Using Soil Moisture Information to Better Understand and Predict Wildfire Danger: A Review of Recent Developments and Outstanding Questions

Running Head: SOIL MOISTURE-WILDFIRE DANGER REVIEW

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Abstract

Soil moisture conditions are represented in existing fire danger rating systems mainly through relatively simple drought indices based on meteorological variables, even though better sources of soil moisture information are increasingly available and have been shown to help improve predictions of fuel loads, fuel moisture, wildfire probability, and wildfire size. Without operational use of this soil moisture information, the potential for more accurate and timely fire danger warnings is unrealized, while increasing wildfire activity harms human and natural systems in various regions around the world. This review summarizes a growing body of evidence indicating that greater utilization of in situ, remotely sensed, and modeled soil moisture information in fire danger rating systems could lead to better estimates of dynamic live and dead fuel loads, more accurate live and dead fuel moisture predictions, earlier warning of elevated wildfire danger, and more precise forecasts of wildfire occurrence and severity. Although important research questions remain, several of which are identified here, the path forward is clear. Soil moisture information can and should be used to improve fire danger rating systems and contribute to more effective fire management for the protection of communities and ecosystems worldwide.

Summary: Soil moisture is an underused resource for improving fire danger rating systems and fire management worldwide. We review key studies describing relationships between wildfires and in situ, remotely sensed, and modeled soil moisture; describe the potential to incorporate soil moisture into wildfire danger assessments; and identify outstanding challenges and opportunities.

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Introduction

At 6:33 a.m. on the morning of 8 November 2018, a small fire was reported under electrical power lines near Camp Creek Road outside the town of Pulga in northern California, USA. Dry conditions and strong downslope winds with gusts >25 m s^{-1} (Brewer and Clements 2020) rapidly transformed that small fire into the deadliest and most costly wildfire in California's history. The Camp Fire burned >62,000 ha, destroyed >18,000 structures, and resulted in 85 fatalities (California Department of Forestry and Fire Protection 2019). This tragedy powerfully illustrates the importance of fire danger rating systems and the need to provide earlier and more accurate warnings for fire management agencies and the public. Toward that end, this review explores recent developments, data gaps, and challenges in applying previously underutilized soil moisture information to better understand, assess, and predict wildfire danger. Up until now, the incorporation of soil moisture information into existing fire danger rating systems has been limited to simplistic models or indices which use standard weather variables to estimate soil moisture, even though such information is becoming increasingly available via in situ measurements, remote sensing, and more sophisticated modeling. One week prior to the tragic Camp Fire, for example, satellite observations showed strong negative soil moisture anomalies across northern California (Fig. 1), conditions that are known to substantially increase the probability of large wildfires (Krueger et al. 2015; Krueger et al. 2016; Sazib et al. 2021), **but the tools needed to effectively put this information into action are currently lacking**.

That soil moisture conditions are important for fire danger rating is not a recent revelation. Prominent fire danger rating systems in Canada, Australia, and the United States use approximations of the moisture of mineral or organic soil horizons to quantify

wildfire danger (Kumar and Dharssi 2015). For example, the Canadian Forest Fire Danger Rating System (CFFDRS) (Stocks et al. 1989; Wotton 2009) includes three moisture indices, termed moisture codes, to represent moisture stored in the organic layers of the forest floor. The Fine Fuel Moisture Code (FFMC) represents fuel moisture of fine surface litter with a depth of 10-20 mm, the Duff Moisture Code (DMC) represents fuel moisture of loosely compacted duff with a nominal depth of 50-100 mm, and the Drought Code (DC) represents fuel moisture of deep organic materials having a nominal depth of 100-200 mm (de Groot 1987) (Fig. 2). While intended to represent moisture of surface organic layers, DMC and DC are strongly correlated to soil moisture of mineral horizons near the surface (D'Orangeville et al. 2016; Pellizzaro et al. 2007), likely in part because of capillary and vapor flow between mineral and organic soil layers (Zhao et al. 2022). When considering soils with deep organic layers at the surface, i.e., deep O horizons in soil science terminology, the water stored in those layers may be viewed as either soil moisture or fuel moisture because the organic layer itself can become combustible at low water contents.

In the recently modified Australian Fire Danger Rating System (Matthews 2022), fire danger ratings for dry eucalypt forests are dependent in part on soil moisture deficit estimated using the Keetch-Byram Drought Index (KBDI, Keetch and Byram 1968). KBDI uses temperature and precipitation data to estimate the moisture deficit in the upper soil layers (mineral and organic, if present) using a water balance approach. KBDI was designed to represent approximately the top 760-890 mm for a fine-textured soil and greater depths for coarser-textured soils (Keetch and Byram 1968) (Fig. 2). Similarly, in the National Fire Danger Rating System (NFDRS) used in the United States (Bradshaw et al. 1983; Burgan 1988; Deeming et al. 1972; Jolly 2018), KBDI helps determine fire danger

ratings through its influence on fuel load. The inclusion of these moisture indices in widely used fire danger rating systems makes it clear that their developers recognized the importance of soil moisture for understanding wildfire danger. But at the time these systems were developed, large-scale soil moisture measurement systems and physically-based hydrologic models were not sufficiently developed, thus moisture indices were instead estimated from commonly measured weather data. Given advances in soil moisture measurement and modeling systems in recent decades, there is a need to reassess how to best represent the moisture of organic and mineral soil layers in fire danger ratings systems and to better understand the effects of those representations on the accuracy of fire danger ratings.

The effectiveness of fire danger rating systems can be determined through retrospective analyses of the relationship between fire danger ratings **and important wildfire metrics including** occurrence and size. For example, a recent analysis of the NFDRS showed generally positive correlations between fire danger ratings and fire sizes across the contiguous US, but there were important spatial inconsistencies. Notably, there was poorer performance in the eastern half of the country compared to the western half, possibly due to regional differences in soil-vegetation-climate interactions and in the timing and length of the fire season (Walding et al. 2018). **Furthermore, large areas in the central US lacked the necessary data to generate fire danger ratings because those areas contained no reporting stations for the Weather Information Management System, which provides weather data for the NFDRS** (Walding et al. 2018). Thus, improvements to the NFDRS will likely need to consider both model structural improvements, as well as new and better sources and types of input data. Currently, the NFDRS and most other fire danger rating systems in use around the world rely on a relatively standard set of input variables that are routinely measured at weather stations, chief among them being air temperature, relative humidity, precipitation, and wind speed (de Groot et al. 2015). **However, as described in this review, a growing body of research provides strong evidence that new sources of soil moisture information can be important predictors of wildfire danger, but this valuable information has not yet been effectively integrated into fire danger rating systems.**

Historically, a major hindrance to such integration has been the limited availability of soil moisture information with adequate duration and spatial extent. That situation is rapidly changing as a variety of new sources of soil moisture information are becoming available**, each with** unique strengths (Fig. 3). **These new data sources include 1) soil moisture measured in situ, 2) soil moisture measured remotely by satellites, and 3) soil moisture data that is generated using physically-based models.** This groundswell of information began with the advent of state and national automated soil moisture monitoring networks in the US in the late **1990s** and the subsequent emergence of similar networks in other countries around the world (Dorigo et al. 2021). In parallel, satellite missions capable of monitoring soil moisture and closely-related variables have been developed and launched by NASA and other space agencies, with substantial increases in daily coverage of **the** Earth's surface since the late **1990s** (Karthikeyan et al. 2017). These advances in soil moisture measurements have occurred alongside advances in numerical soil moisture models, which can now provide soil moisture estimates for large domains with sub-km resolution (Holden et al. 2019). Using **these three types of soil moisture information**, researchers began to generate first glimpses of the strong relationships between wildfire and in situ **soil moisture** (Krueger et al. 2015), remotely-sensed **soil moisture** (Bartsch et al. 2009), and modeled **soil moisture** (Slocum et al. 2010). Subsequent studies have provided new insights into the **relationships between soil moisture and fuel characteristics including fuel loads (e.g., Ellsworth et al. 2013; Sharma et al. 2018), curing (e.g.,Sharma et al. 2021; Wittich 2011), and live (e.g., Bianchi and Defossé 2015; Fan et al. 2018) and dead fuel moisture (e.g., Masinda et al. 2021; Rakhmatulina et al. 2021). Other studies have directly related soil moisture to fire occurrence (e.g., Jensen et al. 2018; Vinodkumar and Dharssi 2019) and fire size (e.g., Forkel et al. 2012; Krueger et al. 2015; Slocum et al. 2010), while still others have identified the impact of vegetation type on soil moisture-wildfire relationships (e.g., Rigden et al. 2020; Schaefer and Magi 2019).** These and other important contributions to our understanding of soil moisture—wildfire relationships have emerged across a wide variety of scientific disciplines, which often are not well-connected, making the accelerating progress difficult to track and synthesize.

A further roadblock complicating the use of soil moisture information for fire danger ratings is that soil moisture conditions can be expressed in a variety of ways, making it more difficult to compare results across studies. For example, soil moisture can be expressed simply as soil volumetric water content (e.g., Ambadan et al. 2020; Schaefer and Magi 2019; Vinodkumar et al. 2021) or water content summed over some soil depth, i.e., soil water storage (e.g., Chikamoto et al. 2015; Krawchuk and Moritz 2011; Slocum et al. 2010). Alternatively, soil moisture can be formulated to represent the amount of soil moisture available to plants (Krueger et al. 2019), and it may also be normalized to allow for comparison across sites or across different soil moisture metrics. This normalization procedure may be based on the physical properties of the soil (e.g., Krueger et al. 2015; Vinodkumar et al. 2017; Waring and Coops 2016) or use statistical techniques (Lyons et al. 2021). To further complicate the situation, soil moisture may be expressed across different

soil depths (Fan et al. 2018; Vinodkumar et al. 2021) and as absolute values or anomalies (O et al. 2020; Sazib et al. 2021). These varied formulations of soil moisture must be understood to properly interpret the growing body of literature establishing the important relationships between soil moisture and wildfire.

Therefore, our objectives are to 1) summarize the rapidly growing body of research on soil moisture—wildfire relationships, 2) broaden the community of researchers aware of and engaged in this line of research, and 3) make a convincing case for more widespread use of soil moisture information in operational fire danger rating systems. This review is organized into four primary sections. The first three sections summarize what is known about the relationships of wildfire and fuel bed properties to 1) in situ soil moisture measurements, 2) remotely sensed soil moisture, and 3) modeled soil moisture. The fourth section explains potential links between soil moisture information and existing fire danger rating systems, using NFDRS as one specific example. We conclude by describing primary challenges and opportunities for using soil moisture information to better understand and predict wildfire danger, including the identification of key areas of needed future research.

In situ soil moisture measurements

In situ soil moisture measurements are the gold standard of soil moisture information (Levi et al. 2019) against which remote sensing and modeled values are evaluated (Fig. 3), and in some geographic areas, in situ soil moisture data are available at sufficient spatial and temporal resolutions to inform wildfire management. The International Soil Moisture Network houses publicly available data from nearly 2700 in situ soil moisture monitoring stations across 65 networks worldwide, a number that is steadily growing (Dorigo et al. 2021). The United States has an especially prolific collection of in situ soil moisture monitoring networks, and the ongoing National Coordinated Soil Moisture Monitoring Network initiative aims to produced harmonized data products from in situ soil moisture measurements from approximately 2000 sites across the nation (Cosh et al. 2021). One of the longest running and densest large-scale soil moisture monitoring networks in the US, and in the world, is the Oklahoma Mesonet (McPherson et al. 2007; Ochsner et al. 2013). Oklahoma is also consistently among the top 10 states in the US for wildfire risk (III 2021); accordingly, data from Oklahoma has proven valuable for understanding soil moisture-wildfire relationships.

A striking example of the connections between soil moisture, fuel bed properties, and wildfire comes from the Marena, Oklahoma, In Situ Sensor Testbed (MOISST) located in north-central Oklahoma. The MOISST site was established in 2010 to compare in situ soil moisture sensing technologies (Cosh et al. 2016) and measure vegetation dynamics in tallgrass prairie (PhenoCam 2021), with fuel bed properties measured at and around the site (Sharma et al. 2018). PhenoCam images collected at the site show markedly different vegetation conditions during August of 2012 and 2013 (Fig. 4). Drought conditions from May through July 2012 resulted in a fuel moisture content for mixed live and dead fuels of only 27% in early August when the photo on the left was taken. The severity of the drought was reflected in the measured soil moisture, expressed as fraction of available water capacity (FAW). **FAW is a measure of plant-available water that is calculated based on measured volumetric water content and the available water capacity of the soil (Krueger et al. 2015), and it can be determined for any landscape (e.g., grassland, forest, cropland) for which these variables are known.** It is defined as the ratio of measured plant available water to the maximum plant available water capacity of the soil, and it typically ranges from 0 (no plant available water) to 1 (maximum plant available water). From May through July 2012, FAW averaged only 0.23 **(i.e., plant available water was at 23% of its possible maximum),** levels indicative of severe drought (Sridhar et al. 2008). In contrast, FAW averaged 0.82 **(i.e., 82% of possible maximum)** over the same period in 2013, which corresponded with green vegetation in August 2013 (photo on the right) and a mixed fuel moisture content of 101%. The low fuel moisture contents in August 2012 contributed to extreme wildfire danger and the devastating Freedom Hill Fire, which ignited approximately 80 km east of the MOISST site the same day the photo was taken. This fire burned nearly 24,000 hectares of mostly prairie, savanna, and woodland over a two-week period; destroyed more than 300 homes; and resulted in Federal Emergency Management Agency assistance claims totaling more than $7 million.

The qualitative soil moisture-fuel bed relationships that are clear in Figure 4, and may be intuitive to fire managers, have been described in detail by recent research based on in situ soil moisture measurements. The soil moisture-fuel moisture relationship was quantified for various shrub species in Italy by Pellizzaro et al. (2007), who found that soil moisture was a better predictor of live fuel moisture than weather variables or weather-derived drought indices. Their finding was corroborated by Qi et al. (2012), who found that soil moisture explained 66% of the variability in live fuel moisture for oak and sagebrush in northern Utah, and soil moisture was more strongly correlated with live fuel moisture than were remotely sensed vegetation indices. Similar linear relationships between soil moisture and fuel moisture have also been reported for grassland fuels in South Africa (McGranahan et al. 2016).

These findings have been corroborated by a series of studies in Oklahoma, the key results of which are summarized in Figure 5. Sharma et al. (2021), using data from a grassland field study close to the MOISST site, reported that when soil moisture was plentiful (FAW values of at least 0.59), mixed fuel moisture was not related to soil moisture, but mixed fuel moisture declined as FAW decreased below this threshold. When FAW dropped below 0.40, the transpiration and growth rate of grassland live fuels declined, reflecting the intensification of drought stress (Krueger et al. 2021). When FAW declined below 0.36, the greenness of the vegetation, as indicated by the normalized difference vegetation index (NDVI), began to decrease (Sharma et al. 2021) (Figure 5). At a still lower FAW threshold of 0.30, the transition of live fuel to dead (i.e., curing rate) increased rapidly, from near 0 g m^{-2} day^{-1} when FAW was > 0.30 to more than 10 g m^{-2} day^{-1} as FAW approached 0.20 (Sharma et al. 2021). This drought-induced curing is vividly depicted in Figure 4, with extremely low soil moisture corresponding with vegetation that was almost completely cured by early August 2012, while little curing had occurred by the same time in 2013 when soil moisture was plentiful. A perhaps subtler distinction in fuel bed characteristics between these years is that the live fuel load in 2013 was more than double that in 2012, which portended potentially high wildfire activity if dry and windy conditions prevailed during the subsequent dormant season. These findings offer a physical explanation for the observed dependence of growing season wildfire size and probability on soil moisture conditions (Fig. 5).

In a different study that used in situ soil moisture data from the entire state of Oklahoma, Krueger et al. (2015) showed that 90% of large growing season wildfires across all Oklahoma landscapes **(forest, shrubland, grassland)** occurred when FAW was < 0.40, which matches the threshold for transpiration reduction due to moisture stress in grassland vegetation (Krueger et al. 2021). These soil moisture-wildfire relationships were further described using probabilistic models in a subsequent study (Krueger et al. 2016). When plant available soil moisture was near its maximum, the probability of a large growing season wildfire across all Oklahoma landscapes was near zero even when temperature, wind speed, and relative humidity conditions were ripe for wildfires (Fig. 4 and Krueger et al. 2016). As FAW decreased to 0.59, the soil moisture threshold below which grassland fuel moisture decreases, wildfire probability increased to 0.10, and for a FAW value of 0.30, the threshold for rapid fuel curing, wildfire probability more than tripled to 0.44 (Fig. 5). These results suggest that soil moisture and weather conditions work in concert to support high growing season wildfire probability. Low soil moisture is associated with decreased fuel moisture and accelerated curing, while high temperatures, low relative humidity, and high wind speed facilitate fire ignition and spread.

When vegetation is dormant, however, current FAW levels were not a strong predictor of the probability of large wildfires in Oklahoma (Krueger et al. 2016), likely because in grasslands dead fuel moisture content was not strongly dependent on soil moisture (Sharma et al. 2021). But dormant season wildfire probability was increased by high soil moisture during the previous growing season. For example, when FAW during the growing season was at least 0.40, the probability of a large wildfire during the subsequent dormant season was approximately double compared with growing season FAW values near 0.20 (Krueger et al. 2016). Vegetation productivity, at least for Oklahoma grasslands, is maximized when FAW > 0.40 (Krueger et al. 2021), contributing to increased fine fuel loads in the subsequent dormant season.

Although there is a lack of evidence for soil moisture effects on dead fuel moisture in grasslands, in situ measurements from a diverse array of sites around the world reveal important links between soil moisture and dead fuel moisture **for surface fuels** in forests. In Australia, the influence of soil moisture on the fuel moisture content of fine dead fuels, i.e., leaf litter, was observed in plantations of Monterey pine (*Pinus radiata*) approximately three decades ago (Pook and Gill 1993). The fuel moisture content for the pine needle litter on the surface was positively correlated with measured soil moisture in the 0-40 cm soil layer, and the correlation was stronger for un-thinned and un-pruned stands ($r = 0.91$) than in thinned and pruned stands ($r = 0.45$). The fuel moisture content of the surface leaf litter was predicted more accurately when soil moisture data were included along with temperature and humidity data in a multiple regression model compared to a similar model without soil moisture data. More recently in Australia, in situ soil moisture measurements have been linked to the fuel moisture content of the **surface and subsurface** litter layer under various *Eucalyptus* species (Zhao et al. 2021). A follow-up experiment showed that dry soil had a limited influence on the fuel moisture content of the litter, primarily through vapor flow between the soil and the litter (Zhao et al. 2022). In contrast, wet soil had a stronger influence on litter moisture content, with evidence for both vapor and capillary flow between the soil and the litter. Similarly, in situ measurements from forested sites in the foothills of the Sierra Nevada in central California showed that soil moisture had a stronger influence than any other environmental or meteorological factor on fuel moisture of 10-h fuels (6 to 25 mm diameter dead fuels) for wet soil conditions (Rakhmatulina et al. 2021). A dominant influence of soil moisture on the moisture content of dead fine fuels was also documented through in situ measurements in Korean pine (*Pinus koraiensis*) and Scots pine (*Pinus sylvestris*) stands in northeastern China (Masinda et al. 2021). **These reports of the connection between moisture of mineral soils and that of overlying organic layers corroborate previous studies correlating soil moisture measurements with moisture codes from the CFFDRS. For example, correlation coefficients ranging from 0.6-0.8 were reported between measured soil moisture and soil moisture estimated from the DC index in Canadian forests (D'Orangeville et al. 2016).**

These findings from diverse ecosystems and geographies highlight the dependencies of fuel loads, fuel moisture content, and wildfire probability on soil moisture. They have also laid the groundwork for a new generation of wildfire danger assessment tools that use in situ soil moisture information. However, even with expanding national and regional scale soil moisture monitoring networks, using in situ data for wildfire danger monitoring and management decisions is still constrained by the limited number of measurement sites in some locations **[e.g., the boreal forest, and most of South America, Africa, and Australia (Dorigo et al. 2021)].** And because soil moisture can vary greatly across even small distances (Famiglietti et al. 2008), point measurements of soil moisture are not necessarily representative of soil moisture at the landscape scale (Fig. 3). Therefore, there is a clear need for supplemental strategies for quantifying soil moisture, which include remotely sensed and modeled soil moisture information.

Remotely sensed soil moisture

Remote sensing technology has advanced rapidly since the first photograph of Earth was taken from space in 1946. Since that time, improvements in sensor fidelity, satellite and rocket launch technology, data storage, and aperture development have enabled many new capabilities, including near real-time operations related to earth sciences and hydrology (McCabe et al. 2017). The ability to characterize the land surface using strategic regions of the electromagnetic spectrum has resulted in opportunities to remotely monitor and assess near-surface soil moisture and vegetation dynamics (Kumar et al. 2020; Mladenova et al. 2020), which are key to understanding the risks and impacts of wildfires. With the advent of refined satellite-based microwave sensors such as the European Space Agency's Soil Moisture Ocean Salinity (SMOS) mission, which launched in 2009 (Kerr et al. 2010), and NASA's Soil Moisture Active-Passive

(SMAP) mission (Entekhabi et al. 2010), which launched in 2015, **evidence is beginning to emerge that** satellite-based soil moisture data **can provide** value for understanding and predicting wildfire danger **in many ecosystems** (O et al. 2020).

Remotely sensed soil moisture data have proven useful for assessing fuel bed properties including biomass accumulation (i.e., fuel production) and fuel moisture content. For example, in southern France live fuel moisture measurements for Mediterranean shrub species were significantly correlated with the preceding 15-day average remotely sensed soil moisture from the European Space Agency's Climate Change Initiative Soil Moisture dataset (ESA CCI SM, formerly known as ESV SM) (Fan et al. 2018). A subsequent study used soil moisture data from SMAP to estimate live fuel moisture of chamise (*Adenostoma fasciculatum*) at 12 chaparral sites in southern California (Jia et al. 2019). At those sites, a statistical model using weighted, accumulative soil moisture and growing degree days outperformed models using vegetation optical depth or other optical indices. There is also some evidence that remotely sensed soil moisture might be useful for estimating dead fuel moisture. Burapapol and Nagasawa (2016) reported that remotely sensed soil moisture based on Landsat and MODIS was closely linked with fuel moisture **of dead leaves** in dipterocarp and deciduous forests in Thailand. Soil moisture based on microwave remote sensing may be preferrable to optical reflectance indices commonly used to characterize fuel moisture [see reviews by Gale et al. (2021); Yebra et al. (2013); and Arroyo et al. (2008)] because microwave sensors are less prone to disturbances from unfavorable weather (e.g., clouds) and because soil moisture is physiologically linked to plant processes (Nolan et al. 2020).

The results of the above regional studies (Fan et al., 2018; Jia et al., 2019) were supported by a nationwide analysis of the ESA CCI SM data and live fuel moisture at >1000 sites across the contiguous US (Lu and Wei 2021). That analysis spanned numerous vegetation types and climate zones and revealed that the correlations between soil moisture and live fuel moisture were typically strongest when soil moisture was measured 10-50 days in advance. Important vegetation types showing a relatively high sensitivity to soil moisture included pine, redcedar, sagebrush, oak, manzanita, chamise, mesquite, and juniper. The SMAP Level-4 surface and root zone soil moisture products, which result from assimilation of SMAP observations into a land surface model, and in situ soil moisture measurements at selected sites both showed somewhat stronger correlations with live fuel moisture than did the ESA CCI SM data.

The links between remotely sensed soil moisture data and fuel bed characteristics make those data useful for assessing wildfire danger. For example, positive soil moisture anomalies observed by Earth Resources Satellite 1 and 2 corresponded with a lower burned area of forest fires in the **boreal forest** of Siberian (Bartsch et al. 2009). **Furthermore, extreme fire events in this region were more closely associated with remotely sensed soil moisture [AMSR-E (Njoku et al. 2003)] than precipitation anomalies or fire danger indices (Forkel et al. 2012).** More recently, SMOS observations over boreal Canada revealed that wildfires occurred more frequently in anomalously low soil moisture conditions (Ambadan et al. 2020). At more southerly latitudes, models using SMOS-derived soil moisture, in conjunction with temperature and site specific variables such as land cover type, explained 68% of variability of maximum fire extent on the Iberian Peninsula (Chaparro et al. 2016). And the inclusion of SMAP soil moisture observations increased skill in predicting wildfire occurrence in the western US relative to the use of vapor pressure deficit alone, particularly in grasslands (Rigden et al. 2020).

Because current soil moisture conditions can influence future fuel moisture and fuel load, soil moisture observations may be particularly helpful for forecasting wildfire danger. In

Australia and California, for example, Sazib et al. (2021) found that soil moisture from SMAP was negatively correlated with wildfires at 1-2 month lead times in moist regions where fuels are typically plentiful, and it was positively correlated with wildfires in drier regions where fuel is scarce. These trends were attributed to a decrease in moisture of surface fuels in moist regions and increased biomass accumulation in dry regions. In an analysis that spanned the globe, O et al. (2020) found that soil moisture from ECV-SM was an important early predictor of wildfires. They reported that in arid regions positive soil moisture anomalies corresponded with increased biomass accumulation followed by wildfire outbreaks at lead times of 5 months. In humid regions, negative soil moisture anomalies were related to wildfires at lead times of four months, presumably because of decreased moisture of surface fuels. Likewise, soil moisture inferred from NASA's Gravity Recovery and Climate Experiment (GRACE) mission was often positively correlated with wildfire occurrence **in herbaceous vegetation, shrublands, and forests at seasonal lead times**, indicating that a wetter pre-fire-season can lead to increased **plant (i.e., fuel) production in these landscapes** (Jensen et al. 2018).

The large spatial extent of remote sensing datasets provides natural opportunities to explore how soil moisture-wildfire relationships vary across different land cover types. Schaefer and Magi (2019) used satellite-based fire counts from NASA (Giglio et al. 2018), land-use and land cover maps (Hurtt et al. 2020), and the ESA CCI SM product (Dorigo et al. 2017) with a biome map (Levavasseur et al. 2012) to study how fires behave relative to soil moisture variability within land cover types and across biomes. They found that the fire-productivity curve shape, which describes resource and climate limits surrounding a zone of optimal fire conditions (Krawchuk and Moritz 2011), was captured within the phase-space of fire and soil moisture. Fire counts were generally greatest when remotely sensed average monthly soil moisture was relatively low, often around 0.1 m^3 m^{-3}. At lower soil moisture levels, the average number of fires decreased with decreasing soil moisture, presumably because of resource limitations (i.e., decreasing fuel availability). At higher soil moisture levels, the average number of fires decreased with increasing soil moisture, likely due to increased fuel moisture contents. But the shape of the fire-soil moisture curve differed as a function of biomes and land cover types. **For example, the occurrence of fires in boreal forests (Fig. 6, lower panel), which have a shallower rooting depth than forests in other biomes (Fan et al. 2017), relates to soil moisture availability in a way that is similar to grasslands (Fig. 6, upper panel), which also have shallow root depths**. This apparent effect of root depth on the sensitivity of fire occurrence to soil moisture under different biomes reinforces the value of soil moisture as a predictor of fire danger. Consistent with these results, Forkel et al. (2017) showed that across the world, biophysical models of fire activity (e.g., Rabin et al. 2015) performed better when remotely sensed soil moisture (and moisture state in general) was considered.

These global scale analyses are possible because, unlike in situ soil moisture measurements, remotely sensed measurements provide data on soil moisture conditions across large spatial domains. However, remotely sensed measurements typically represent soil moisture conditions in only the top few centimeters of the soil (Abbaszadeh et al. 2021) and have lower temporal resolution compared to in situ networks. **Furthermore, remotely sensed soil moisture measurements have historically shown a limited ability to accurately monitor soil moisture conditions where a dense vegetative canopy is present (Djamai et al. 2015; Dorigo et al. 2015). But recent advances provide unequivocal evidence that remote sensing measurements are sensitive to soil moisture under forest canopies (Ayres et al. 2021; Colliander et al. 2020)**. There is a clear need to focus future research on remotely sensed soil moisture-wildfire relationships at higher spatial resolution and for specific land cover types. Such studies may enhance the relevance of satellite-based soil moisture data to fire managers. These types of studies may also be particularly well-suited for linking with model-based approaches as described in the next section.

Modeled soil moisture

Given the historical lack of in situ and satellite measurements, proxies and estimates of soil moisture conditions have long been used in the context of wildfire danger. Approaches have ranged from drought indices based on simplified soil water balance models (e.g., Keetch and Byram 1968; Mount 1972; Palmer 1965), to actual soil moisture values simulated using more complex process-based models (Carrega 1991; Holden et al. 2019), to hybrid approaches that incorporate measured soil moisture data into plant growth models (Krueger et al. 2021). These approaches have been applied across widely-varying time horizons, with some showing the possibility to facilitate predictions of soil moisture, and subsequently wildfire, for time frames potentially spanning decades (Chikamoto et al. 2015). The Keetch-Byram Drought Index (KBDI) (Keetch and Byram 1968), in particular, has been used extensively to address the challenges of representing moisture deficits and their influence of wildfire danger. For example, KBDI has been used in the McArthur Mark 5 forest fire danger index (Holgate et al. 2017), the Fosberg fire weather index (Goodrick 2002), and the US National Fire Danger Rating System (Burgan 1988).

Developed in the southern United States in the **1960s** to predict moisture deficits in **duff and mineral soil layers**, KBDI is a unitless index ranging from 0-800. The KBDI calculation attempts to address important physical processes such as canopy interception of precipitation and the effects of biomass on rates of soil water loss. However, it has significant limitations. For example, it does not include humidity, wind, or radiation in its estimate of soil water loss. The model also uses climatological average precipitation as a surrogate for both leaf area and canopy interception, based on the assumption that wetter sites support more vegetation. Finally, KBDI does not consider variability in soil properties, instead assuming a water holding capacity of 8 inches for all soils. Given these limitations, it is not surprising that in situ and remotely sensed soil moisture are more strongly related to wildfires than KBDI in grasslands in the western US (Rigden et al. 2020) **and grasslands, shrublands, and forests** in Oklahoma (Krueger et al. 2017).

When compared to in situ soil moisture observations in Australia, KBDI showed a large wet bias relative to measurements in the 0-30 cm and 0-90 cm soil layers, had correlations with measured soil moisture that vary widely across climate zones and were sometimes negative, tended to dry down too slowly after wet periods, and performed more poorly than simulations from a physically-based land surface model (Holgate et al. 2017; Vinodkumar et al. 2017). Although KBDI can be calibrated to represent temporal variations in live fuel moisture at specific sites, it is unable to accurately represent spatial variations in live fuel moisture, and thus is not recommended for use in operational fire management (Ruffault et al. 2018). Replacing drought indices like KBDI with more robust soil moisture models has been noted as a priority for improving fire danger rating in the US (Jolly 2018) and is well underway in Australia (Vinodkumar and Dharssi 2019; Vinodkumar et al. 2021).

Process-based models link vegetation growth and functioning with soil properties and climate information and are sometimes referred to as land surface models or soil-vegetation-atmosphere-transfer models (Moran et al. 2004). These models can be particularly useful because they represent plant physiological processes, allowing vegetation to be modelled accurately over space and time, and thus capture many of the vegetation fuel attributes that are relevant for fire spread models (Landsberg et al. 2003). One example is the TOPOFIRE model, which was recently developed to provide high spatial resolution, daily estimates of soil moisture, fuel moisture, and fire danger data and maps for the conterminous US (Holden et al. 2019) (Figure 7). Another recent example is the modeling system developed by the Australian Bureau of Meteorology based on the Joint UK Land Environment Simulator (JULES) called the JULES-based Australian Soil Moisture Information (JASMIN) system (Vinodkumar and Dharssi 2019). The JASMIN system was specifically designed for application in operational fire prediction and risk management.

Such models hold promise, not only for wildfire decision support, but also for revealing a new foundational understanding of soil moisture—wildfire relationships. For example, modeled soil moisture values from the US National Oceanic and Atmospheric Administration Climate Prediction Center have been used with remotely sensed active fire data to understand global patterns in the constraints of **fine** fuel loads and fuel moisture on wildfire occurrence (Krawchuk and Moritz 2011). Fuel moisture content strongly influences fire ignition and spread, and recent simulations from a physics-based model showed the close interaction of soil moisture with the fuel moisture of the litter layer **in shrubland, woodland, and forests** (Zhao et al. 2021). Likewise, soil moisture modeled using TOPOFIRE has been shown to be a better predictor of canopy water content across the western US than is atmospheric vapor pressure deficit (Lyons et al. 2021). In fact, gridded 5-km resolution live fuel moisture estimates in **grasslands, shrublands, and forests** have been generated for Australia based on soil moisture values simulated with the JASMIN system (Vinodkumar et al. 2021). These live fuel moisture predictions used soil moisture as a leading indicator with a 14-d lag period. The 0-35 cm soil layer was determined to be the best layer for live fuel moisture prediction. This is similar to the 0-40 cm layer used for in situ soil moisture measurements in several prior wildfire-related studies (Krueger et al. 2015; Krueger et al. 2016; Krueger et al. 2017; Pook and Gill 1993; Sharma et al. 2021). There is a clear need for further development and refinement of process-based models specifically designed to capture soil moisture-fuel load-fuel moisture-fire danger relationships and for the application of those models for greater scientific understanding and improved fire danger ratings.

One limitation to process-based modeling approaches relative to simple drought indices is the increased complexity of model inputs and sometimes intensive calibration needs. Necessary inputs typically include gridded data sets for climate conditions, soil properties, and vegetation type and condition. Obtaining these input data at the necessary spatial and temporal scale and resolution can be challenging. For example, soil maps are often compiled at broad spatial scales, often do not cross political boundaries, and sometimes use inconsistent nomenclatures (Mulder et al. 2011; Zheng et al. 1996). Some critical soil attributes, for example soil depth and available water capacity, can be hard to derive using traditional soil mapping techniques, making these even more challenging to input into fire danger models. Levi and Bestelmeyer (2018) summarize available spatial soil information datasets for fire modeling in the US and suggest that advances in soil modeling can lead to improved soil property maps and therefore more accurate fire predictions.

One promising approach is to use process-based models in an inverse fashion to estimate the necessary soil physical properties. For example, forest leaf area index has been shown to be indicative of soil properties, with increases in leaf area associated with increases in fertility and available soil water (Waring 1983; White et al. 1997). Therefore, by modeling tree growth and variables such as leaf area index, soil physical properties can be inferred, which can then be input into land surface models. Following this approach with the 3PG model (Landsberg and Waring 1997), Coops et al. (2012) predicted available soil water storage capacity across western North America and compared model predictions of leaf area with those observed from satellite observations. They developed soil maps at a much finer scale (1 km) than those previously available over the area. When these updated soil maps were integrated into modeling, the forest model predictions more closely matched the anticipated growth of a key forest species in the area compared to models driven solely from pre-existing soil map information.

There appears to be great potential for these types of hybrid approaches that incorporate in situ or satellite soil moisture measurements into process-based models. For example, predictions of grassland fuel loads can be improved by direct insertion of in situ soil moisture observations into a simulation model's soil water balance routine (Krueger et al. 2021), or a soil moisture model can be improved by assimilating satellite-based soil moisture observations, as demonstrated in Bolten et al. (2010). Hybrid approaches have also proven useful when predicting areas of vegetation stress, which may be more prone to wildfires. For example, areas of increased land surface temperature and decreased greenness are likely to be subject to lower vegetation growth and increased stress (Nemani et al. 1996). If prolonged, these stresses can result in increased litter fall, increased non-photosynthetic vegetation, and drier soil, which in turn correspond with increased fuel load. Based on this concept, Mildrexler et al. (2009) developed a global disturbance index using remotely sensed land surface temperature and greenness and demonstrated that this index could identify areas of broad scale vegetation stress. Waring et al. (2011) applied this index over western North America and demonstrated that increases in the area designated as stressed were positively correlated with the areas of increased simulated soil water stress and wildfire. Waring and Coops (2016) then compared simulated soil moisture with satellite derived area burned (Fig. 8, left). Using a decision tree approach, they identified four seasonal combinations of current and antecedent soil moisture conditions that predicted where forest fires >1 km^2 occurred with 69% accuracy (Fig. 8, right).

These studies add to the growing body of evidence that an accurate accounting of soil moisture status, either by in situ measurements, remote sensing, or modeling, can improve our ability to anticipate when and where wildfires will occur. While soil moisture models can suffer from errors caused by inaccuracies in input data and the model structure, they are appealing because of their capability to incorporate diverse data sources including measured soil moisture and vegetation condition (Fig. 3). Yet as described in the following section, soil moisture information has thus far been largely absent from major fire danger rating systems.

Potential for inclusion of soil moisture information into fire danger rating systems

In this section we explore the potential for integration of soil moisture information into fire danger rating systems. We begin with a brief review of some of the leading fire danger rating systems and how they incorporate weather and other information to estimate fuel bed properties, estimates that could potentially be improved by incorporating soil moisture information.

National fire danger rating systems

Fire danger rating systems integrate inputs representing multiple fire danger factors, often via a model, into one or more qualitative or numerical indices of fire danger. Some systems also model physical characteristics of the fire, such as fire intensity, rate of spread, and flame length. Fire danger rating systems provide assessments of fire danger over broad geographical areas, encompassing up to millions of hectares, and are typically not designed to provide detailed fire danger information at the field scale. Spatially, when calculated over a grid, the fire danger for each grid cell represents the average fire danger at a given time over that cell, assuming homogeneous fuels, weather, and topography within the cell. Such systems are used to provide public warnings, set preparedness levels, provide a good indication of the difficulty of fire suppression over a wide range of conditions, and to help wildfire managers make wise tactical and strategic management decisions (NWCG 2002).

While there are a number of fire danger ratings systems across the world, ranging from national to regional to local scales, it is instructive to look at three national systems that have been widely used for many decades, those of Australia, Canada, and the United States. While a new Australian system is becoming operational in 2022 (AFAC 2022), the previous system consisted of two fire danger indices, each with six fire danger categories: the McArthur Forest Fire Danger Index (FFDI) and the McArthur Grassland Fire Danger Index (GFDI) (McArthur 1966, 1967; Noble et al. 1980). The FFDI and GFDI each required temperature, relative humidity, wind speed, and rainfall as weather inputs. The FFDI assumed a standard eucalyptus forest in its calculations, while the GFDI assumed a standard grassland. For each, the fuel type and total fuel load (live + dead) were constant. For the FFDI, fuel availability (drought factor) was calculated from soil moisture deficit, time since last rain, and rainfall amount (Matthews 2009). The soil moisture deficit used KBDI or the Soil Dryness Index (SDI, Mount 1972). For the GFDI, the degree of curing was also an input, which was typically estimated by ground-based visual observations, satellite imagery, or a combination of both.

The Canadian Forest Fire Danger Rating System (CFFDRS, Stocks et al. 1989) has been in its current form since 1992, with a series of improvements planned for release beginning in 2025 (CFSFDG 2021). It consists of two major subsystems, the Fire Weather Index (FWI) System (Van Wagner 1987) and the Fire Behavior Prediction (FBP) System (FCFDG 1992). The FWI System uses a standard jack pine forest and consists of six components: three moisture indices **(fine fuel moisture code, duff moisture code, and drought code)** that represent three organic layers at or beneath the forest floor (Fig. 2), and three fire danger indices, including FWI itself. Weather inputs are temperature, relative humidity, wind speed, and rainfall. The FBP **System** consists of 16 available fuel models, including a grass model that requires degree of curing as an input (De Groot 1993). The system incorporates three outputs from the FWI System and uses topography in its calculations. Foliar (live) fuel moisture is modeled using elevation, geographical location, and date; thus, the foliar moisture remains the same on a given date and location from year to year. Outputs of the FBP **System** include physical characteristics of the wildfire (e.g., rate of spread and fire intensity).

The National Fire Danger Rating System (NFDRS) of the United States was originally released in 1972 (Deeming et al. 1972) with major updates in 1978 (Bradshaw et al. 1983) and 1988 (Burgan 1988). The latest version (NFDRS2016) includes five standard fuel models, reduced from 20 in the 1978 and 1988 versions (Jolly 2018). As with the two former versions, NFDRS2016 separately calculates live and dead fuel moisture as well as the dynamic fuel load transfer (i.e., curing or green-up) between 1-hour dead (< 6 mm diameter dead fuels) and live herbaceous fuels (Fig. 9). The live fuel moisture and dynamic fuel load transfer calculations in NFDRS2016 are a function of Growing Season Index (GSI), which is a function of temperature, relative humidity, and photoperiod (Jolly et al. 2005). As with the 1988 NFDRS, the new system uses KBDI as a drought surrogate to linearly increase the dead fuel loads when KBDI increases above a threshold of 100. The inputs to NFDRS2016 are temperature, relative humidity, rainfall, wind speed, solar radiation, and photoperiod (based on latitude and day of year). The outputs from NFDRS consist of four components describing the wildfire danger: Spread Component, Energy Release Component, Burning Index, and Ignition Component.

Potential pathways for inclusion of soil moisture information

Within fire danger rating systems like those described above, there are at least five potential uses for soil moisture information: 1) as a replacement or supplement for drought indices; 2) as an input for live and 3) dead fuel moisture modeling; 4) as an input to estimate curing for herbaceous fuels; and as 5) as an input for estimation of fuel loads. We now briefly discuss each of these potential uses within the context of NFDRS2016 (Fig. 9), which provides a representative example for how soil moisture could potentially be used in fire danger rating systems worldwide.

First, soil moisture measurements or simulations from process-based models could be used to replace drought indices in fire danger rating systems. Moisture indices **that can represent** soil moisture have been used in fire danger rating systems across the world, including KBDI and SDI in the Australian FFDI system, the drought code in the Canadian FWI System, and KBDI in the US NFDRS system. **A growing body of evidence indicates that new sources of soil moisture information are useful for predicting wildfire danger across a variety of landscapes including grasslands, shrublands, and temperate and boreal forests, and soil moisture information may be more closely related to wildfire danger than traditional drought indices (e.g., Ambadan et al. 2020; Bartsch et al. 2009; Chaparro et al. 2016; Forkel et al. 2012; Krueger et al. 2015; Rigden et al. 2020; Schaefer and Magi 2019).** For example, in Oklahoma in situ soil moisture measurements provided an average of ten days earlier warning than KBDI for the largest growing-season wildfires (Krueger et al. 2017). For one of the largest wildfires in that study, the Chester Fire, soil moisture reached dangerously low levels (FAW ≤ 0.2) more than 3 weeks before the actual fire, while KBDI never reached levels considered dangerous (≥ 600), thus providing no advance warning at all. When FAW is < 0.2, as it was leading up to the Chester Fire, grassland curing rates of ~13 g m^{-2} d^{-1} can occur (Sharma et al., 2021), which could result in the accumulation of >270 g m^{-2} of dead fuel in 3 weeks, or near 100% curing given typical grassland fuel loads for the region (Krueger et al., 2021). Analyses from Australia indicate that SDI is on average more strongly correlated with in situ soil moisture measurements than is KBDI, but like KBDI, SDI exhibits slower dry downs than in situ soil moisture and greater variation in performance across regions than more advanced process-based models (Holgate et al. 2016). These results suggest that soil moisture measurements or simulations from process-based models could effectively supplement or replace drought indices in fire danger rating systems.

A second potential use of soil moisture information is for live f**uel moisture modeling in fire danger rating systems. Soil moisture has been shown to be a strong predictor of live fuel moisture in grasslands, (Sharma et al. 2021), shrublands (Pellizzaro et al. 2007; Qi et al. 2012), and forest understory (Bianchi and Defossé 2015). In fact, soil moisture observations have shown stronger correlations with live fuel moisture than drought indices in some Mediterranean shrub species (Pellizzaro et al. 2007) and stronger than remotely sensed vegetation indices in Gambel oak and sagebrush (Qi et al. 2012).** In NFDRS2016, live fuel moisture is estimated using GSI, a simple empirical index for vegetation phenology based on photoperiod, vapor pressure deficit, and air temperature (Jolly et al. 2005 and Fig. 8).

We are not aware of any peer-reviewed evaluations of the accuracy of live fuel moisture estimates based on GSI, **although GSI shows temporal trends similar to live fuel moisture content in sagebrush and chamise** (Jolly 2018). Based on the evidence from the literature, we hypothesize that inclusion of soil moisture information as an additional input variable in the GSI calculation would lead to improved live fuel moisture estimates. Alternatively, live fuel moisture could be directly estimated from soil moisture information as has been successfully demonstrated in Australia (Vinodkumar et al. 2021).

Third, soil moisture could also be useful for dead fuel moisture estimation in fire danger rating systems. Soil moisture influences near-surface air temperature and humidity (McKinnon et al. 2021), and water movement between the soil and dead surface fuels has been observed **in shrubland and eucalyptus forests** (Zhao et al. 2022; Zhao et al. 2021) **and aspen forests** (Samran et al. 1995). NFDRS2016 estimates dead fuel moisture using the Nelson model, which uses temperature, relative humidity, solar radiation, and precipitation as inputs (Nelson Jr 2000). The Nelson model has shown reasonable accuracy in estimating dead fuel moisture with r^2 values ranging from 0.51-0.79 (Carlson et al. 2007), but for some landscapes like **conifer forests** there is evidence that dead fuel moisture models incorporating soil moisture information provide better estimates than those that omit soil moisture information (Masinda et al. 2021; Pook and Gill 1993; Rakhmatulina et al. 2021). These studies highlight the potential to improve fire danger rating systems by using soil moisture information for estimating dead fuel moisture, particularly for dead surface fuels at forested sites.

Improving representation of the curing of herbaceous fuels is a fourth promising use of soil moisture information. Few studies have directly considered the relationship between soil moisture and curing, but the limited available data suggest a strong relationship between soil moisture conditions and the rate of curing in grasslands (Sharma et al. 2021). Likewise, positive correlations between the fuel moisture content and soil moisture content in grasslands have been observed during the curing period from the end of the growing season into mid-winter (McGranahan et al. 2016). **The degree of curing in herbaceous fuels can be determined** through direct measurements, visual estimates, remote sensing, or soil moisture deficit or **plant phenology models (Duff et al. 2019). For example, in NFDRS2016 the dead herbaceous fuel load transfer is estimated as a function of the degree of curing, which is estimated from the GSI plant phenology model**. Unpublished data show a negative relationship between GSI and grass curing ($r^2 = 0.41$) for one site in North Dakota, USA (Jolly, 2018), but few, if any, published studies have compared GSI with curing levels measured in situ. Given that soil moisture deficits enhance curing (Wittich 2011), soil moisture information could perhaps be used as an additional input for the estimation of GSI and therefore curing, or the curing rate could be directly estimated from soil moisture observations.

A fifth potential use of soil moisture information in fire danger rating systems is for the estimation of fuel loads. Current fire danger rating systems assume a constant fuel load (live + dead) regardless of the differences in weather from one growing season to the next. But loads can vary substantially year-to-year, especially for herbaceous fuels. For example, incorporation of soil moisture observations into a simple, process-based plant growth model can provide improved predictions of grassland productivity and fuel loads (Krueger et al., 2021). Likewise, soil moisture is a significant predictor of live fine fuel loads at guinea grass (*Megathyrsus maximus*) dominated sites in Hawaii (Ellsworth et al. 2013). There is also evidence for an important role of soil moisture conditions in regulating the growth rates of shrubland fuels in the Arctic (Ackerman et al. 2017; Martin et al. 2017; Myers-Smith et al. 2015). Accounting for soil moisture effects on fuel production rates could lead to better approaches to represent dynamic fuel loads and could potentially improve the performance of fire danger rating systems.

While research provides evidence for these proposed uses of soil moisture in wildfire danger rating, the supporting studies have been relatively few and often of limited geographic scope. Substantiating research across diverse geographic locations and biomes is essential to support implementation on a large scale. Furthermore, the usefulness of soil moisture information in fire danger rating systems is dependent on the way such information is generated. In situ soil moisture measurements can monitor conditions deep into the soil profile rather than just the top few centimeters. Therefore, these in situ measurements effectively represent root zone conditions, and they can be located in diverse vegetation types (e.g., grasslands, shrublands, forests). A main limitation of in situ measurements is that each measurement typically represents only a small area and may not adequately reflect heterogenous soil moisture conditions in the surrounding landscape. Unlike in situ observations, which are lacking in many regions, satellite remote sensing is available globally and can provide useful large-scale estimates of soil moisture conditions. But remotely sensed soil moisture measurements have limited capacity to monitor conditions below the 5-cm depth and limited accuracy beneath dense forest canopies, and less resolution in time as compared to in situ measurements. In contrast, simulated soil moisture information from process-based models can represent the entire root zone, can be extended to almost any land cover and land use type, and have flexible spatial and temporal resolution. Yet, the accuracy of these simulated values is limited by the availability and quality of the necessary soil, vegetation, and weather input data and by uncertainties in the model structure and parameters. Another limiting factor is the sometimes large computational requirements for running the simulations. The use of soil moisture information in fire danger rating systems may need to rely on a combination of all three sources to represent the best available information across a range of relevant scales.

Challenges and opportunities

We have described a steadily growing body of evidence indicating the need for and potential benefits of using soil moisture for wildfire danger assessments. While this research is promising, many questions remain. First, and perhaps most important, while the current body of research supports a litany of *potential* uses of soil moisture in fire danger rating systems, the practical benefits of these uses remain largely untested and logistical challenges likely remain. Pioneering efforts in the operational use of soil moisture information in fire danger rating systems include the use of in situ soil moisture measurements in OK-FIRE, a weather-based decision support system for wildland fire managers in Oklahoma that produces maps of growing-season wildfire danger, updated every 30 minutes, based on soil moisture (Oklahoma Mesonet 2021). These maps supplement similar maps based on KBDI for operational fire management decisions. Similarly, the operational use of remotely sensed soil moisture data is being explored by the Barcelona Expert Centre (BEC), which downscales SMOS soil moisture data to create near-real time fire risk maps (BEC Team 2018) that are currently used by Barcelona Provincial Council to provide wildfire early warning (Chaparro et al. 2016). And in Australia, modeled soil moisture values are being used to generate dynamic nationwide live fuel moisture estimates designed for use in operational fire danger ratings (Vinodkumar and Dharssi 2019; Vinodkumar et al. 2021). Further research specifically aimed at techniques for incorporating soil moisture into wildfire danger systems is critically needed, as well as evaluation of fire danger ratings with and without soil moisture information.

Other important research needs and opportunities abound in this context. Some key research questions include: 1) What representations of soil moisture (absolute values, scaled values like FAW, anomalies, percentiles, etc.) are best suited for wildfire danger assessment? 2) What are the soil depths for which moisture conditions are most strongly related to fuel production rates, fuel moisture, and wildfire occurrence and size? 3) How can the various sources of soil moisture information (in situ, remotely sensed, modeled, or a combination of these) best be leveraged for improving operational fire danger assessments? 4) How can soil moisture information be used to produce accurate dynamic estimates of live and dead fuel loads in fire danger rating systems? 5) How are soil moisture conditions related to and predictive of wildfire occurrence and severity in organic soil layers, where the soil itself is the fuel (Elmes et al. 2018; Prat-Guitart et al. 2016; Reardon et al. 2007; Rein et al. 2008)? 6) How do pre-fire soil moisture conditions influence burn severity, soil heating, and post-fire impacts of both wildfire and prescribed fire across different landscapes? These questions must all be answered in parallel with continued research aimed at refining and expanding in situ, remotely sensed, and modeled soil moisture products.

After clearing these scientific hurdles, there remains the further challenge of convincing wildfire professionals of the importance of soil moisture compared with more familiar wildfire danger metrics. For example, the importance of KBDI has been engrained in generations of wildfire professionals, and it benefits from widespread familiarity and is inherently understood. It is critical that soil moisture be distinguished from other drought indicators, or it risks being overlooked as just another drought metric. The challenge for scientists is to formulate soil moisture information into a form that is easily understood and used by fire managers. Acceptance may be gained through a “snowball approach”, where use of soil moisture encourages acceptance, and greater acceptance encourages greater use. If available soil moisture information had been included in operational fire danger rating systems in the US, would it have resulted in earlier warning of extreme fire danger prior to the Camp Fire in 2018? Would it have helped save the lives of any of the 85 people who died from the fire? We do not know. But we know that we now have sufficient soil moisture information and adequate scientific evidence to begin using that information to improve fire danger rating systems around the world. So, let's begin.

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Figures

Fig. 1. Soil moisture conditions on 1 Nov. 2018, one week prior to the Camp Fire in northern California, the deadliest and most destructive wildfire in the state's history. The map shows the surface soil moisture anomaly as reported by NASA's SMAP satellite mission, indicating exceptionally dry soil conditions conducive to high fire danger in northern California (image: USDA NASS [Crop Condition and Soil Moisture Analytics] system).

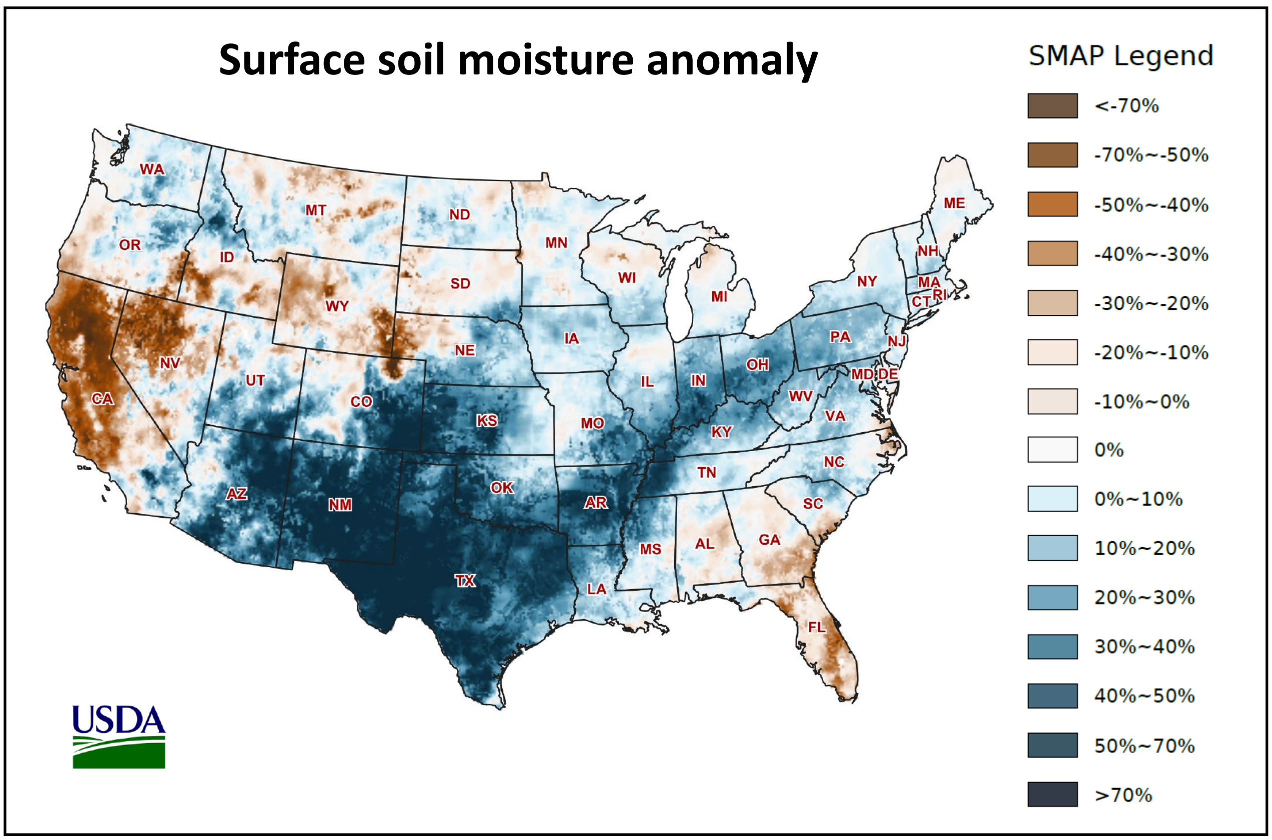

Fig. 2. Diagram of a hypothetical forest soil profile with a thick layer of organic soil or duff at the surface. The diagram approximates the relationships of the soil layers to moisture indices used in fire danger rating systems in Canada (CFFDRS), the United States (NFDRS), and Australia (AFDRS). These indices do not use measured soil moisture, account for physical properties of the soil, or directly account for impacts of overlying vegetation. Instead, moisture content is calculated using simplistic water balance approaches based on commonly measured weather variables (e.g., temperature, relative humidity, wind speed, and rainfall).

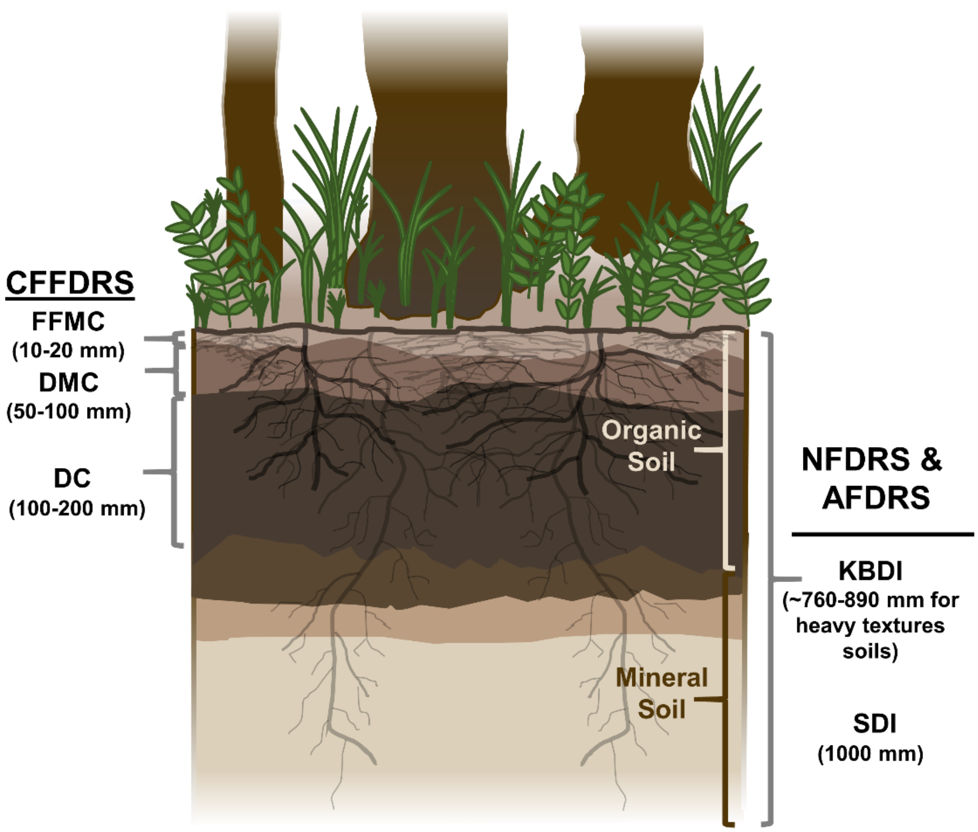

Fig. 3. A variety of in situ, remotely sensed, and modeled soil moisture data sources have been recently developed, with each having unique qualities making them well suited for wildfire danger modeling.

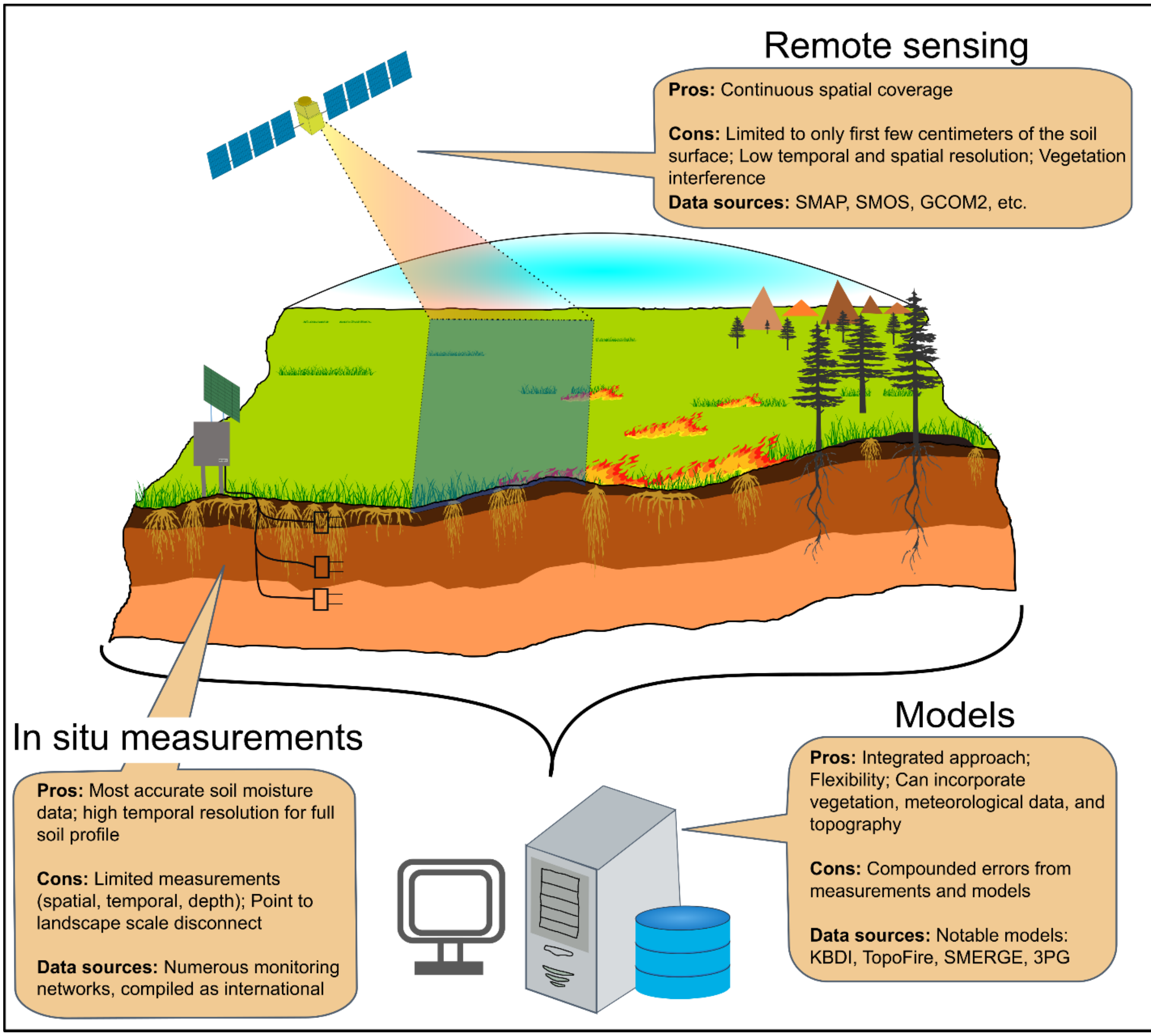

Fig. 4. PhenoCam images collected over grassland near Stillwater, Oklahoma on 2 August 2012 (left) and 6 August 2013 (right), show the influence of soil moisture on vegetation, and by extension, fire danger. The graph shows the measured fraction of available water capacity (FAW) at the image location, with colors indicating relative wildfire danger and solid circles and diamonds representing the mixed (live + dead) fuel moisture and fuel load on days the images were collected. Photo Credits: University of New Hampshire Phenocam Network (adapted from Levi et al., 2019)

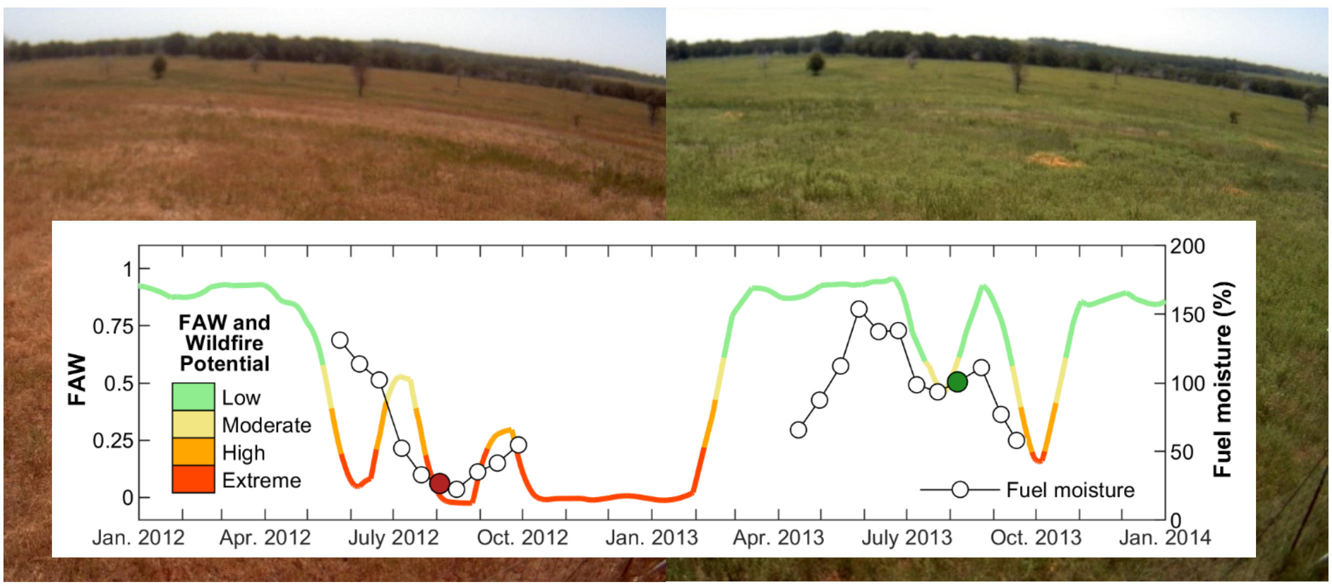

Fig. 5. Frequency distribution (histograms) and probabilistic relationship (solid black curve) between fraction of available water capacity (FAW) and large growing-season wildfires in Oklahoma from 2000–2012, adapted from Krueger et al. (2015) and Krueger et al. (2016). Subsequent research provided physical explanations and thresholds for empirical soil moisture-wildfire links (Krueger et al. 2021; Sharma et al. 2021). These thresholds describe how live grassland fuels transition to dead fuels as soil moisture declines, beginning with a drop in live fuel moisture (FAW = 0.59) followed by decreased transpiration and growth (FAW = 0.40). Next, vegetative greenness declines (FAW = 0.36), which culminates in rapid fuel curing as soil moisture conditions continue to deteriorate (FAW = 0.30).

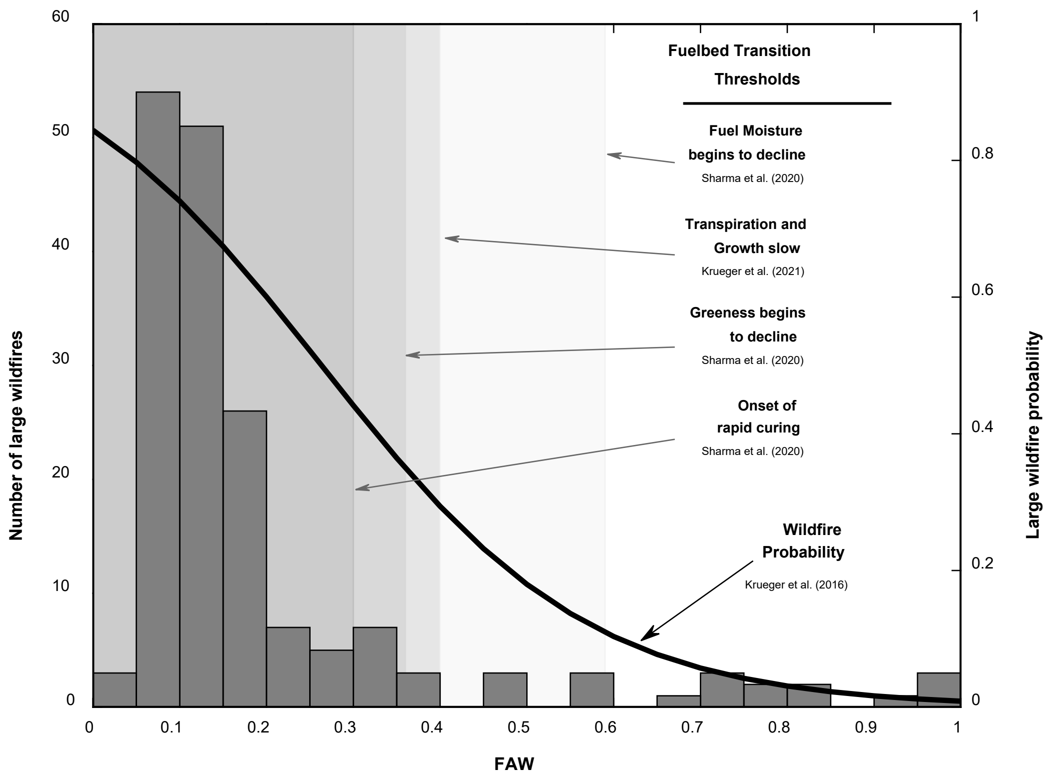

Fig. 6. Fire-soil moisture curves for different land cover types (grasses on the left, and forests on the right) in different biomes (boreal, grassland-savanna, temperate, and tropical) showing the resource and climate limits at low and high soil moisture values, respectively. The curves are derived from monthly-averaged soil moisture for the 0-5 cm soil layer from the European Space Agency Climate Change Initiative (version 4.2) and monthly fire counts from MODIS Collection 6. The area analyzed in each biome is shown on the maps in red, where this shading denotes where greater than 75% of the grid cell is a single land cover type. The area covered by grasses in temperate and tropical biomes (about 5.7 million km^2, or 13% of global grasses) and area covered by forests in grassland-savanna biomes (about 4.0 million km^2, or 11% of global forests) were excluded due to weaker statistical signal. The shape of the fire-soil moisture curves varies across land cover types and across biomes, suggesting that soil moisture may be a viable predictor of biome-scale fire danger for different land cover types (adapted from Schaefer and Magi, 2019).

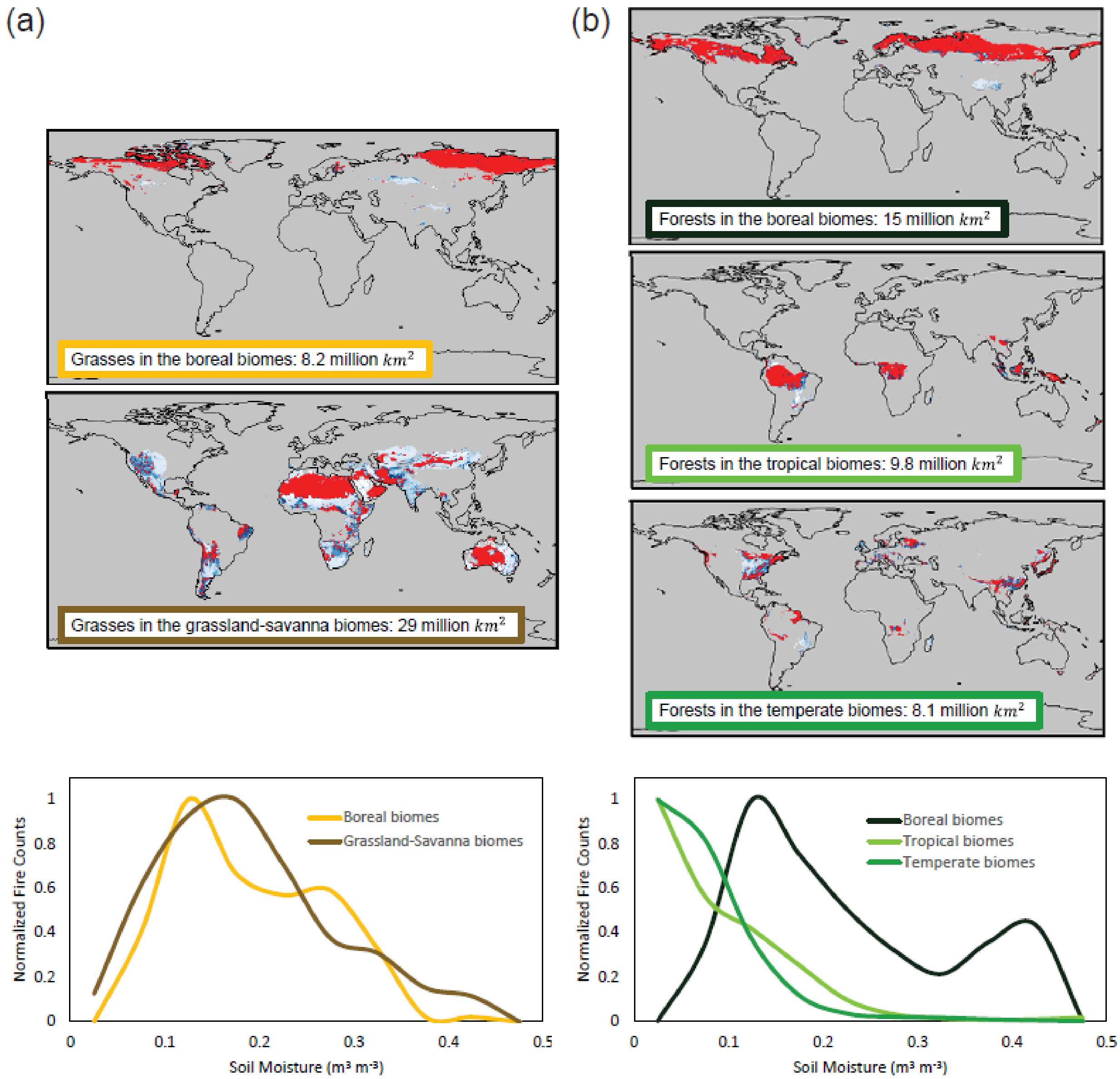
(a)
(b)
Grasses in the boreal biomes: 8.2 million km^2
Grasses in the grassland-savanna biomes: 29 million km^2
Forests in the boreal biomes: 15 million km^2
Forests in the tropical biomes: 9.8 million km^2
Forests in the temperate biomes: 8.1 million km^2
Boreal biomes
Grassland-Savanna biomes
Normalized Fire Counts
Soil Moisture (m³ m⁻³)
Boreal biomes
Tropical biomes
Temperate biomes
Normalized Fire Counts
Soil Moisture (m³ m⁻³)

Fig. 7. Example soil moisture output from TOPOFIRE for the 3 March 2019. Soil moisture maps for the conterminous United States are produced daily as part of the TOPOFIRE processing chain (Holden et al., 2019).

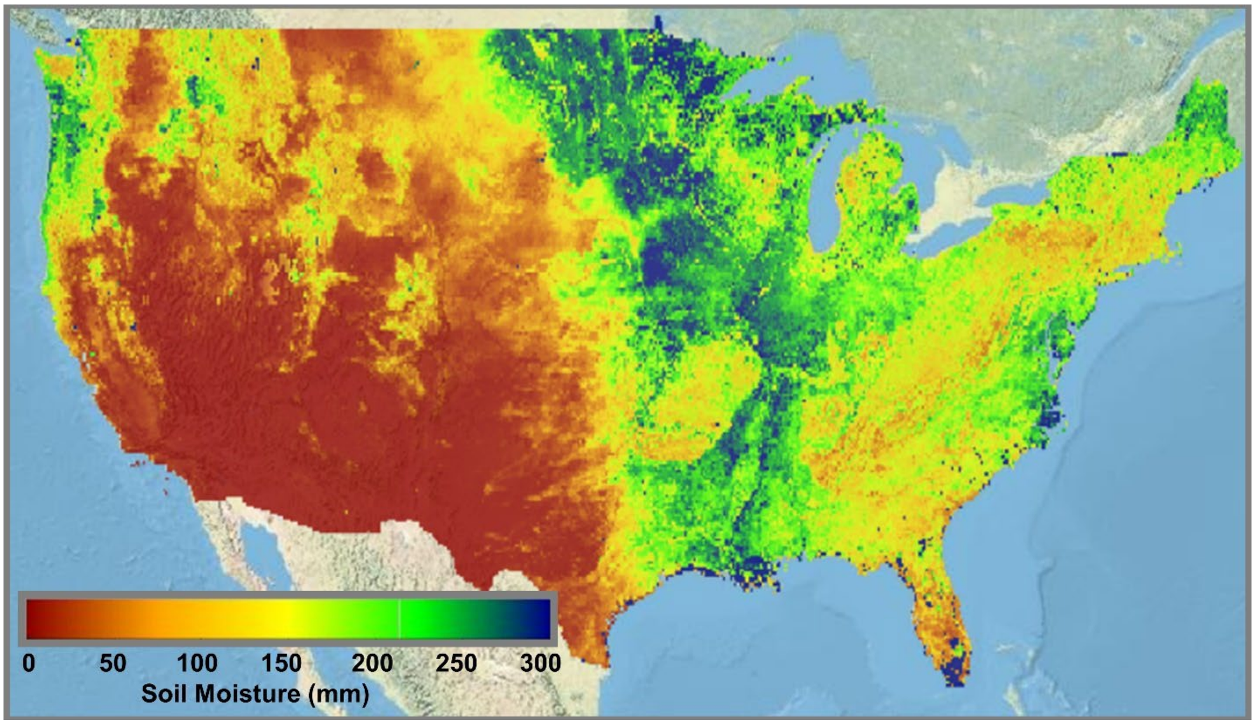

Fig. 8. Example of model predictions of wildfires (red) based on available soil water (ASW) for forested portions of western North America in 2004, along with the locations of MODIS active fire hotspots (black dots) for the same period (left panel). The right panel shows the relative importance of different seasonal functions of available soil water used to predict MODIS Active hotspot occurrence of wildfires in 2001, 2004, and 2007 (adapted from Waring and Coops, 2016).

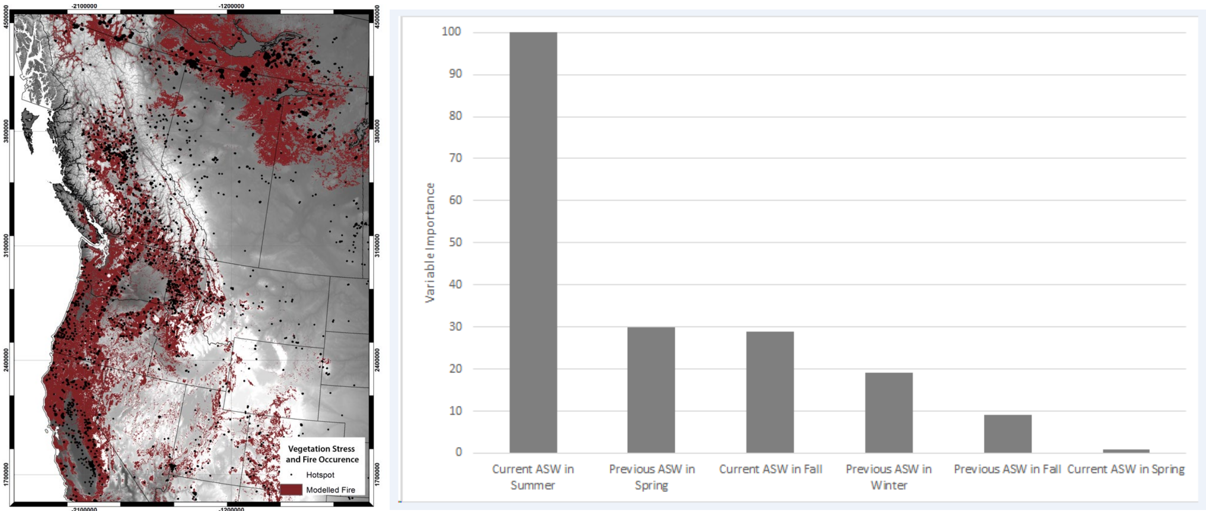

Fig. 9. Structure of the United States National Fire Dander Rating System NFDRS2016 adapted from Jolly (2018). Possible uses of soil moisture information in NFDRS2016 are numbered and in dark blue boxes, and potential downstream effects of the inclusion of soil moisture information are in light blue boxes. These potential uses include (1) supplementing or replacing KBDI, (2) live fuel moisture modeling, (3) dead fuel moisture modeling, (4) to estimate herbaceous curing, and (5) fuel load modeling.