(1 - e^{-0.115RH})$$
$$FM_{\text{vanWangner},s} = 0.618RH^{0.753} + 0.000454e^{0.1RH} + 0.18(21.1 - T)(1 - e^{-0.115RH}) \tag{15}$$

FM_{Simard}, $FM_{vanWagner}$ and FM_{Nelson} models are so well established in the literature, that they are often used as the benchmark against which other models are compared (Nieto et al., 2010; Sharples et al., 2009).

3. Results

3.1. Field validation of FM_{CS505} data

We found good agreement between both the 10- and 1-h suspended fuel moisture contents and the automated sensors at the Cumberland Plain site (R^2 = 0.80 and 0.71, respectively; MAE = 3.1% and 2.5%, respectively, β_0 was not different from 0 and β_1 was not different from 1 at P < 0.05 for both cases, Fig. 2). The 1-h fuel moisture measurements at the ground surface (profile) fuel were reasonably correlated with FM_{CS505} (R^2 = 0.63), though FM_{CS505} was consistently lower than profile moisture, especially when profile moisture was above 20% (β_1 > 1 at P < 0.05).

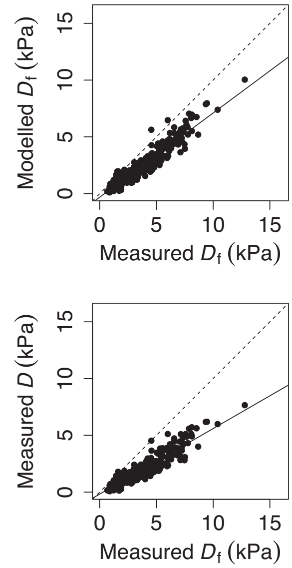

Fig. 3. Relationships between measured fuel-to-atmosphere D (D_f) and modelled D_f (Eq. (5), upper panel) and measured air D (lower panel). D_f was highly correlated with modelled D_f (R^2 = 0.88) and with measured D (R^2 = 0.85).

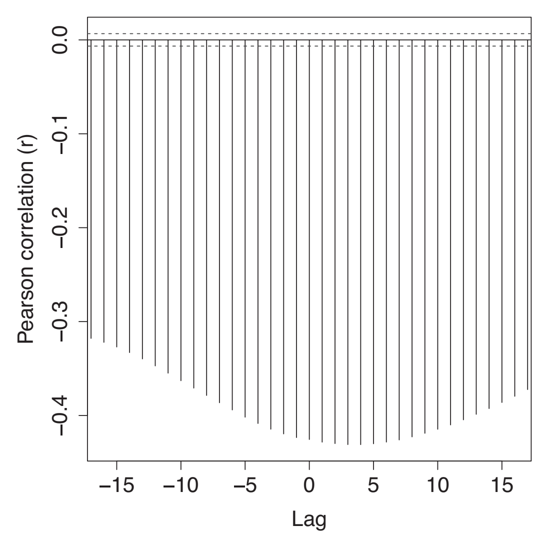

Fig. 4. Results of the lagged correlation (Pearson's r) between half-hourly D and $FM_{CS505.}$ Maximum correlation occurred at lag 4 (that is, 2 h).

3.2. Testing model assumptions

D_f was reliably estimated from Eq. (5) (Fig. 3, R^2 = 0.88, β_0 = −0.31 ± 0.01 mean ± 95% CI, β_1 = 0.74 ± 0.02), and was highly correlated with (albeit significantly lower than) D (Fig. 3, R^2 = 0.85, β_0 = −0.17 ± 0.16, β_1 = 0.58 ± 0.03). Moreover, the assumption that the time lag between half-hourly D and FM_{CS505} is less than a day was corroborated experimentally. Across sites, the maximum absolute lagged correlation occurred at 2 h (four 30-min observations, Fig. 4).

We observed a similar performance for Eqs. (1), (6) and (7), though Eq. (7) had significantly lower AIC than predictions from Eqs. (1) (ΔAIC = 19) and (6) (ΔAIC = 14) at the Cumberland Plains site (Table 2). Eq. (7) also had a lower MBE and MAE, though the R^2 of the predicted vs observed relationship was lower for Eq. (7) than Eq. (1). We compared the fit of Eq. (7) independently for the adsorption and desorption phases with the combined fit for both phases to test whether hysteresis affected model performance. We observed no hysteresis effect on model performance (ΔAIC = 4, data not shown). Additionally, we observed no effect of rain on model performance over the entire validation dataset, and no further correction was deemed necessary (Appendix A). This lack of a rain effect is surprising as the model only accounts for a steady-state equilibrium with the atmosphere, and ignores the effect of water inputs. A partial explanation may be that, during rains, fuel moisture will reach the saturation point (25–30%) after as little as 2 mm of rain (Vinney, 1991) and, concomitantly, D will sharply drop as relative humidity approaches 100%. Therefore, under rain, the range of possible D-FM spaces is very limited (of low D and high FM). At any rate, all these results support the use of the simplified model in Eq. (7), which is the model that will be used from here on.

3.3. Model validation

FM_D had an MAE of 3.67% over the entire validation dataset (Table 3). The performance of FM_D increased over the range of critical fuel moisture for fire occurrence; MAE decreased to 2.91% when FM_{CS505} was below 20%, and 1.77% when FM_{CS505} was below 10%. MAE was similar to or even lower than the reported instrument error (MAE between 2.5 and 3.1%). Moreover, model predictions showed little bias as indicated by low values of MBE (0.73%, to 1.01%, depending on fuel moisture data range), and β_1 was not significantly different from 1 when FM_{CS505} was below 20% or 10% (Table 1).

3.4. Model comparison

FM_D showed superior performance across all conditions and sites relative to the other models. FM_D always had the lowest MAE, MBE and AIC, and β_1 always approached unity. FMI showed a lower AIC than FM_D in the low FM_{CS505} values (<20% and <10%), but higher MAE and MBE, and a β_1 significantly different from 1. Consequently, FMI systematically underpredicted FM_{CS505} at any moisture range, and always showed higher MAE and MBE than FM_D.

$FM_{empirical}$ predicted negative FM_{CS505} at the Desert Grassland site. This was driven by the effect of time since last rain. The model was calibrated with data from the Eucalypt woodland, where the maximum time since last rain was 38 days, whereas time since rain approached 300 days at the Desert Grassland (Table 1). This is a well-recognized problem for empirical models (extrapolation beyond the range of calibration), which require caution when applied at other sites without re-parameterization.

FM_{Nelson} provided the best fits among the other equilibrium models (i.e., in comparison with $FM_{vanWagner}$ and FM_{Simard}), though it had larger errors than FM_D (Table 3, Figs. 5 and 6). FM_{Nelson} reproduced the FM_{CS505} temporal pattern at some, but not all, sites.

The drought indices of KBDI and DF showed comparatively poor performance; they failed to capture the temporal dynamics of FM_{CS505} (Table 3, Figs. 5 and 6) and showed comparatively high errors and biases. F_d usually had the largest errors after KBDI and DF, though it captured the FM_{CS505} temporal patterns at some of the sites, such as the Desert Grassland and the Pinyon Juniper woodland (Fig. 6c).

4. Discussion

We developed and validated a semi-mechanistic model to predict fine fuel moisture based on atmospheric evaporative demand. Our model provides accurate and precise estimates of daily minimum fine fuel moisture across a range of environmental conditions and sites. Our model (Eq. (7)) outperformed existing models and it

Table 3
Final model validation of FM_D (Eq. (7)) across sites. The validation dataset (independent from parameterization dataset) includes 100% of the Californian dataset (at 3 site-years), and 75% of the Australian dataset (at 1 site-year, the parameterization dataset is comprised of only the 25% remaining Australian dataset). Error intervals, when present, indicate 95% CI.

Model	Full dataset						FM_{CS505} <20%						FM_{CS505} <10%					
	AIC	MBE	MAE	R^2	β_1	β_0	AIC	MBE	MAE	R^2	β_1	β_0	AIC	MBE	MAE	R^2	β_1	β_0
FM_D	1797	0.73	3.67	0.67	0.86 (±0.03)	2.55 (±0.56)	1281	0.94	2.91	0.48	1.02 (±0.06)	0.67 (±0.74)	505	1.01	1.77	0.19	1.02 (±0.18)	0.88 (±1.32)
KBDI	4454	75.42	75.41	0.05	−0.21 (±0.05)	91.35 (±0.84)	3811	78.75	78.75	0.09	-0.63 (±0.20)	95.57 (±1.40)	1980	84.01	84.01	0.17	-2.33 (±0.44)	107.24 (±3.34)
DF	4396	71.04	69.02	0.05	−0.22 (±0.06)	87.16 (±0.92)	3763	74.39	74.39	0.09	−0.69 (±0.14)	91.73 (±1.52)	1958	79.81	79.81	0.17	-2.51 (±0.50)	104.24 (±3.50)
F_d	2637	−1.02	9.74	0.20	0.73 (±0.04)	2.55 (±1.34)	2089	−0.16	8.33	0.19	1.36 (±0.17)	−3.90 (±1.98)	870	−1.16	5.53	0.19	2.31 (±0.42)	-10.24 (±3.00)
$FM_{empirical}$	3002	−12.33	14.71	0.33	1.03 (±0.08)	−12.69 (±1.34)	2470	−12.1	13.91	0.27	1.75 (±0.18)	−19.83 (±2.0)	1310	−14.51	15.76	0.26	4.66 (±0.70)	-39.96 (±4.96)
FMI	2024	−3.43	4.58	0.56	0.47 (±0.02)	3.62 (±0.38)	1178	−1.78	3.11	0.45	0.74 (±0.05)	0.86 (±0.56)	474	−0.97	2.40	0.26	1.17 (±0.16)	-2.16 (±1.24)
FM_{nelson}	2481	−8.08	8.69	0.42	0.59 (±0.04)	−2.71 (±0.66)	1888	−6.82	7.31	0.27	0.81 (±0.08)	−4.91 (±0.92)	921	−6.24	6.55	0.11	1.18 (±0.30)	-7.50 (±2.16)
$FM_{vanWagner}$	2308	−6.49	6.63	0.54	0.36 (±0.02)	2.07 (±0.31)	1491	−4.49	4.67	0.41	0.55 (±0.04)	0.17 (±0.44)	581	-3.02	3.26	0.23	0.82 (±0.12)	-1.75 (±0.92)
FM_{Simard}	2476	−7.80	8.04	0.34	0.24 (±0.02)	2.38 (±0.32)	1652	−5.39	5.67	0.19	0.35 (±0.04)	1.31 (±0.50)	622	-3.2	3.7	0.15	0.73 (±0.14)	-1.33 (±1.08)

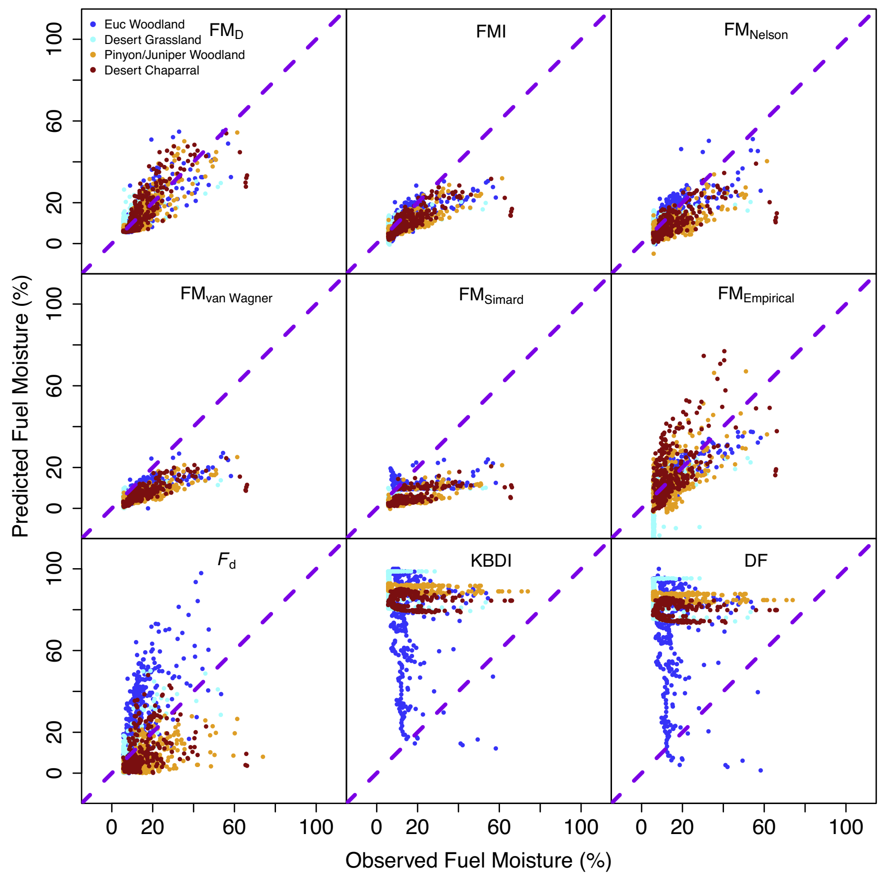

Fig. 5. Predicted vs observed dead fine fuel moisture across models. The dashed line indicates the 1:1 relationship. Different colors indicate different sites. To keep consistency in the scale of the *y*-axis, some negative values predicted by $FM_{empirical}$ are hidden (but can be viewed in Fig. 6a), and KBDI and DF were linearly rescaled such that they would vary between 0 and 100%. The actual values of these 2 drought indices is shown in Fig. 6c. FM_D was the model that best fitted the data over the entire moisture range.

requires just an estimation of the slope of the fuel moisture relationship with *D*, along with knowledge of the range of fuel moistures. The MAE we observed with FM_D was comparable to our instrument error, indicating that further model improvement may be hindered by measurement precision. The model was validated with data collected in a different biome and continent from the data used for parameterization, indicating that the results are generalizable and not site-specific. Our results indicate that fuel moisture (FM_{CS505}) drops below 20% when maximum daily *D* reaches 1.17 (±0.13) kPa, and below 10% at 2.22 (±0.24) kPa; these fuel moistures correspond to increasing combustion probability.

4.1. Implications for fire management

FM_D can be readily calculated for operational purposes. Once the microclimatic parameter, *D*, has been determined, fuel moisture can then be easily calculated (Eq. (7)) with parameters from Table 2.

Many previous studies of fuel models emphasized moistures below 30% to 20% (Nelson, 1984a; Sharples and McRae, 2011; Slijepcevic et al., 2013), which is the range below the fibre saturation point, and at which fuel typically becomes available for burning. It is thus not surprising that FMI, FM_{Nelson}, FM_{Simard} or $FM_{vanWagner}$ showed a bias toward underprediction over the entire data range, with MBE ranging from −3.43 to −8.08%, depending on model. We suspect that this type of underprediction leads to a large number of 'false positives' (underestimating high FM), and that the tendency toward 'false positives' may limit the utility of fuel models for operational purposes. Accurate estimates of fuel moisture when the fuel bed is relatively dry are obviously important, but the ability of a model to predict high bed moisture should not be neglected. FM_D, with an MBE of 0.73% and an MAE of 3.67%, was the only model that was able to predict fuel moisture under both wet and dry conditions (Table 2).

Under low moistures (FM_{CS505} < 20% and FM_{CS505} < 10%) FMI showed lower AIC than FM_D, indicating higher model parsimony. This can be explained, at least partly, because FMI did not require any parameter estimate. However, FM_D showed lower MAE, MBE and β_1 not different from 1.

Our study cautions against the use of drought indices as proxies for FM. This is not surprising, as Keetch and Byram (1968) noted 'We emphasize that the drought index described in this report is not in any way a substitute for ... moisture parameters'. Nonetheless, KBDI and McArthur's drought factor (which is based on KBDI) are widely used for both operational and research purposes.

New models are often either compared against other models rather than field data (Sharples et al., 2009; Snyder et al., 2006), or are compared against only brief time series of field data (Matthews, 2013; Viney, 1991). This approach assumes that 'benchmark models' such as FM_{Nelson}, $FM_{vanWagner}$or FM_{Simard} provide accurate estimates of field FM (Table 3). In turn, this implies that progress toward a universal model of fuel moisture may be hampered by a lack of field data. Our strategy focused on both the development of a semi-mechanistic model of dead fine fuel moisture, and the validation of the model against observations that were collected in contrasting ecosystem types.

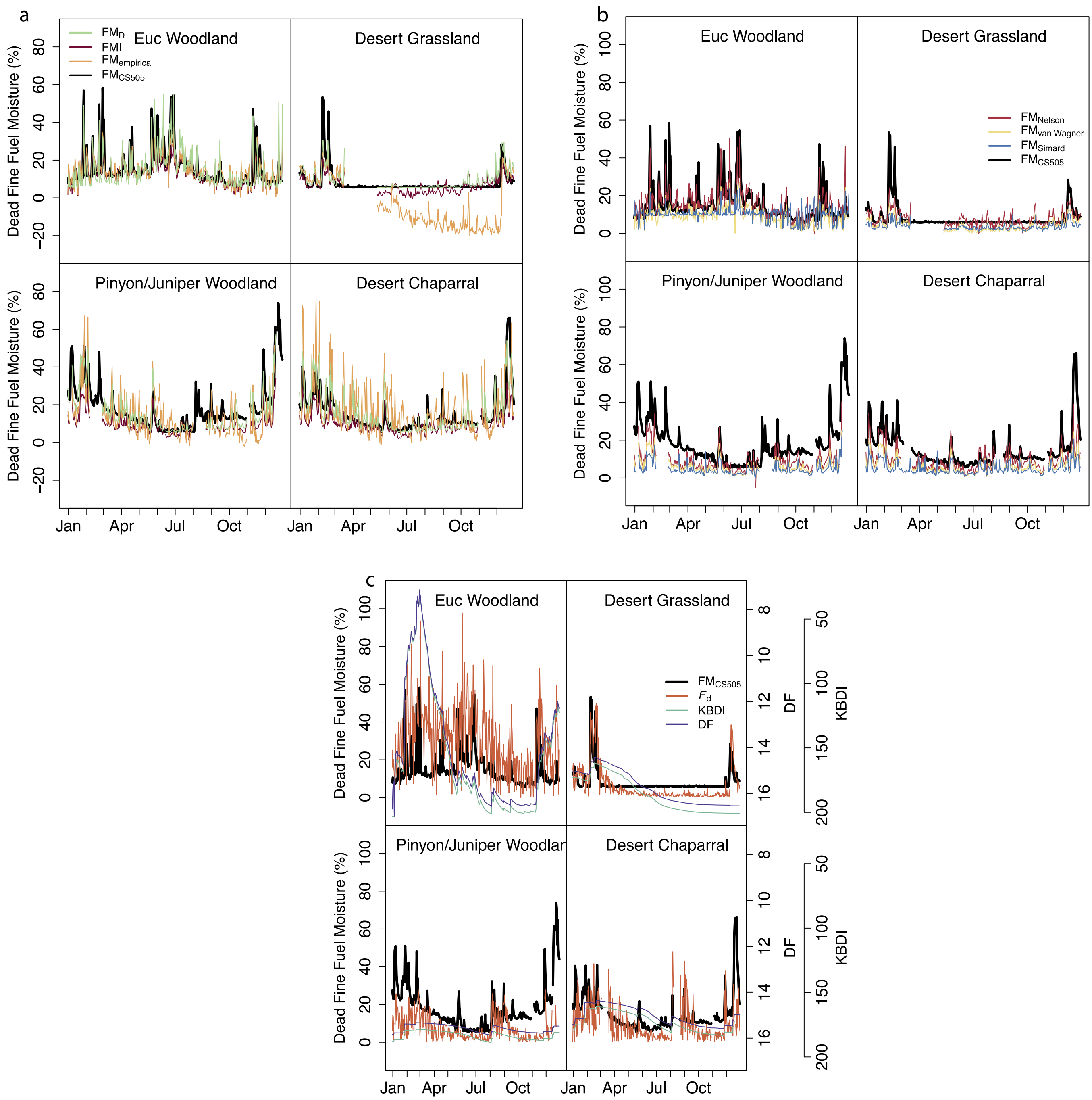

Fig. 6. Temporal pattern of (a) observed fuel moisture (FM_{CS505}) and fuel moisture modelled from FM_D and the empirical models of FMI and $FM_{empirical}$; (b) observed fuel moisture (FM_{CS505}), and fuel moisture modelled from the equilibrium models (FM_{Nelson}, $FM_{vanWagner}$, FM_{Simard}); (c) observed fuel moisture (FM_{CS505}), and predictions from the drought indices (KBDI, DF and F_d). FM_D was the model that best described temporal patterns in FM_{CS505}. Note that the scale of the *y*-axis in (a) is different from (b) and (c).

4.2. Large-scale estimates of fuel moisture

The need to understand dead fuel moisture goes beyond fire science. As an example, ecosystem ecologists and biogeochemists require litter moisture to understand the controls on decomposition (Cornwell et al., 2009). Studies of litter decomposition often rely on soil water content as an indicator of moisture limitation, whereas our model may provide a direct estimate of litter moisture content.

Our proposed model provides an avenue for using remotely sensed imagery to predict fuel moisture at large spatial scales. While the literature on remote sensing estimations of live fuel (e.g. canopy foliage) moisture content is rich, and important advancements have been made in recent years to understand how live fuel moisture influences fire activity (Caccamo et al., 2012; Yebra et al., 2013), we are unaware of published studies on remote sensing of dead fine fuel moisture. Our model opens the door to such studies.

Several approaches are available to estimate *D* at regional scales; this information can be used for regional estimates of FM_D. MODIS and other satellite sensors provide thermal imagery that can be used to estimate regional *D* (García et al., 2013; Hashimoto et al., 2008; Nieto et al., 2010; Zhu et al., 2013). Likewise, meteorological agencies provide gridded records of *D*, which can be used for regional estimates of fuel moisture.

Model parameterization and performance could have been improved if T and RH were measured under the canopy instead of 5–10 m above the canopy. However, it is unlikely this issue explains the performance of the other models relative to FM_D, since the associated error would be expected to affect all models equally. Our approach of using above-canopy data is advantageous since weather stations are often placed above the vegetation layer. Moreover, remote-sensing estimates of regional D that rely on land surface temperature are often more similar to above- than below- canopy conditions. However, closed-canopy forests with high leaf area indices and a decoupling between above-canopy and below-canopy D may present a challenge to this approach, and the assumption that above canopy measurements can be used to predict under-canopy fuel moisture. An improved understanding of the use of thermal imagery and gridded meteorological data to quantify below-canopy conditions in closed forest is an important topic for future studies.

4.3. Application to thicker fuel beds

Our model is designed to operate with dead fine fuel, meaning that the time to equilibrate with the atmosphere is 24-h or less. Although fuel diameter and time lag are often equated, Viney (1991) noted that particle thickness does not necessarily imply a given time-lag. For instance, we observed a generally higher FM in profile '1-h' fuel (<6.35 mm) than suspended '10-h' FM_{CS505} data (19.1 mm, Fig. 2). This likely indicates the profile fuel had a longer effective time lag despite its smaller diameter relative to the suspended '10-h' fuel. It was beyond the scope of our study to investigate how size class is related to time lag, but one could speculate this is driven by positioning of profile fuel on the ground in the litter bed, which could decouple it from the atmosphere relative to the suspended fuel. The fuel moisture sensors were placed on the ground at the California sites, and 30 cm above ground at the Australian site. The model accurately predicted fuel moisture regardless of sensor position, and independently of potential changes in litter depth with time at the California sites. This indicates that the model is robust to predict fuel moisture at different locations within the ecosystem, provided the time-lag does not exceed 24-h. We did not test our model in deep fuel beds, where effective time-lags may be larger than 24-h. We anticipate the model will not work at 24-h scales in those conditions, but may work at longer time scales.

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Appendix A.

See Fig. A1.

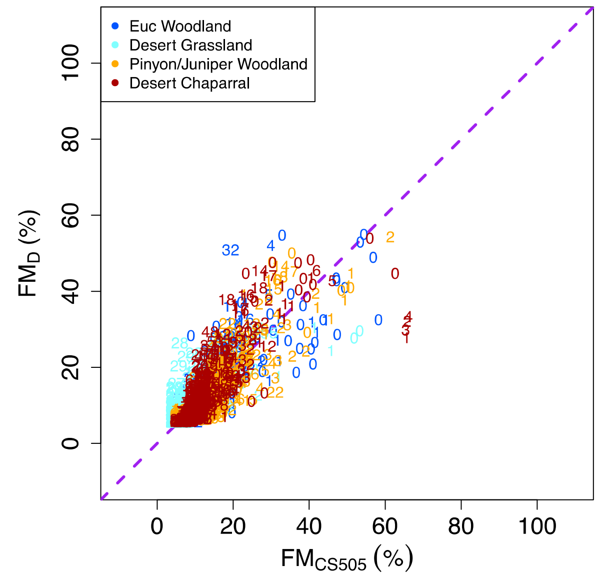

Fig. A1. Predicted (FM_D) vs Observed (FM_{CS505}) dead fine fuel moisture. Numbers indicate days since last rain. The dashed line indicates the 1:1 relationship. We observed no bias in model prediction even after precipitation inputs.

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